Deep Learning for Thyroid Nodule Detection and Classification

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1. Project Background

In recent years, the occurrence of thyroid cancer has drastically increased, making early assessment of thyroid nodules progressively critical [1]. Thyroid cancer is the most frequent endocrine malignancy, with an incidence rate of approximately 14.6 per 100,000 individuals in the United States, predominantly influencing women, where it positions as the seventh most prevalent form of cancer [1]. Consequently, there is a growing requirement for trustworthy imaging methods to examine thyroid nodules, with ultrasound (US) imagery being the generally used modality because of its non-intrusive nature, cost-effectiveness, and ability to furnish detailed representations of nodule qualities like dimensions, form, and composition.

Despite its advantages, traditional ultrasound imaging faces significant difficulties. Issues like low pictorial resolution, speckle noise, and high variability in nodule visual appearance complicate the analysis of consequences [2]. The effectiveness of regular image processing techniques is regularly hampered by these factors, leading to subjective assessments that heavily depend on the radiologists' experience. This subjectivity can result in numerous benign nodules being unnecessarily analyzed, contributing to a high rate of non-diagnostic cases and amplified patient unease.

Recent innovations in deep learning (DL) have rekindled interest in the automated processing of thyroid ultrasound representations. DL strategies offer promising options for boosting the accuracy and proficiency of thyroid nodule evaluation [3]. Through automatic learning of complicated patterns, DL systems can mitigate or eliminate some challenges associated with conventional diagnosis (such as lack of expertise, human bias, time, etc.). However, there are still a great number of hurdles and constraints that must be overcome. For example, there is a scarcity of high-quality annotated thyroid ultrasound image datasets, which are necessary for training and evaluating DL systems. Additionally, the inherent variability of ultrasound images can make it difficult for DL algorithms to generalize to new instances [2]. This project aims to overcome these challenges and design a DL model to assist physicians in ultrasound imaging analysis.

2 Objectives

The goal of this project is to develop an end-to-end deep learning pipeline that can automatically detect and segment the fine-grained information about the boundaries and regions of thyroid nodules and classify their malignant risk levels directly from areas extracted from the detection process. This will be accomplished through three main technical objectives:
1. Use and train different object detection and segmentation algorithms to locate nodule boundaries. Find the algorithm that outputs the best performance
2. Use supervised machine learning methods to analyze the features extracted from the detected nodule region of interest (ROI) and classify the cancer probability according to the Ti-RADS assessment system.
3. Develop a user-friendly clinician platform to demo the automated pipeline, allowing thyroid ultrasound upload and prediction retrieval.

3 Project Methodology

3.1. Data Collection and Annotation

Approximately 500 thyroid ultrasound scans from various sources will be collected and annotated for this project. The scans will be annotated to generate nodule masks and labels, recording characteristics such as size, shape, ratio, etc.
1. The Digital Database of Thyroid Ultrasound Images (DDTI) [4]: This openly available database contains 99 cases and 134 images. Each case is presented as an XML file with the expert's annotation and patient's information.
2. Stanford AIMI Thyroid Ultrasound Cine-clip Dataset [5]: This dataset contains 167 patients with biopsy-confirmed thyroid nodules (n=192) from Stanford University Medical Center.
3. Queen Mary Hospital Dataset: In collaboration with Queen Mary Hospital, approximately 100 de-identified scans with expert annotations will be acquired.

3.2. Nodule Detection Model Development

1. Train a YOLOv10 model on thyroid nodule dataset
2. Train a Mask R-CNN model on thyroid nodule dataset
3. Analyze the performance of the YOLOv10 and Mask R-CNN model on the validation dataset. Evaluation metrics will include:
    - Average Precision (AP)
    - Intersection over Union (IoU) scores to evaluate the overlap between predicted bounding boxes and ground truth locations.
    - Precision-Recall curves to visualize the trade-off between precision and recall attained at varying confidence thresholds.
4. Monitor the above metrics during training and select the optimal model

providing the best performance.

3.3. Classification Task Development

1. Begin the classification task by designing a convolutional neural network (CNN) to classify nodules based on ACR-TIRADS risk labels [6].
2. Utilize features extracted from the segmentation masks to enhance classification performance.
3. Train the classification model and evaluate its performance using metrics such as:
   - Accuracy: To determine the overall correctness of the classifications.
   - F1 Score: To balance precision and recall for assessing model performance on imbalanced classes.

3.4. Platform Development and Integration

Frontend and Backend Development: Select the frameworks to create an intuitive user interface and handle data processing.
Database: Use a database system to store user data, uploaded images, and analysis results securely.

4 Project Schedule and Milestones

4.1 Data Preparation and Literature Review

(Sep 1, 2024 - Oct 1, 2024)
This phase will primarily involve a literature review, focusing on recent work in relevant areas and attempts to reproduce their results. Methods for each step outlined in the methodology will be selected. Additionally, image collection, annotation, and preprocessing will be completed.
Deliverables:
- Summary of the literature review
- Completed environment setup
- Data acquisition and preprocessing finalized

4.2 Train and Evaluate the YOLOv10 and Mask R-CNN Models

(Oct 2, 2024 - Nov 15, 2024)
This phase will involve training and evaluating the YOLOv10 and Mask R-CNN models, implementing a preliminary framework. Concurrently, work will proceed on drafting the interim report.
Deliverables:
- Preliminary framework implementation
- Test results for YOLOv10 and Mask R-CNN
- Draft of the interim report

4.3 Completion of the Classification Model and Performance Evaluations

(Nov 15, 2024 - Jan 15, 2024)
This phase will focus on finalizing the classification model and conducting

comprehensive performance evaluations.
Deliverables:

- Completed classification model
- Performance evaluation report with metrics and analysis

4.4 Development and Testing of the Clinician Platform for Automated Analysis

(Jan 16, 2024 - Apr 15, 2024)
This phase will involve the development and rigorous testing of the clinician platform designed for automated analysis.
Deliverables:

- Fully developed clinician platform
- Final implementation of the platform
- Comprehensive final report
- Materials for exhibition

5 Reference

[1] Vahdati S, Khosravi B, Robinson KA, Rouzrokh P, Moassefi M, Akkus Z, Erickson BJ. A Multi-View Deep Learning Model for Thyroid Nodules Detection and Characterization in Ultrasound Imaging. Bioengineering. 2024; 11(7):648. https://doi.org/10.3390/bioengineering11070648

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[3] D. Liu, K. Yang, C. Zhang, D. Xiao, and Y. Zhao, "Fully-Automatic detection and diagnosis system for thyroid nodules based on ultrasound video sequences by artificial intelligence," Journal of Multidisciplinary Healthcare, vol. Volume 17, pp. 1641–1651, Apr. 2024, doi: 10.2147/jmdh.s439629.

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[5]"Stanford AIMI shared datasets." https://stanfordaimi.azurewebsites.net/datasets/a72f2b02-7b53-4c5d-963c-d7253220bfd5

[6] B. Botz and D. Smith, "ACR Thyroid Imaging Reporting and Data System (ACR TI-RADS)," Radiopaedia.org, Apr. 2017, doi: 10.53347/rid-52374.