Ultrasound-Based Methods for Thyroid Nodule Detection and Classification: A Review

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Abstract

Thyroid cancer, one of the most common endocrine malignancies, requires early and accurate diagnosis to improve patient outcomes. Recent advances in ultrasound-based techniques, including imaging protocols and computer-aided diagnostics, have significantly enhanced the detection and classification of thyroid nodules. This review explores the integration of machine learning, deep learning, and artificial intelligence in thyroid nodule diagnostics, examining their accuracy, reliability, and clinical utility. By evaluating state-of-the-art methods, including feature extraction, classification models, and segmentation approaches, the paper highlights the transformative role of technology in addressing challenges such as nodule differentiation, dataset limitations, and overdiagnosis. The findings emphasize the potential of combined clinical and computational strategies to enhance diagnostic precision, reduce unnecessary interventions, and optimize resource utilization. Future directions focus on improving dataset diversity, developing explainable AI models, and fostering collaborative, multi-center research to establish standardized protocols for thyroid nodule evaluation.

Keywords: Ultrasound imaging, thyroid cancer, machine and deep learning, diagnostic accuracy, computer-aided diagnosis.

Introduction

As an essential hormone gland, the thyroid has a significant impact on the body's growth, development, and metabolism. By continuously delivering a consistent amount of thyroid hormones into the bloodstream, it aids in the regulation of numerous bodily functions. The thyroid gland generates extra hormones when the body requires more energy in specific circumstances, such as when it is growing, cold, or pregnant. This organ, known medically as glandulathyreoidea, is located beneath the voice box at the front of the neck. It resembles a butterfly. The two side lobes are joined at the front by a thin strip of tissue and rest against and around the trachea, or windpipe. Figure 1 shows the structure of thyroid gland [29].

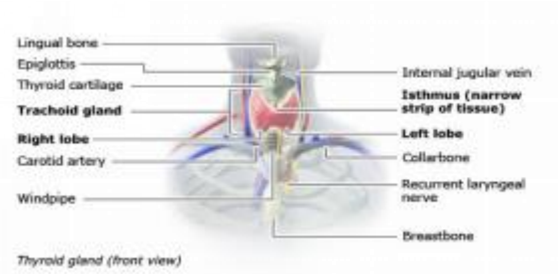

Fig. 1. Thyroid gland (front view)[29]

Thyroid cancer is a type of cancer that begins in the thyroid's tissues. Differentiated thyroid cancer, which encompasses follicular and papillary cancer, medullary thyroid cancer, and anaplastic thyroid cancer are the three primary kinds of thyroid cancer. Thyroid cancer is identified in women aged 25 to 65, those with specific genetic disorders, those with a family history of thyroid cancer, and those exposed to specific radiation types, including radiation treatments to the head or neck. At initially, it might not show any signs. Occasionally, it is discovered during a standard physical examination. As the cancer spreads, you can experience symptoms. A lump (nodule) in the neck, difficulty breathing, difficulty swallowing, pain when swallowing, hoarseness, or other vocal abnormalities that do not go away are some of the symptoms. Thyroid tests, other blood or imaging tests, a physical examination that includes looking for lumps, swelling, or anything else out of the ordinary around the neck, and a biopsy are some of the methods our healthcare provider may use to determine whether we have thyroid cancer [31].

According to endocrine pathology experts, changes in lifestyle and increased environmental contamination have been the main causes of the 25% increase in thyroid cancer cases during the previous five years. Additionally, due of their hormonal levels, women are even more likely to get thyroid cancer. Thyroid cancer risk can be raised by lifetime exposure to a variety of chemicals, heavy metals, nitrates, toxins, and radiation. Additionally, fast food disrupts the endocrine system. Radiation and iodine deficiency are two of the main causes of thyroid cancer. The 29 districts that make up Uttar Pradesh's teral belt are iodine deficient, therefore residents of these districts are more likely to get thyroid cancer. According to specialists, India ranks fourth globally and has the second-highest number of thyroid cancer patients in Asia, behind China [30].

