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The Clinical use of Artificial Intelligence in the Analysis of Chest Radiographs and Computed Tomography Scans

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1. Abstract

1.1. Introduction: Computer-assisted detection (CAD) systems based on artificial intelligence (AI) utilizing convolutional neural networks (CNN) have demonstrated successful outcomes in diagnosing lung lesions in several studies. This study aims to report the clinical implication in a real clinical practice, demonstrating efficacy in commonly encountered cases and categorizing the lung nodules that they can effectively detect.

1.2. Case Presentation: Between June 1, 2022, and August 31, 2022, our hospital conducted chest X-ray and chest CT cases utilizing CAD software. Four subjects were selected as examples that could demonstrate the efficiency of CAD software. Their images and electric medical records were reviewed. They were clinically diagnosed with pneumonia, pneumothorax, and lung nodule. The program provided assistance in the diagnosis, and in one patient, it was able to detect a neglected nodule, finally confirming malignancy.

1.3. Conclusions: These commercially available CAD systems are capable of detecting variable lung lesions including a subtle nodule that may be overlooked. In the future, CAD systems have the potential to replace the workload of diagnostic radiologists and decrease labor costs.

2. Introduction

Chest plane radiography is an extensively employed for assessing a wide range of thoracic diseases. It stands out as the most prevalent modality in chest imaging, offering notable advantages such as affordability, accessibility, brief examination duration, and minimal radiation exposure. However, it necessitates expertized knowledge and attention to detail due to its single two-dimensional nature [1]. Some oversights and mistakes can lead to medical malpractice claims or even lawsuits, posing significant legal and professional consequences for healthcare providers [2]. Indeed, the reported sensitivity of chest radiographs in identifying malignant pulmonary nodules ranges from 36% to 84% [3-6], illustrating a considerable variance in diagnostic efficacy. Additionally, the substantial volume of chest radiographs poses a challenge to ensuring prompt and accurate interpretation. Due to the limitations in detecting pathological conditions on X-rays, additional computed tomography (CT) scans are often performed for the diagnosis of pulmonary diseases.

Artificial intelligence (AI) has forged notable advancements in diagnostic imaging, excelling in segmentation, detection, and disease differentiation, as well as prioritization, thereby positioning itself at the forefront of future diagnostic imaging technologies [7]. While AI can function as a decision support system—allowing radiologists to accept or reject its diagnostic recommendations, as explored in this review—it is vital to note that there is currently no AI-based device capable of autonomously diagnosing or classifying radiology findings in its entirety. A number of products aiming at radiological triage have been developed [8], allocating triage and notification of certain findings some degree of autonomy, given that no clinician is tasked to re-prioritize the algorithm's outputs. Additionally, AI algorithms could potentially be utilized to suggest treatment options grounded on disease-specific predictive factors [9], and to automatically monitor and prognosticate overall survival, thereby assisting physicians in formulating forthcoming treatment plans for patients [10]. The advent of deep learning technology has brought about significant advancements in the field, enhancing the accuracy and efficiency of chest radiographic interpretations for improved patient care.

In order to evaluate the additional benefits of employing a deep learning-based algorithm as a secondary reader, several studies have compared the performance of readers with and without CAD assistance and demonstrated that observer performance improves when aided by computer-aided diagnosis (CAD) [11, 12]. Many research studies have been conducted to advance and assess CAD systems specifically designed for chest radiography [13, 14]. In light of these challenges, substantial efforts have been invested in developing and implementing CAD systems for chest radiography. Notably, a recent study by Nam et al. [15] revealed that their deep learning–based algorithm, when employed as a secondary reader, not only significantly augmented the performance of all 18 participating physicians in detecting nodules on chest radiographs but also exhibited standalone performance that surpassed that of 15 out of the 18 physicians. Deep learning-based CAD systems have demonstrated remarkable performance and achieved results that are comparable to, or even surpassing, the capabilities of physicians in detecting a wide array of abnormalities such as nodules, tuberculosis, and pneumothorax [16, 17]. While nodules are crucial, chest radiographs also necessitate the evaluation of varied disease patterns. Recent research has explored the advantages of automated detection systems in this context. Cicero et al. [18] used a training dataset derived from chest radiograph reports, enabling their deep learning–based model to diagnose five categories of abnormalities—pulmonary edema, effusion, pneumothorax, cardiomegaly, and consolidation—with an AUC (Area Under the Curve) of 0.85–0.96. Studies by Dunnmon et al. [19] and Annarumma et al. [20] demonstrated clinically viable performance in automated classification and triaging of chest radiographs, pinpointing and categorizing multiple patterns of abnormalities. Moreover, Hwang et al. [12] exhibited that a deep learning–based algorithm not only outperformed readers in discerning chest radiographs depicting major thoracic diseases but also aided readers in enhancing their performance. Nonetheless, despite the consistently commendable performance of such algorithms, the precision in disease diagnosis lingers at an insufficient. In light of radiologists reviewing abnormal patterns identified by automatic detection systems, a practical approach might focus on learning to recognize aberrant image patterns as opposed to specific diseases.

