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Research on Thyroid Cancer Detection and Classification Using Deep Learning over Ultrasound Images

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Abstract
The automated classification of thyroid nodules using ultrasound images is a crucial method for detecting thyroid nodules and improving diagnostic accuracy. This project aims to develop a novel model based on deep learning, specifically utilizing convolution neural network (CNNs). In the field of medical images analysis, the application of deep learning techniques has garnered significant attention for detecting and classifying thyroid cancer, particularly through the analysis of ultrasound images. This research investigates the potential of CNNs and other deep learning algorithm to enhance the precision and efficiency of thyroid cancer diagnosis. By processing benign and malignant thyroid nodules ultimately aiding in early and accurate detection, which is vital for better patient outcomes and informed technology with medical diagnostics, showcasing the significant advancements deep learning brings to the identification and classification of thyroid cancer using ultrasound imaging.

Keywords: Convolution Neural Network (CNNs), Thyroid Cancer, Ultrasound Images, and Deep Learning.

1. Introductions

Thyroid cancer, one of the most common endocrine cancers globally, represents a major health cancer. Early and accurate detection is critical for effective treatment and better patient outcomes. In recent years, the application of deep learning techniques to medical images analysis has shown great promise in enhancing the diagnosis of thyroid cancer. This study delves into the use of deep learning methods, particularly Convolutional Neural Network (CNNs), for identifying and classifying thyroid cancer, with a focus on ultrasound images.

Ultrasound imaging provides a non invasive and easily accessible approach to evaluating thyroid nodules. However, the manual interpretation of these images is heavily reliant on the radiologist's experience, often leading to inconsistencies between observers and diagnostic challenges. Deep learning, with its ability to automatically recognize intricate patterns within large datasets, offers a promising way tp overcome these issues. By utilizing the detailed information in ultrasound images, deep learning models can detect subtle features that might be overlooked by humans, offering a more reliable method for distinguishing between benign and malignant thyroid nodules.

Various machine learning approach have proposed to automatically detect and analyze thyroid nodules in ultrasound images **[1] [2]**. After selecting and reducing features, these extracted features are ultimately fed into a classifier for classification. With the rise of deep learning, particularly convolutional neural network (CNNs)**[3]**, the effectiveness of computer aided diagnosis system in diagnosing diseases from medical images has become on par with or even superior to that of radiologists[4],[5]. The size of the dataset used to train deep learning models is critically important. When a large dataset with numerous diverse instance is provide, the models performance can be greatly improved.

Deep learning algorithms utilize the enhanced computing power of graphics processing units to create large and more complex neural network capable of segmenting ultrasound images across different anatomical region **[6] [7]**. Many deep learning models can be efficiently scaled and trained on extensive datasets **[8][9]** in various domains, including natural language processing, facial recognition, and machine supported by well established pre processing techniques, contributes to their effectiveness. In the field of clinical medicine, deep learning models have also achieved impressive results.

This research seeks to explore the current literature and provide a detailed and uo-to-date review of the latest deep learning techniques used in thyroid cancer detection and classification. By thoroughly analyzing the methods, challenges, and successes in this field, the study aim to employ 12 classifications using sequential model architecture for improved accuracy in detecting thyroid cancer. Additionally, it emphasizes the crucial need to advance these techniques for earlier detection and more precise classification, ultimately enhancing patient care and management.

2. Literature Review

Corina Maria Vasile et.al [10] and colleagues have identified that various thyroid conditions, such as asymptomatic and postnatal inflammatory diseases, hyperthyroidism with pathogenic or hashimotos thyroiditis, fatal hyperthermia, asymptomatic thyroiditis, and potentially some types of neonatal thyroid disorders, are associated with autoimmune origins.

Yasaman Sharifi et.al [11] and associated explain that the thyroid gland located at the front of neck. It produces two essential hormones, T3 and T4 that regulate metabolism and development. Abnormal growth of thyroid cells can result in nodules, which are lumps that can be identified using imaging methods.

K.V Sai Sunder [12] et.al In medical imaging it is frequently observed that machine learning and deep learning algorithms are effective for analyzing images. For this particular task, the algorithms are effective for analyzing images. For this particular task, the algorithm is expected to differentiate between benign and malignant medical images, especially in the context of diagnosing cancer.