According to George et al. [20], there are notable clusters of thyroid cancer cases close to the Thiruvananthapuram coastline region, indicating regional changes in the pattern of thyroid cancer cases. Between 2012 and 2016, a total of 1937 TC cases—1563 women and 374 men—were identified. In 25 percent of administrative units, the incidence rate was greater than 15 per 100,000 people. Of the three geographic zones, the coastal, midland, and highland regions had 56.9%, 23.9%, and 19.2% of TC cases, respectively. But only 5%, 68%, and 27%, respectively, are included in the comparable areas. According to the findings, during the 5-year period, the TC incidence rates (per 100,000 people) were 7.8–42.4 in the coastal region, 3.9–14.9 in the midland, and 6.0–15.9 in the highland. During the study period, the total incidence rate was 18.3 among women and 4.6 among males, with 57% of the 7 administrative units in the coastal area exhibiting an incidence rate >15. According to the density map, the northwest areas of the Thiruvananthapuram district are home to the majority of the administrative units with a high incidence (>15 per 100,000).

The five ultrasound features of thyroid nodules used in TI-RADS (Thyroid Imaging Reporting and Data System) are: composition, echogenicity, shape, margin and punctate echogenic foci. Each item is given points. The points are added from all categories to determine the TI-RADS level, each with a recommendation. Nodules smaller than 5 mm do not need any follow-up, even if they are TI-RADS 5. This is because it is very unlikely that nodules smaller than 5 mm will become a clinical significant malignancy. The cutoff point of 2.5 cm for fine needle aspiration (FNA) in mildly suspicious TR3 lesions is based on studies showing that thyroid carcinomas don't have a decreased survival until they reach this threshold value. Theprocess of detecting thyroid cancer using the ultrasound characteristics of thyroid nodules is summed up in Figure 2. Large studies have demonstrated a strong link between the ACR-TIRADS category and the risk of cancer. The following is the risk of cancer: [32]

TR1: 0.3 percent
TR2: 1.5%
TR3: 4.8%
TR4: 9.1%
TR5: 35 percent

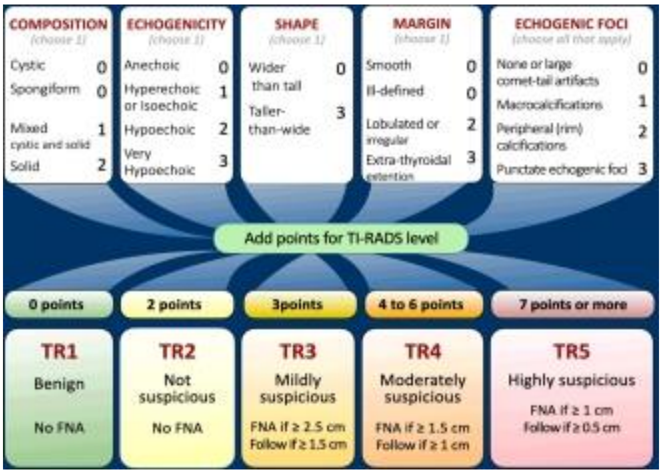

Fig. 2. Five ultrasound features of thyroid nodules [32]

Overview of Existing Frameworks

The estimates of cancer incidence in India by sex, age group, and anatomical site for 2022 were given in the Sathishkumar et al. [5] paper. Using secondary data, they conducted the study at the ICMR National Centre for Disease Informatics & Research in Bengaluru, Karnataka, India. According to their analysis, the number of cancer cases in India is projected to rise from 1.46 million in 2022 to 1.57 million in 2025. The crude rate of incidence per 100,000 people nationwide in 2022 is 100.4; for males, it is 95.6, and for females, it is 105.4. Male lung cancer and female breast cancer continue to be the most common cancer locations.

Chaganti Rajasekhar et al. [6] suggested a method that combined deep learning and machine learning models with feature selection. In addition to features derived by FFS, BFS, BiDFE, and other tree classifiers, deep learning and machine learning models are used. The findings show that, when combined with the RF model, additional tree classifier-based chosen features typically yield the best accuracy of 0.99. The data for the study was obtained from the UCI thyroid disease dataset having 9172 sample observations and each sample had 31 features. To balance the dataset, they selected 400 samples from 6771 normal category records and 200 from other categories samples having some thyroid related disease.