In addition, if small lung nodules are neglected on chest X-rays or if a lung nodule is identified, further evaluation with CT may be necessary to provide a more detailed information. Recently, the introduction of Lung-RADS, suggested by American college of Radiology (ACR), has facilitated the characterization and subsequent management of lung nodules [21]. In order to mitigate variations in interpretation and discrepancies in management decisions, CAD for Lung-RADS categorization of pulmonary nodules has been suggested. It has been recognized as a valuable tool for enhancing the sensitivity of nodule detection [22]. Recent advancements in deep learning applications in medical imaging have extended beyond simple nodule detection, enabling automatic segmentation [23], classification [24], measurement of nodules, and assessment of their malignancy risk [25].

The widespread utilization of AI assisted CAD on plain radiography for thoracic imaging, alongside CT to pinpoint abnormalities, amplifies the volume of imaging cases available to adeptly train AI algorithms [26]. Not only does chest X-ray furnish voluminous data by virtue of being one of the most employed imaging modalities, but thoracic imaging also inherently bears the potential to supply an abundant dataset conducive for crafting AI algorithms. Consequently, there exists a dual potential: not only to successfully develop AI algorithms but also to ensure that AI-based devices find applicability in a substantial number of cases. Recognizing this, numerous algorithms within thoracic imaging have been forged, with one instance notably pertaining to the diagnosis of COVID-19 [27].

Artificial Intelligence (AI) has garnered notable attention in the field of diagnostic imaging research. A majority of studies have sought to validate the diagnostic capabilities of their respective AI algorithms, typically through isolated comparisons of algorithmic diagnostic accuracy to that of manual readings [28]. However, various factors seem to inhibit AI-based devices from independently diagnosing pathologies in radiology [29], and a limited subset of studies have engaged in observer tests in which the algorithm acts as a secondary or simultaneous reader in conjunction with radiologists, a context that more closely mirrors clinical settings [30]. While evaluating the diagnostic accuracy of AI-based devices on their own is possible, there's concern that such assessments may not fully represent the broader clinical ramifications of their use. This stems from the potential oversight of human-machine interactions and the subsequent human decision-making dynamics. As a result, we have explored and highlighted clinical applications of commercially available AI-assisted CAD software. Our hospital has implemented a CAD software system for both chest X-ray (Med-Chest X-Ray system, version 1.1.0.0, VUNO Inc.), and chest CT (VUNO Med-LungCT AI, v.1.0.0.17; VUNO Inc.), which has been extensively utilized for the majority of acquired images. We plan to present a series of clinically significant cases to highlight the clinical impact of CAD. These case demonstrations aim to reveal the valuable contributions brought about by the CAD system in our diagnostic and management processes.

3. Case Presentation

3.1. Case Selection: Between June 1, 2022, and August 31, 2022, our hospital has installed CAD software, which is applied to almost all chest X-rays and chest CT scans, either for clinical needs or as part of routine health care check-up. From CAD system applied dataset, we chose a few examples of patients who had been diagnosed with various conditions, including pneumonia, pneumothorax and pulmonary nodules, all detected by the software. By focusing on these selected cases, we aim to demonstrate the clinical relevance of CAD in the identification and diagnosis of these specific thoracic conditions. Written informed consent was waived due to its retrospective study design. The present case series report was deemed exempt from ethical review by the institutional review board, adhering to the ethical guidelines for medical studies.

3.2. Imaging Techniques: Chest CT scans were acquired using multidetector-row scanners from two vendors (GE Healthcare, Milwaukee, USA; Siemens Medical Solutions, Erlangen, Germany). The parameters were as follows: 120 kVp, 100–400 mA, Images were reconstructed with section thickness of 2.5 mm and interval of 2 mm, section thickness of 2 mm and interval of 2 mm. Images were reconstructed in axial, coronal, and sagittal planes.

