A Deep Learning-Based Approach for Real-Time Automated Detection of Thyroid Nodules in Ultrasound with an Out-Focus Alarm System

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Purpose or Learning Objective:

Ultrasound, known for its high sensitivity, detects thyroid nodules in up to 67% of adult examinations, underscoring its pivotal role in thyroid pathology assessment. Furthermore, nearly 50% of patients referred for thyroid ultrasound because of a previously identified nodule are found to harbor additional lesions [1]. Despite these advantages, ultrasound is inherently operator-dependent [2,3], which can lead to variability in diagnostic accuracy, particularly when examinations are performed by less experienced operators.

Most existing studies on ultrasound-based thyroid nodule detection have been retrospective,[4] concentrating predominantly on detection performance without addressing key clinical application challenges such as scanning speed and operator assistance. In this study, we propose a deep learning-based model that automates the detection of thyroid nodules in real time during clinical ultrasound examinations and incorporates an Out-Focus alarm system that assists the operators in evaluating areas that may have been missed or require further evaluation, enhancing its clinical utility.

Methods or Background:

Datasets and Ethical Considerations

For model development and internal validation, we utilized all available images from the open-source TNSCUI2020 dataset Grand Challenge dataset[5] and the MT-Small Dataset from Kaggle.[6] For external validation, thyroid ultrasound images were retrospectively collected from 498 adult patients at a tertiary hospital between January 2017 and December 2021. All external validation procedures received approval from the Institutional Review Board of Seoul National University Hospital (IRB No. H-2210-132-1373) and were conducted in strict accordance with relevant guidelines. This study was funded by the Korea Medical Device Development Fund (No. RS-2022-00141091).

Image Preprocessing

Prior to model input, all ultrasound images were preprocessed to enhance the segmentation of thyroid nodules. Standard techniques such as resizing and normalization were applied. In addition, contrast and edge enhancement algorithms were implemented to accentuate nodule features. To mitigate variability arising from different manufacturers and inconsistent DICOM tag values, a pixel histogram standardization procedure was performed to ensure uniform imaging properties across all samples.

Deep Learning Model Architecture

We employed an Attention U-Net [7] architecture for the automated segmentation of thyroid nodules. The model output, in the form of a predicted nodule mask, underwent post-processing via a morphological transformation-based approach[8] to refine the segmentation results

Out-Focus Alarm System

After the deep learning model produced a segmentation mask, an Out-Focus alarm system was implemented to determine whether the predicted mask extended beyond the image boundaries. The system defined a boundary margin along the top, bottom, left, and right edges of the image, triggering a count whenever the predicted mask exceeded this margin. The alarm system performed real-time frame-by-frame counting, and an alarm was activated when the count exceeded a predefined threshold for consecutive frames. In this study, the threshold was set to three consecutive frames, and the performance of the alarm system was evaluated across different boundary margin settings.

Results or Findings:

Model Performance

In internal validation, the deep learning model achieved a Dice Similarity Coefficient (DSC) of 86.68% at an inference speed of 8.05 frames per second (FPS) (0.124 ± 0.023 seconds per image). In the external validation cohort, the model recorded a DSC of 75.66% with an inference speed of 5.51 FPS (0.181 ± 0.011 seconds per image). Additionally, the model demonstrated a pixel accuracy of 87.71%, a sensitivity of 99.56%, and a specificity of 66.03%.

Out-Focus System Performance

Analysis of the out-focus alarm system revealed that increasing the boundary margin led to improvements in sensitivity and precision. However, specificity, overall accuracy, and negative predictive value (NPV) tended to decline with larger margins. An 8% boundary margin was identified as optimal, achieving the highest balanced accuracy of 83.06%.

Conclusion:

In conclusion, we developed an optimized real-time thyroid nodule detection model integrated with an Out-of-Focus system. This integration significantly improved the reliability of ultrasound-based detection, regardless of the operator's experience level. Our approach shows promise in standardizing the quality of thyroid ultrasound screenings across various clinical settings.

However, it is important to acknowledge the limitations of our study. Since our validation was conducted using retrospectively collected ultrasound images, future prospective evaluations in real clinical settings are necessary to fully assess the system's performance and clinical utility. Furthermore, the external validation revealed a limitation in specificity due to the composition of the two open datasets used, which consisted solely of positive cases. This imbalance in the training data led to the generation of false-positive results when the model was applied to negative images. To address this issue, additional fine-tuning with a balanced dataset including negative cases is required to improve the model's specificity and overall performance [9].

These findings highlight both the potential of AI-assisted thyroid nodule detection systems and areas for future research and improvement. Future studies should focus on incorporating a balanced dataset of both positive and negative cases to enhance the model's discriminative capabilities and clinical applicability, ultimately leading to more accurate and reliable thyroid nodule detection in diverse clinical settings [10].

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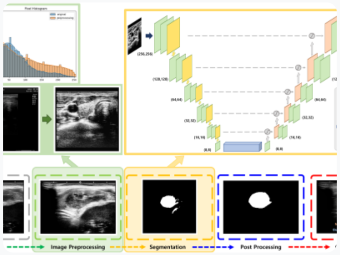

Fig 1: The Entire Process of a Deep Learning-Based Automatic Segmentation Model

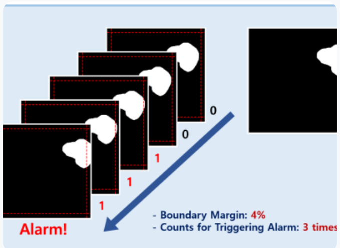

Fig 2: Example of the Out-Focus System

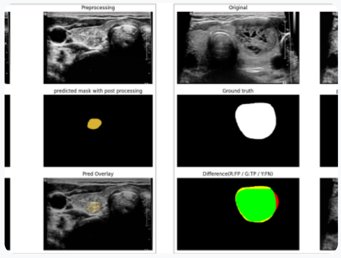

Fig 3: Visualization of prediction results using TNSCUI2020 examples

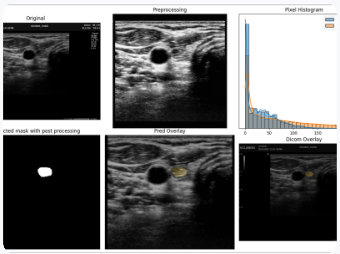

Fig 4: Visualization of prediction results using DICOM examples

Specificity(%)	PPV(%)
89.64	97.32
66.03	84.28

Table 1: Results of the Deep Learning-Based Automatic Segmentation Model

uracy(%)	Sensitivity(%)	Specificity(%)	PPV
98.60	51.32	99.61	73
98.00	57.39	99.32	73
97.48	62.35	99.11	76
97.01	67.11	99.00	81
95.12	63.10	98.57	82

percentage of margin from the top, bottom, left, and right e

Table 2: Results of the out-focus system for each boundary margin