Shui-Boon Soh et al. [7], reviewed the highlights the importance of laboratory testing in clinical practice, covers the range of tests used in the diagnosis and treatment of thyroid problems, highlights common difficulties in their interpretation, and offers recommendations for sensible test ordering. Thyroid nodules, thyroid cancer, and hyper- and hypothyroidism all require testing in the laboratory to be properly managed. They suggested that when interpreting these kinds of tests, it is critical to be aware of the limitations and traps. When results are inconsistent, medical professionals and laboratory personnel should consider potential assay interferences or the effects of co-occurring drugs, and interpret the data in light of the specific clinical context.

The study of Haymart, Megan R et al. [18] explores how the choice of initial imaging (thyroid ultrasound vs. other methods) impacts thyroid cancer diagnosis and outcomes. Patients undergoing ultrasound are typically younger and healthier, with lower-risk cancers, leading to better survival rates but heightened cancer-related concerns. Recommendations include reducing inappropriate ultrasound use, following guidelines, and improving research on cancer overdiagnosis. Data from SEER-Medicare and propensity score analysis were used to analyze demographics, clinical factors, and survival outcomes, emphasizing the study's findings and implications for clinical practice.

In the research study of Habchi et al. [1], a thorough review of deep neural networks was provided, which highlighted the field's recent upsurge in popularity due to its higher accuracy than alternative approaches. A variety of training structures and algorithms were described along with their advantages and disadvantages. Lack of clear datasets and platforms requires careful attention in order to develop powerful and effective cancer detection algorithms that can distinguish more advanced cancers. Moreover, this study emphasizes the need for increased research efforts in the diagnosis of thyroid cancer, particularly considering the diagnostic accuracy that physicians need. Novel study possibilities in thyroid cancer detection have been opened by emerging technologies, such as explainable AI, edge computing, Reinforcement Learning, panoptic segmentation, and recommender systems.

Islam et al. [2] presented an experimental study for different machine learning algorithms: statistical classifiers, neural networking classifiers and tree-based classifiers to predict thyroid risk. They used Sick-euthyroid dataset to predict the thyroid risk. The experimental result shows that from all the algorithms, the ANN classifier performs well with an accuracy of 0.9587, the CatBoost with accuracy of 0.9538 and XGBoost with the accuracy of 0.9533. They proposed that in order to predict thyroid risk, the neural networking classification algorithms outperform other methods in terms of accuracy and F1 measure when applied to the Sick-euthyroid dataset, according to comprehensive trials and analysis.

Sharma et al. [3] used two datasets for the study – ultrasound TDID dataset, collected by Pedraza et al.[21] and published by the Universidad Nacional de Colombia in 2015 and histopathological dataset provided by Thompson et al. [22]. They extracted feature vectors from histopathological and ultrasound images using Mixer-MLP, Swin Transformer and Deit deep learning-based feature extraction techniques. They then reduced the dimensionality of the extracted feature space using six feature reduction techniques (PCA, TSVD, FastICA, ISOMAP, LLE, and UMAP). The FOX optimization algorithm handles the weighted average ensemble learning and feature selection processes. They evaluated the models proposed and examined in this work using the MEREC-TOPSIS approach. According to their research, the best model is Model21, a hybrid model that uses PCA, FOX optimization, and Swin Transformer for feature selection. On the histopathology and ultrasound datasets, this model demonstrated the best accuracy rates, coming in at 90.65% and 99.13%, respectively.

Chen D. et al. [4] used a dataset of 1480 patients and of 1558 thyroid nodules collected between Jan. 2011 and Apr. 2016. They considered different the ultrasonic characteristics such as AP/T, tumor size, solid component, micro-calcifications, hackly border, irregular shape, hypo-echogenic area, present halo, unclear border and central vascularity. They proposed that LLR together with Random Forest algorithm performs better than other methods in identifying malignancy.

For thyroid classification using ultrasound pictures, Zhao et al. [8] suggested a technique that blends CNN-extracted features with image texture features. 1874 sets of clinical ultrasonography thyroid nodule groups were gathered. As an evaluation metric, the harmonic average F-score based on precision and recall is employed. With an F-score of 92.52%, their experimental findings demonstrate that the Feature Fusion Network can differentiate between benign and malignant thyroid nodules.