3.3. CAD Software: The deep learning-based detection system used for analyzing simple plane radiograph was a Med-Chest X-Ray system (version 1.1.0.0, VUNO). This software was developed using a dataset of 15,809 chest X-rays, sourced from two tertiary hospitals. The collection included 7,204 normal and 8,605 abnormal images, which featured various conditions such as nodules/masses, interstitial opacity, pleural effusion, and pneumothorax [17]. This system exhibits high sensitivity and specificity, marking the location of lesions on the input chest X-rays and indicating their probability and disease type. This software has been commercially available in South Korea since July 2019 and in Europe since June 2020. The deep learning–based software for chest CT (VUNO Med-LungCT AI, v.1.0.0.17; VUNO Inc.) was applied for the Lung-RADS categorization of nodules on chest CT. This software was created using Convolutional Neural Network (CNN)-based Super-Resolution (SR) algorithms applied to CT scans of 100 pathologically confirmed lung cancers [31]. After the detection of nodules, a segmentation-based analysis was performed to determine the type of nodules and measure their size. Subsequently, all identified nodules were prioritized based on their Lung-RADS categories. A window displaying the nodule list based on the CAD results was shown below the CT. This list provided information for CAD-detected nodules, including their location, nodule type, two-dimensional diameters, average diameter of the nodule and its solid component, as well as their corresponding Lung-RADS category (Figure 1).

3.4. Image Analysis : A chest radiologist with 22 years of experience carefully determined clinically significant subjects from the dataset available in the hospital's PACS system. Two readers with 9 years of experience in radiology independently reviewed the plane radiographs and CT scans of the selected cases. The final diagnoses were determined through a consensus reached by considering the findings from the CT scans, X-rays, electric medical record and the assistance provided by CAD.