Junho Song [13] et.al thyroid nodular disease becomes more common with age and is quit prevalent. The most commonly used diagnostic technique is fine needle aspiration (FNA). However, between 59% and 85% of nodules tested by FNA are benign and do not require additional treatment. Additionally, FNA incurs considerable medical expenses potential risks.

Jianningchi [14] et.al In the last twenty years, the detection of thyroid nodules has greatly increased, often finding them incidentally. Surgical or needle biopsy methods (FNA) enable precise evaluation of whether these nodules are benign or exhibit minimal activity, which reduces patient risk and helps lower substantial medical costs.

N.Swapna Goud [15] et.al Deep learning has become prominent in clinical imaging due to its flexibility and effectiveness in managing complex tasks. This study examines various methods for analyzing small datasets to achieve significant outcomes without prior preparation. By using a simple CNN to classify thyroid ultrasound images, and avoiding any pre training or adjustments to models such as Inception-v3 or Vgg-16, we assess these approaches based on accuracy, sensitivity, and specificity in our evaluation.

This technique is the second most popular method for classifying thyroid nodules. **Zhang et.al [16]** proposed an adversarial learning based strategy for tissue detection in medical images by producing synthetic images. Their approach leverages Wasserstein GANs, deep convolutional GANs, and boundary equilibrium GANs. They reported an accuracy of 98.83% in recognizing tissues from these synthetic images.

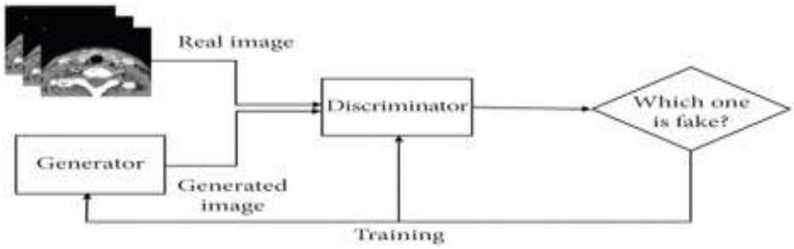

Figure 1 simple structure of the GANS model

Yang W. [17] et.al in a separate research by Yang and Qian, a semi supervised learning model was introduces that integrates domain – specific knowledge into the training of dual-path conditional GANs. They also proposed a semi-supervised support vector machine for thyroid nodule classification. Their findings indicated that this model successfully mitigates the inconsistent results often encountered with small datasets.

Zhao [18] et.al. A novel method for classifying thyroid cancer was designed, emphasizing multimodal domain adaptation. Tom manage visual inconsistencies between different data types, the researches created semantic consistency GANs and employed adversarial learning between two domains, incorporating a self attention mechanisms. The study achieved an accuracy rate of 94.30% in classifying benign and malignant nodules.

Shi [19] et.al they proposed an adversarial augmentation technique guided by domain knowledge to create medical images. This involved developing term and image encoders to capture domain expertise based on radiologists insights. Domain knowledge was used as a condition to improve the quality of thyroid nodule images and regulate the auxiliary classifier GANs. The model was tested on thyroid nodule classification from ultrasound images, achieving an accuracy of 91.46%.

In another study, **Ferreira [20]** and his team enhances the body of research by using gene expression analysis to automatically categorize tumor samples. The research aimed to formulate a method for differentiating five types of cancer thyroid, skin, stomach, breast, and lung using RNA seq datasets. They employed auto encoders to initialize weights in deep neural networks and compared the results of three distinct encoders. The findings indicated an average F1 score of 99.03 for the RNA- seq data.

Li [21] et al To classify thyroid nodules, a stacked denoising sparse auto encoder was used. The study involved developing a classifier based on immune related genes, utilizing the stacked denoting sparse auto encoder with gene expression data from thyroid nodule tissues. The results indicated an accuracy of

92.9% in distinguishing between benign and malignant thyroid nodules.

Long short term memory (LSTM) is an advanced deep learning method capable of learning sequential dependencies in prediction problems and falls under the category of recurrent neural network (RNNs). These algorithms are specifically designed to overcome the challenge of long term dependencies and retain information over extended durations. **Chen et.al [22]** and his team proposed a new approach that segmented the report into two levels: a word vector level and a sentence representation level, both of which utilized bidirectional LSTM and an attention mechanism. This approach resulted in a model with impressive performance.