The U-Net approach was applied by Rehman et al. [9] to segment ultrasound pictures of the thyroid. The VGG-16 framework is widely used in the medicine for the automatic detection and the segmentation of the thyroid nodule pictures, serves as the foundation for the deep learning model they constructed. A TDID difficult thyroid dataset with a lot of noise, hazy borders, and no calipers was used to test their approach. The experimental findings demonstrated that the suggested approach worked better than the most advanced U-Net model. With a 99% accuracy rate, the suggested segmentation network successfully separated the thyroid nodule and produced more accurate predictions.

DT Nguyen et al. [10], classified the ultrasound-based thyroid nodule images in both spatial and frequency domains using two different CNN architectures. They combined the classification results of the two CNN networks and employed a weighted binary cross-entropy loss function to address imbalanced training samples. They have used TDID dataset to proposed method providing more precise predictions for diagnosing thyroid nodule conditions, offering valuable support to doctors, especially radiologists, in clinical practice.

Aversano et al. [11] used a range of the machine learning methods to examine the data. Specifically, they were compared the results of ten different classifiers. Most of the algorithms showed promising results, especially the Extra-TreeClassifier, which attains an 84% accuracy rate. They also used a catboost classifier, which helped them achieve a 71% precision. Using SVM, Kumar identified the thyroid stage with 83.37% accuracy.

Thyroid stage was identified by V. Kumar et al. [12] using SVM with an accuracy of 83.37%. Their method is unable to separate very small cystic components, but it is able to detect thyroid nodules and cystic components from a normal thyroid gland. The Institutional Review Board approved their study, which complied with the Health Insurance Portability and Accountability Act. Every patient gave his or her written consent. The study included 234 patients, ages 57±15 years, 177 of whom were female and 57 of whom were male.

The study by Xu Ping et al. [13] introduced a novel diagnostic model for ultrasound images utilizing a combination of long- and short-term memory neural networks (LSTM) and C-LSTM. Their method is particularly focused on diagnosing thyroid contrast-enhanced ultrasound images. The comparative analysis conducted against support vector machine (SVM) and manual feature (MF) based approaches is noteworthy. The research used data of 84 patients with thyroid diseases admitted to the hospital over a span of two years. Results demonstrate that the C-LSTM model outperforms SVM and MF methods in terms of sensitivity, specificity, and accuracy, with statistically significant differences ($P < 0.05$). Additionally, the C-LSTM model showcases advantages in terms of lower parameter count and computational complexity compared to SVM and MF methods. Furthermore, within the C-LSTM model itself, there's a notable improvement in performance when compared to a modified version, C-LSTM-0, with reduced parameters and computational load, again with the statistical significance ($P < 0.05$). Overall, the study highlights the potential of the proposed C-LSTM model as an effective and efficient tool for the diagnosis of thyroid diseases through ultrasound imaging.

Zhang, Fengying et al. [14] used documented data available at the Weifang Hospital of Traditional Chinese about the ultrasound scans of 384 patients suffering solid thyroid nodules collected between Jan 2016 and Oct 2020. Based on these ultrasound scans, they used the adaptive wavelet transform-based AdaBoost algorithm (AWT-AA) classification model to detect and classify the thyroid nodules. With a 95% accuracy rate, their proposed method outperformed current thyroid nodule classification systems. Additionally, their suggested system performed better in terms of accuracy, sensitivity, and specificity than professional radiologists.

Das Debottama et al. [15] reviewed papers from 2018 to 2022 focusing on thyroid nodule detection by deep-learning techniques. They proposed that the best approach to guarantee a sizable database with a diverse range of data to train the designs was to conduct a multicenter diagnostic investigation. In order to automate the labeling process, unsupervised learning has grown in importance. An automatic labeling solution for image data can be found by using an Auto Encoder (AE) or Restricted Boltzmann Machine (RBM), which have been shown to be useful for feature extraction. Further advancements in preprocessing methods could also result in better performance.