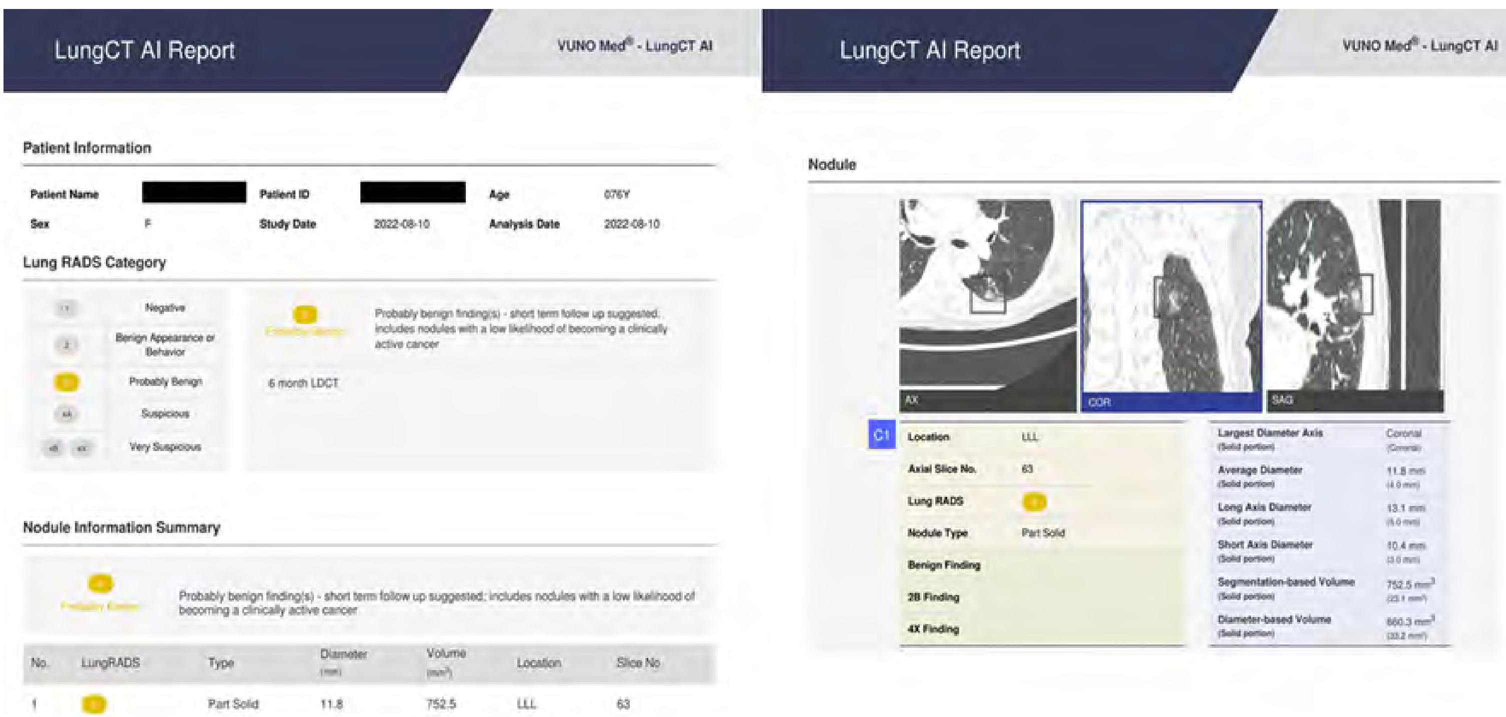

Figure 1: Lung Rads radiologic report written by VUNO Med-LungCT

4. Results

(Table 1) shows the demographic and characteristics of 4 patients. All of the patients were male. Two of them complained of dyspnea, while the other two did not exhibit any specific symptoms related to the lung conditions. In both case 1 and case 2, the AI-assisted CAD software promptly and accurately identified common lung diseases from plain radiographs. This timely detection facilitated immediate medical treatment and interventions, ensuring prompt attention from clinicians. For case 3, the software rapidly and efficiently analyzed an incidentally discovered pulmonary nodule. It immediately provided details on its size, volume, and potential malignancy risk as indicated by the Lung-RADS category. In case 4, the patient had a previously overlooked small nodule on a CT scan conducted two years ago and his final diagnosis was lung cancer.

Table 1: Characteristics of patients

Case Number	Sex	Age(years-old)	Chief complaint	Diagnoses
1	male	27	Dyspnea, fever	Pneumonia
2	male	26	Dyspnea	Pneumothorax.
3	male	67	Incidental finding	Lung RADS 4a pulmonary nodule
4	male	70	Health check up	NSCLC

5. Discussion

In ordinary clinical settings, encountering patients complaining dyspnea is not uncommon situation. As a fundamental investigation, chest X ray is usually performed to assess such cases. However, there are instances where immediate management is necessary, yet the prompt radiological interpretations by expertized radiologists may not be readily available. Moreover, inexperienced physicians run the risk of overlooking conditions that require urgent management or hospitalization. After identifying potential lung diseases via X-ray or for screening purposes, chest CT is a commonly used diagnostic tool. However, the expert reading process following the radiologic scan often raises concerns about time and cost consumption. In the case of patient 1, he presented with dyspnea and fever, and showed prominent consolidation on the simple plane radiograph. VUNO-med software detected the consolidation effectively with a 99% probability, and it was confirmed to be pneumonia caused by concurrent infection of Streptococcus pneumoniae and COVID-19 (Figure 2). However, for Patient 2, who presented with dyspnea but no other specific symptoms, the CAD software detected pneumothorax with a 99% probability and pleural effusion with a 26% probability (Figure 3). Without conducting inspiration and expiration X-rays or chest CT scans, inexperienced physicians run the risk of failing to identify the underlying cause. CAD systems that quickly highlight lung lesions with high sensitivity immediately after imaging, whether in outpatient or emergency settings, become crucial tools to ensure timely actions are not missed for both physicians and patients.

In the clinical setting of South Korea, when patients are admitted for treatment due to various conditions, a chest X-ray is commonly performed as a basic examination to assess underlying diseases. In the case of patient 3, a pulmonary nodule was incidentally discovered during this admission process. To evaluate the observed nodule on the chest X-ray, a CT scan was conducted and analyzed using CAD. The software automatically and rapidly diagnosed the Lung-RADS category along with the diameter, characteristics, volume, and location of the pulmonary nodule (Figure 4). Moreover, the assistance provided by CAD software greatly aids in preventing neglected lung nodules. In the case of patient 4, who was undergoing regular health check-up CT scans every two years, a lung nodule (category 4a) was detected for the first time through CAD analysis. Comparing it with the CT scan from two years ago, it was observed that the size of the previously neglected tiny nodule had increased (Figure 5a, 5c). Through consensus made by readers, it was evaluated as Lung RADS category 4b, and subsequent wedge resection confirmed the pathology to be adenocarcinoma.