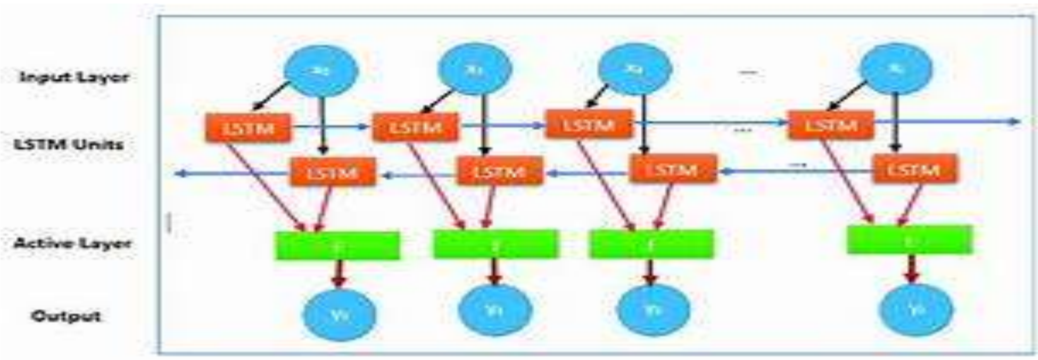

Figure 2 LSTM reorganization of thyroid cancer

Wu [23] et.al Used machine learning algorithms including Gradient Boosting Trees, k-nearest neighbors, decision trees, Naïve Bayes, logistic regression, random forests, and LSTM models on time series tumor marker data from two large asymptomatic groups, comprising 163,174 records. Among these models, the LSTM proved most effective in managing irregular data.

These algorithms address the issues encountered with training conventional deep neural networks, such as becoming stuck in local minima due to ineffective parameters, slow learning progress, and the necessity for large training datasets. The only research applying the DBN method to thyroid nodule diagnosis is by **pavitra and parthiban [24**]. They developed a novel pigeon inspired optimization method named PIO- DBN for diagnosing and classifying thyroid conditions. The PIO-DBN model reached highest accuracy rates of 98.91% and 96.28% on the thyroid datasets used for evaluation.

Begum A. M [25] et.al and associates define recurrent neural networks (RNNs) as a type of artificial neural network intended for managing sequential or time series information. Their unique characteristic is their "memory", which allows information from previous input to affect both current input and outputs. These deep learning models are frequently used for problems involving ordered or temporal sequences. In the context of thyroid cancer nodule diagnosis, a Bidirectional RNN was used to assess the likelihood of thyroid disease in patients, resulting in an accuracy of 98.72%. Furthermore, **Santillan [26]** and colleagues examined the ability to distinguish malignant from benign thyroid lesions using five different neural network methods, with the RNN model demonstrating superior performance, achieving an accuracy of 98%.

Luoyan wang [27] and colleagues introduce an innovative deep convolutional neural network (CNN) model called n-ClsNet for thyroid nodule classification. This model is composed of a multi scale classification layer, several skip blocks classification layer generates feature maps at various scales to optimize the use of image features. Subsequently, the skip blocks propagate information at different scale to capture multi scale features for classification. The HAC block is used in place of the down sampling layer to fully capture spatial information. When evaluated on the TNUI 2021 dataset, the n-ClsNet model achieved an average accuracy of 93.8% in classifying thyroid nodules, surpassing many leading state-of-the-art classification approaches.

Wang [28] et al. (2020) developed a dual attention ResNet based classification system foe the precise automatic classification of thyroid nodules. They used ResNet200 as the central network framework for this process, while recognizing that classification networks designed for natural images may not be entirely compatible with medical imaging.

Song [29] et al. (2018) developed a cascade convolutional neural network framework, which validated the effectiveness of CNNs for detecting and identifying thyroid nodules. **Zhang [30]** and his team employed a tripartite classification, module based on a CNN to extract nodule information from ultrasound images.