Anari Shokofeh et al. [16] reviewed that CNN is the most popular deep learning method for thyroid cancer diagnosis. The VGG16 method is widely used for thyroid nodule classification. They have also reviewed that LSTM, GANs, and RNNs methods have been utilized in some research. Additionally, they proposed that there are insufficient public datasets for thyroid cancer imaging; as a result, it is imperative to provide consistent assessment metrics and trustworthy, easily accessible databases.

Machine learning approaches were employed by Vadhiraj, Vijay Vyas, et al. [17] to describe the ultrasound classification of thyroid lesions. They made advantage of an open-source scientific community's digital database of thyroid ultrasound images, which had 134 ultrasound images and 99 patient examinations. Of these patients, 66 had nodules categorized as malignant, and 33 had lesions classified as benign. Developing a CAD model that can distinguish between benign and malignant thyroid nodules is the goal of this research. In order to finish preparing ultrasound pictures for their study, they employed median filters. They cited the fact that the median filer is non-linear and retains important features even after eliminating noise as the explanation. Even after the original image's contrast changed, they discovered a notable decrease in noise. In order to identify the boundary of the nodule, which indicates the area of interest for feature extraction, the suggested model employed a segmentation procedure to split the image into several segments. Then, using a set threshold, they assigned values for 0 and 1 (black and white) and reduced the high-frequency noise using the Optical Character Recognition (ORC) picture enhancement technique. Two models were built in this work, one using the ANN technique and the other using SVM. According to this study, SVM achieved an accuracy score of around 96%, outperforming ANN on all performance parameters.

Lincango-Naranjo et al. [19] examined 18 studies that included 4668 thyroid cancer patients and were carried out between 1991 and 2018. With ages ranging from 18 to 89, the majority of individuals were female (76%) and had thyroid cancers of the papillary (88%) and follicular (6%), as well as other (6%), kinds. Their research demonstrates that there is a significant incidence of incident thyroid cancer in many different parts of the world. Nearly all papillary thyroid micro-carcinomas and half of all thyroid cancers discovered are accidental, indicating that incidental thyroid cancer is still a major contributor to the rise in the incidence of thyroid cancer overall. A discussion about the misuse of ultrasounds was sparked by subgroup analysis, which revealed that incidental thyroid cancer is typically tiny cancers with a slow course that are largely diagnosed by ultrasound. Interventions meant to lessen this

According to Zhu, Yi-Cheng et al. [20], the VGG-16T model demonstrated good specificity, sensitivity, and accuracy in distinguishing between benign and malignant thyroid nodules. In addition to the fully connected layers, they created a Visual Geometry Group (VGG)-16T model with extra batch normalization (BN) and dropout layers. The study's internal training, validation, and testing data set comprised 592 patients with 600 thyroid nodules, whereas the external test data set included 187 patients with 200 thyroid nodules. The VGG-16T model's sensitivity, specificity, and accuracy for the internal data set were 87.43%, 85.43%, and 86.43%, respectively. The VGG-16T model obtained an area under the curve (AUC) of 0.829 for the external data set.

According to Ou D, Yao J, et al. [23], ultrasound image characteristics can provide useful information for follicular neoplasm identification. They examined the clinical characteristics and ultrasound image characteristics of follicular thyroid cancer (FTC) and follicular thyroid adenoma (FTA). 304 patients who received care at the Zhejiang Cancer Hospital (ZJCH) between March 2009 and 2018 served as the basis for their investigation. According to their research, patients in the FTC group experienced more nodular goiter problems than those in the FTA group, and FTC patients were marginally older than FTA patients ($P = 0.003$). Age, nodular goiter conditions, nodular border conditions, internal echo, calcification, blood flow signals, TI RADS grading, and cystic solidity conditions were among the various factors taken into consideration during the ultrasound diagnosis process used to distinguish FTC and FTA. FTC is linked to calcification, poor echo, mixed nodular goiters, unclear borders, and highly categorized TI RADS.

