Deep learning-based automated Lung-RADS classification algorithm for LDCT lung cancer screening

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METHOD

▪ **Dataset**
- 1,785 LDCT (low-dose computed tomography) series were used for the development of the proposed algorithm.
- HU (Hounsfield units) normalization and resizing to 128×128×depth were performed as a pre-processing process in datasets.

▪ **Proposed Lung-RADS classification algorithm**
- The modified Faster-RCNN was trained to detect the location of lung nodules with transfer learning.
- The patches obtained using the bounding box of the detected nodules were used as input to the subsequent segmentation model.
- A segmentation model based on 3D Unet3+, including a classification-guided module, was used to classify the texture of detected nodules into 3-class (solid, ground-glass-opacity, and part-solid) and then extracted masks.
- The size of the nodule was measured through the average length of the major and minor axes in the central slice of the nodule.
- Based on Lung-RADS (lung imaging reporting and data system) version 1.1, our model calculated the RADS score considering the size and texture of the nodules, similar to radiologists' Lung-RADS score calculation method.
- For specific performance comparison and analysis, only nodules with a Dice score of 0.2 or more were evaluated, so that localization of nodules was considered.

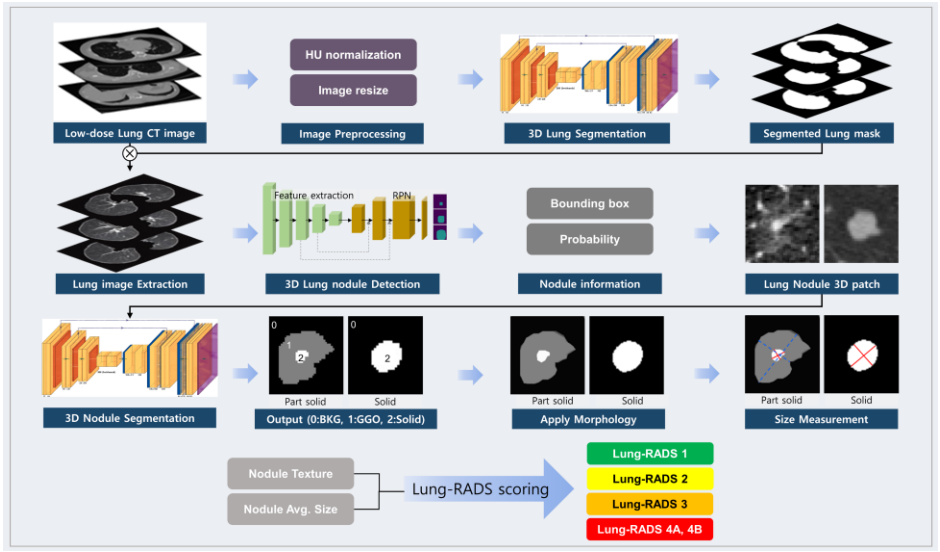

Figure 1. Overview of the proposed Lung-RADS classification algorithm

PURPOSE

▪ **Lung-RADS** is a widely adopted criterion for global lung cancer screening.
▪ However, calculating Lung-RADS is not only time-consuming due to the interpretation of hundreds of LDCT slices but also exhibits variability in classification among radiologists.
▪ We have devised a **deep learning-based automated Lung-RADS classification algorithm** to address these challenges.

RESULTS

Table 1. The results of the nodule detection model and Lung-RADS classification

		Baseline	Ours
Nodule detection	Sensitivity (95% CI)	49.02 ($46.50 \le p \le 51.52$)	67.43 ($65.02 \le p \le 69.75$)
	Specificity (95% CI)	80.67 ($72.86 \le p \le 87.55$)	91.09 ($84.32 \le p \le 95.37$)

		2	3	4A	4B
Lung-RADS classification	Accuracy (95% CI)	61.02 ($57.01 \le p \le 64.92$)	78.45 ($74.97 \le p \le 81.66$)	81.41 ($78.09 \le p \le 84.43$)	96.38 ($94.57 \le p \le 97.72$)

▪ The performance of the nodule detection model increased by **1.38** and **1.13** times in sensitivity and specificity, respectively, compared to the conventional Faster-RCNN.
▪ As a result of the Lung-RADS classification, the accuracy of each Lung-RADS 2, 3, 4A, and 4B was measured as **61.02, 78.45, 81.41,** and **96.38 %.**

CONCLUSION

▪We proposed the **automated Lung-RADS classification algorithm** consisting of two-stage models.
▪The proposed algorithm achieved **high accuracy** in obtaining Lung-RADS, particularly excelling in **categories 4A and 4B**, which are classified as malignancy.
▪The proposed algorithm is expected to be **helpful as a diagnostic aid system** for LDCT lung cancer screening.