Ardakani [31] et al. (2018) developed a computer aided diagnosis (CAD) system based on textural and morphological characteristics to distinguish thyroid nodules in ultrasound images using a support vector machine classifier. This system divided 60 thyroid nodules (20 malignant and 40 benign) into 17*17 pixel patches, from which direction independent features were extracted through two threshold binary decomposition. These features were subsequently utilized with random forests (RF) and SVM classifiers to determine whether the nodules were malignant or benign, achieving an accuracy of 91.6%.

In a different study, **Prochazka [32] et.al (2019)** employed a histogram analysis and a segmentation based fractal texture analysis method, focusing solely on direction independent features. These features were employed in SVM and classifiers to sort nodules into malignant or benign categories. The leave one out cross validation approach showed an overall accuracy of 92.42% for RF and 94.64% for SVM. Likewise, **Lu [33] et.al (2020)** extracted images of 59 patients. They used a multi kernel support vector machine classifier with 10 linear kernels to merge features from various categories, achieving the highest accuracy of 94.44% for the subclass.

Tao Y [34] et.al in this research, fivefold cross validation was applied to the proposed deep learning (DL) models performance. The diagnostic accuracy of the mature DL model was compared to that of radiologists using the test set, and it was determined whether DL could assist radiologists in enhancing their diagnostic precision. Specificity, sensitivity, accuracy, positive predictive value, negative predictive value, and the area under the receiver operating characteristic curves (AUC) were measures, with a peak accuracy of 86.2%. The DL models based on multimodal ultrasound images performed exceptionally well in the differential ultrasound images performed exceptionally well in the differential diagnosis of suspicious thyroid nodules (TNs), significantly boosting the diagnosis effectiveness of junior radiologists and providing an objective evaluation for subsequent clinical and surgical decision making stages.

Potipimpanon P [35] et.al Ultrasonography (US) is the primary method for assessing thyroid nodules. Artificial intelligence (AL) is widely used in medical diagnostics to provide additional insights. The main purpose of this study was to gather the combined sensitivity and specificity of AL and radiologists using thyroid US imaging. Another goal was to compare ALs diagnostic performance with that of radiologists. The accuracy of AI and radiologists was similar in terms of AUC (AI 89%, radiologists 91%). Meta regression analysis found that deep learning AI had significantly higher sensitivity and specificity than traditional machine learning AI.

J. Ma, F [36] et.al we proposed a combined approach for diagnosing thyroid nodule that fuses two pre trained convolutional and fully connected layers. First, each network is separately trained using the ImageNet dataset. Then, we combine the feature maps generated by the convolutional layers, pooling and normalization of both CNNs. Ultimately, the merged feature maps are evaluated with a softmax classifier to diagnose thyroid nodules. This method was evaluated using 15000 ultrasound images gathered from two local hospitals. The results indicate that this CNN based technique is both accurate and effective for thyroid nodule diagnosis. Moreover, merging the two CNN models led to a substantial improvement in performance, with an accuracy of 83.02%. This demonstrates the potential for clinical use of this method.

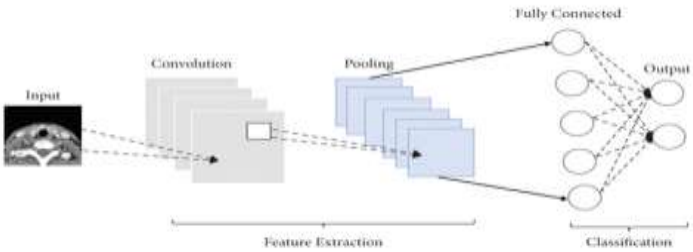

Figure 3 CNN architecture model

S. Y. Ko [37] et.al we developed a deep convolutional neural network (CNN) to identify thyroid malignancy using ultrasound (US) and compared its diagnostic accuracy with that of experienced radiologists. The CNNs were trained and evaluated using retrospective data from 439 and 150 US images, respectively. The diagnostic performance of the CNNs was compared with that of the radiologists. Out of the 589 thyroid nodules, 396 were cancerous and 193 were non cancerous. The area under the curve (AUC) for thyroid malignancy diagnosis demonstrated similar diagnostic accuracy to experienced radiologists in distinguishing thyroid malignancy on US.