Ghobad Azizi et Al. [24] study tested that evaluating thyroid nodule (TN) on the basis of margin irregularities and three-dimensional ultrasound (3-D-US) has a higher sensitivity and specificity than two-dimensional ultrasound (2-D-US) in distinguishing benign from malignant TNs. They used fine needle aspiration biopsy and both 2-D-US and 3-D-US for investigating 344 thyroid nodules. They categorized TNs into four groups according to how the margins appeared in 3-D-US and both multivariate and bivariate analyses were applied. In malignant TNs, 2-D-US revealed micro-calcifications and uneven margins more frequently ($p < 0.001$). The sensitivity and specificity of irregular margins on 2-D-US were 61.4% and 79.3%, respectively. The sensitivity and specificity of irregular margins on 3-D-US were 86.4% and 83.3%, respectively.

Yi-Jia Lin et al. [25] presented a deep learning framework for the automated detection and segmentation of papillary thyroid cancer (PTC) using cytological whole slide images (WSIs). The 131 digitized WSIs in the dataset include 11 ThinPrep (TP) slides and 120 thyroid fine needle aspiration (FNA) slides that have all been stained with Papanicolaou stain. A training set (21%) and a testing set (79%), respectively, are separated out of the dataset. With a remarkable accuracy of 99% for both FNA and TP slides, the methodology uses a deep learning model based on a VGG16 backbone modified for semantic segmentation. The framework processes slides up to 7.8 times quicker than the benchmark models (U-Net and SegNet) in terms of recall, accuracy, runtime efficiency and F1-score.

Nugroho et al. [26] study was based on Internal and External Characteristics of ultrasound images of thyroid nodules. The collection consists of 210 photos for external characteristics and 300 for interior characteristics, collected from 131 patients. Their methodology includes pre-processing with adaptive median and speckle reduction filters, segmentation with active contour techniques, feature extraction of geometric and texture attributes, and classification with Support Vector Machines (SVMs) for external features and Multilayer Perceptrons (MLPs) for internal features. The system achieved high accuracy rates of 97.78% for exterior and 94.44% for interior features, exhibiting a consistent performance. Its strengths include a thorough feature analysis and real clinical utility delivered through an easy-to-use interface. However, its scalability was limited by the spatially localized dataset and manual procedures used in ROI selection and segmentation.

The study of Miles Nan Xi et al. [27] introduced a machine learning framework to enhance the preoperative diagnosis of thyroid cancer using a dataset of 724 patients and 1,232 nodules. The authors employed six models, including Random Forest and Gradient Boosting Machine (GBM), to classify nodules as benign or malignant, using ultrasound features and clinical data. Random Forest exhibited the best accuracy (79.3%) and area under the curve (AUC) (85.4%), while GBM achieved the highest sensitivity (87.5%). The model significantly outperformed expert assessments, highlighting its potential as a diagnostic aid. Strengths of the study include rigorous validation through cross-validation and bootstrap analysis, and identification of important predictors like calcification and nodule composition. However, its reliance on a single dataset and the exclusion of raw image features from modeling limit its generalizability and scope.

Mourad Moustafa et al. [28] used data from the SEER database, which contains 25,063 thyroid cancer entries with 34 clinical characteristics for the study. They evaluated the data using machine learning models such as artificial neural networks (ANNs) and feature selection methods (Fisher's discriminant ratio, Kruskal-Wallis, Relief-F). Methodologically, the authors created three multilayer perceptron (MLP) models: MLP-1 (seven variables, 94.5% accuracy), MLP-2 (three variables using feature selection, 91.1%), and MLP-3 (TNM staging-based, 80.9%). Their models had high prediction accuracy and strong variable selection. However, an imbalanced dataset (97.5% living cases) and the lack of recurrence data, limits broader applicability of their model.

Conclusion

The review emphasizes how important ultrasound-based approaches are for the identification and categorization of thyroid nodules, especially when combined with sophisticated computational tools. Deep learning and machine learning have shown impressive gains in diagnostic efficiency and accuracy, providing dependable, non-invasive substitutes for conventional techniques. Nonetheless, issues including the requirement for uniform assessment measures, overfitting concerns, and the scarcity of datasets continue to exist. The creation of interpretable AI models and cooperative, multi-center research are necessary to close these gaps, gain the trust of clinicians, and guarantee broad adoption. The medical community can improve early thyroid cancer detection and individualized therapy by combining clinical knowledge with technology breakthroughs, which will ultimately improve patient outcomes.

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