J. Chi [38] et.al this research introduced a computer aided diagnosis (CAD) system for identifying thyroid nodules in ultrasound images. We utilize a deep learning approach to extract relevant features from these images. The images undergo pre processing to adjust their size and eliminate any imperfections. A pre-trained GoogleNet model is then fine tuned with these processed images, resulting in improved feature extraction. These features are analyzed using a cost sensitive random forest classifier to categorize the nodules as either “malignant” or “benign”. The results confirm that the enhanced Google Net model achieves a high classification accuracy of 98.29%.

K. J. Y. Shin [39] et.al this research was carried out to assess how effectively machine learning can distinguish between follicular adenoma and carcinoma using preoperative ultrasonography (US). The study included 252 nodules from 245 patients with follicular carcinoma. The average sensitivity, specificity, and accuracy of two experienced radiologists in differentiating follicular adenoma from carcinoma using preoperative US images were 24.0%, 84%, and 74.1% and 68%, respectively.

Jingzhe Ma [40] et.al we propose a deep learning model named YOLOv3-DMRF, which builds upon the YOLOv3 architecture. This model features a DMRF-CNN along with multiscale detection layers. The DMRF-CNN employs dilated convolutions with varying dilation rates to effectively propagate edge and texture details to deeper network layers. Additionally, two detection layers with different scale are used to identify thyroid nodules of various sizes. We trained and evaluated YOLO3-DMRF using two

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datasets, resulting in 10485 images after data augmentation. The results indicate that YOLOv3-DMRF excels compared to other models in terms of mean Average Precision (mAP) and detection time, achieving mAP and detection time scores of 90.05% and 95.23%, respectively.

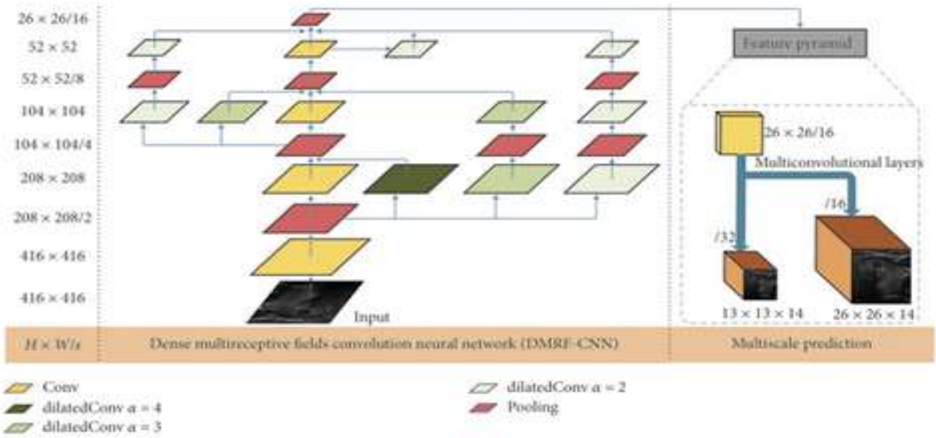

Figure 4 LOLOv3-DMRF multiscale detection layers.

L. Pedraza [41] et.al Computer aided diagnosis (CAD) system have been developed to support radiologists in detecting and diagnosing abnormalities, with numerous pattern recognition methods proposed for secondary opinions. However, these methods have been evaluated with different datasets, making their performance hard to compare. The dataset includes B-mode ultrasound images with comprehensive annotations and diagnostic details of suspicious thyroid lesions by expert radiologists. It covers a range of lesions, including thyroiditis, cystic nodules, adenomas, and thyroid cancers, with precise lesion delineation provided in XML format. The diagnosis of malignant lesions was confirmed through biopsy.

W. Song [42] et.al we have developed a multi task cascade convolutional neural network framework (MC-CNN) to utilize contexture information for thyroid nodules. This framework is based on a large collection of clinically confirmed thyroid ultrasound images with precise and detailed ground truth labels. Key benefits of our framework include its multi task cascade design, which features two stages of meticulously designed deep convolutional networks that detect and identify thyroid nodules in a layered approach, and its ability to capture diverse intrinsic features in a global yo local manner. After the initial detection, potential areas of interest are processed further by spatial pyramid augmented CNNs to integrate multi scale discrimination information for detailed thyroid recognition. The framework achieves a mean Average Precision (mAP) performance of up to 98.2% accuracy.

Xinyu Zhang [43] et.al The proposed models outperform existing statistical and machine learning approaches, achieving diagnostic accuracies of 0.989 with ultrasound images and 0.975 with computed tomography (CT) scans using the single input dual channel setup. Furthermore, a patient specific approach was developed for thyroid cancer diagnosis, achieving an accuracy of 0.95 with the double input dual channel model and 0.94 with the four channel model. Our assessment indicates that ultrasound images and CT scans deliver similar diagnostic results through computer aided systems, with ultrasound showing slightly higher accuracy, while CT scans are more effective for patient specific diagnostic designs.

M. Guo [44] et.al we proposed using a deep learning convolutional neural network (CNN) approach for the automatic classification of TUSP images and compared the performance of CNN models with different architectures. Results from the test set show that the 18 layers CNN model ResNet, performs well in the automatic classification of TUSP images, achieving an accuracy of 83.88%. This demonstrates that deep learning techniques can effectively classify TUSP images and provides a basis for the automated diagnosis of thyroid conditions.
Ko SY [45] et.al we developed a deep convolutional neural network (CNN) for identifying thyroid malignancy in ultrasound (US) images and compared its diagnostic performance with that of experience radiologists. The CNNs were trained and evaluated using a retrospective dataset consisting of 439 and 159 Us images, respectively. We assessed and compared the diagnostic accuracy of both radiologists and CNNs. The AUCs for the three CNNs were 0.845, 0.835, and 0.850. The performance of the CNNs in terms of AUC was comparable to that of the radiologists, with no significant difference observed.
Zhu Y [46] et.al in this study, transfer learning is utilized to classify thyroid nodules as malignant or benign based on ultrasound images. The pre processing step involves extracting the region of interest (ROI). Two data augmentation approaches are employed: standard augmentation techniques and a custom small convolutional network developed by us. Following dataset augmentation, a pre trained residual network is used for transfer learning, the dataset augmented with traditional methods, and the dataset augmented using our convolutional network. The highest accuracy, 93.75%, was achieved with the dataset augmented by our custom convolutional network.
Shokofeh Anari [47] et.al ultrasound imaging is widely used to detect and analyze thyroid nodules. Nevertheless, evaluated entire slide images can be time consuming and difficult for specialists. To make the evaluation of ultrasound images more efficient, there is a need for automated, reliable, and objective solutions. Recent developments in deep learning have greatly improved computer aided diagnosis (CAD) and image analysis, delivering new solutions for the evaluation of thyroid nodules. Convolutional neural networks (CNNs) are particularly focused on identifying and classifying nodules, helping to determine whether they are malignant or benign.
Li H [48] et.al In our study, we developed a detector specifically for thyroid papillary carcinoma in ultrasound images, inspired by the cutting edge object detection network faster R-CNN. To boost detection precision, we introduced a spatial constraint layer to the CNN, which helps capture features from the area around cancerous regions. By combining shallow and deep layers of the CNN, the detector improves its capability to identify smaller and more blurred cancerous regions. Our findings show that 93.5% of papillary thyroid carcinoma areas were detected automatically, while 81.5% of benign and normal tissues were successfully, excluded, all without the need for additional immunohistochemical markers or human input.
Yinghui lu et.al [49] This study outlines the process for developing forecasting systems, including feasibility and demand analysis, system design, and other preliminary development tasks. It details the functionality of the thyroid nodule prediction system and related activities like system testing. Utilizing thyroid images from a collaborating hospital as a dataset, the study employs a cyclic convolutional neural network model for training and testing in the development of a thyroid nodule prediction system. The results show that the prediction system attains a high level of accuracy.
Fatemeh Abdolali et.al [50] Our method is based on a deep learning framework that utilizes a multi task R-CNN model. We introduced a specialized loss function with regularization to focus on detection rather than segmentation. Validation was performed with 821 ultrasound images from 20 patients. The

model successfully detects various thyroid nodules. The results show that our method is effective for thyroid nodule detection, outperforming earlier state of the art methods such as Faster R-CNN and conventional mask R-CNN.

Table 1. Survey table

No	Author	Methodology	Highlight	Accuracy
51	Zaho	SSD network, ResNet 50	Employed ResNet50 as the backbone and incorporated the convolutional block attention module prior to the addition of a fire module.	94.8% 87.5%
52	Ma	SPR-Mask R-CNN: Faster-R-CNN, ResNet	A novel deep learning framework that consists of a feature extraction network, region proposal network, object detection head, and spatial pyramid RoIAlign-based segmentation head.	61.1% 82.8%, 68.5%
53	Luo	Cascade R-CNN, ResNet, feature pyramid network	We summarize the current progress on integrating medical domain knowledge into deep learning models for various tasks, such as disease diagnosis, lesion, organ and abnormality detection, lesion and organ segmentation.	60.8%, 85.9%, 68.%
54	Yang	Pre- trained VGG13,U-net to segment	Incorporating domain knowledge into both segmentation and classification task.	90.0%,
55	Wang	ResNet50, XG Boost	The AI diagnosis model showed higher diagnostic accuracy for suspicious thyroid nodules than ultrasonographers.	76.8%
56	Peng	ResNet, ResNeXt, DenseNet	ThyNet could help radiologists improve diagnostic performance and avoid unnecessary fine needle aspiration.	89.1%
57	Xu	LSTM	Enhanced ultrasound images based on the deep learning C-LSTM model can effectively improve the diagnostic effect of benign and malignant thyroid masses.	79.4%
58	Chen	Inception ResNetV2, Fully connected classifier	Thyroid Imaging Reporting and Data System (TI-RADS) was higher than that of a model trained on benign and malignant status based on surgical histopathology analysis.	91%
59	Ni	DenseNet121, ResNet50, Inception V3, LSTM	The DL model, utilizing dynamic ultrasound videos, surpasses ultrasound radiologists in differentiating thyroid nodules.	91.3%, 92%, 91.2%, 89.6%

60	Lee	VGG16,VGG19,Xception,	A deep learning-based CAD system could accurately classify cervical lymph node metastasis.	75.7%
61	Wu	Inception ResnetV2, LSTM	deep multimodal learning network relied generally more on image modalities than the data modality of clinic records when making the predictions	90%, 86%
62	Qiao	AlexNet, VGGNet, ResNet	Deep learning model are effective in evaluating thyroid scintigraphy for diagnosis	85.5%, 83.8%
63	Zhang	ResNet	The HT-CAD strategy based on CNN significantly improved the radiologists' diagnostic accuracy of HT	83.2%

3. Conclusion and Future Enhancement

The projects conclusion sows encouraging outcomes in detecting and classifying thyroid nodules. Although challenges like data scarcity and clinical validation persist, the project establishes a foundation for enhancing thyroid cancer diagnosis using deep learning. While most cases progress slowly and well differentiated, the disease can rapidly spread to adjacent tissues tissues if not diagnosed in time. Timely and precise diagnosis greatly enhances the like hood of effective treatment, resulting in a higher success rate. Current research aims to create computer aided diagnostic tools to help radiologists detect thyroid nodules more efficiently, thereby shortening critical diagnostic times. Additionally, deep learning models can be utilized to enhance and train radiologist’s skill. Studies indicate that AI greatly boosts the performance of less experienced radiologists. This paper surveys research from 2018 to 2022 previous reviews have mainly addressed the segmentation and classification of thyroid nodules, but this review centers on the detection of thyroid nodules through deep leaning techniques. While significant progress has been made in analyzing thyroid ultrasound images using deep learning techniques, current methods still face challenges like limited data, lack of accessible and validated datasets, and the absence of standardized evaluation metrics, which need to be resolved in feature research. The lack of labeled data frequently limits the use of deep learning in medical images analysis. Creating more precise DL architectures requires the collection of more extensive labeled datasets. A multicenter diagnostic study is a crucial method for compiling a broad database with varied data to train these models effectively.
Recognizing the level of malignancy in a thyroid nodule is just one part of the process; it is also crucial to ensure effective treatment and to keep track of the nodules development over time. The clarity of ultrasound images is often limited, making it difficult for doctors to trust the models results and proceed with additional diagnostic steps. Future iterations of this model could incorporate a website where individuals can upload their ultrasound images to check for thyroid issues or confirm they are in a safe range. Enhancements could focus on making the tool more user friendly for both individuals and medical facilities, while continuing to improve efficiency and accuracy in detection.

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