Beyond identifying nodules or lung diseases, deep learning algorithms applied on chest CT showed exceptional efficiency in measuring lung nodules. Since the eighth edition of the TNM lung cancer staging system was introduced, tumor size focuses on the invasive component at pathological evaluation, excluding the lepidic growth component [32]. Given this, assessing the size of the solid portion in CT images becomes crucial, especially for subsolid lesions with ground-glass opacity. The solid portion's size on CT aligns well with the pathologically evaluated invasive component size [33] and is indicative of the prognosis [34]. Thus, recent guidelines for managing lung nodules rely on both the size of the solid on CT images [35]. Conventionally, radiologists manually measure the solid portion size. Yet, achieving accurate and consistent measurements is tough due to observer variability [36]. Some research has explored semiautomated measurement methods to reduce this variability, using various Hounsfield unit thresholds [37]. These methods have shown reduced variability and better alignment with pathological measurements than manual methods [38]. However, semiautomated methods aren't without flaws for clinical use. Presently, solid portion segmentation isn't accurate enough, often necessitating manual corrections. In our cases, AI-assisted CAD provided immediate and accurate measurements of the nodule, simultaneously displaying its long and short diameters as well as its volumetric measurement. (Figure 5b).

Although not quantitatively included in this study, previous reports have indicated that evaluations of deep learning-based chest plane radiography minimize bias and improve diagnostic performance [39]. The performance of the readers was consistently improved with the support of the deep learning-based CAD system, irrespective of their level of experience. However, in terms of per-lesion sensitivity, the increment for thoracic radiologists was relatively smaller and not statistically significant. This could be attributed to their already high-performance during observer-alone sessions and their greater confidence in decision-making, leading to less noticeable changes with the assistance of the CAD system. The reduced reading time for all readers further enhances the performance benefits of the deep learning-based CAD system support. Other previous studies evaluating chest radiography CAD have also assessed reading time as an important factor [40]. Several studies on AI-assisted radiology produces mixed findings based on physicians' experience. Some studies show that less experienced physicians benefit more from AI assistance [39, 41, 42]. In contrast, others found greater benefits for more experienced radiologists [43, 44]. Gaube et al. [45] observed that less experienced physicians tend to more readily accept AI's advice, suggesting that reluctance to use AI was not due to distrust but rather confidence in their own skills. Oda et al. [43] discovered that less experienced physicians didn't necessarily benefit from AI. They proposed two explanations: The variability in diagnostic performance among less experienced radiologists led to inconclusive statistical results—a point also raised by Fukushima et al. [44]. AI tends to reduce false negatives more than false positives, and less experienced radiologists often have more false positives. However, Nam et al. [15] indicated that less experienced physicians were more prone to adjusting their false-negative diagnoses with AI, thereby benefiting more. Nam et al. emphasized the significance of addressing false-negative findings for reducing radiological errors. Despite differing views on which experience level benefits most from AI, a consistent observation from Oda et al, Nam et al., and Gaube et al. is that AI effectively reduces false-negative findings, reinforcing the push for its broader clinical adoption.

For AI-based devices to be valid in diagnostic imaging, they must surpass the accuracy of their intended human users. This is essential because less experienced observers may be swayed by incorrect advice due to availability bias [46] and premature closure [47]. To incorporate more studies, we accepted variations in AI performance due to different algorithms, recognizing this as a limitation that adds to our review's heterogeneity. We didn't evaluate the AI algorithms' standalone diagnostic performance or inspect their training and test datasets. There's a potential publication bias as studies might favor high-performing AI algorithms. For successful implementation, users must exhibit enhanced performance. Several studies centered on observer tests in controlled settings to minimize biases. Yet, there are limited clinical trials on AI-based devices in real-world clinical environments [48]. Notably, no trials exist for AI devices with thoracic CT or chest X-rays, whether standalone or assisting humans [49]. AI can beneficially support physicians as supplementary readers. Further research is crucial to understand AI's influence on decision-making and its integration into realistic clinical scenarios.

While the cases presented in this study demonstrated the practical benefits of a deep learning-based CAD system through common clinical scenarios, there are limitations to the two CAD software programs designed for plain radiographs and CT scans. Firstly, there are numerous diseases that can be detected using these two imaging modalities. However, Med-Chest X-Ray is only capable of describing five types of detection algorithms (consolidation, nodule, pneumothorax, pleural effusion, interstitial opacity). Important findings such as cardiomegaly, pneumoperitoneum, and pneumomediastinum are not designed to be detected by this program. Additionally, VUNO Med-lung CT is limited in its ability to recognize tuberculosis or mediastinal disease. Nevertheless, improving reading time, sensitivity and detection rate in the interpretation of chest imaging has the greatest clinical impact. Therefore, CAD-aided lung evaluation is expected to contribute significantly to enhancing diagnostic efficiency and accuracy, thereby making a substantial contribution to clinical outcomes

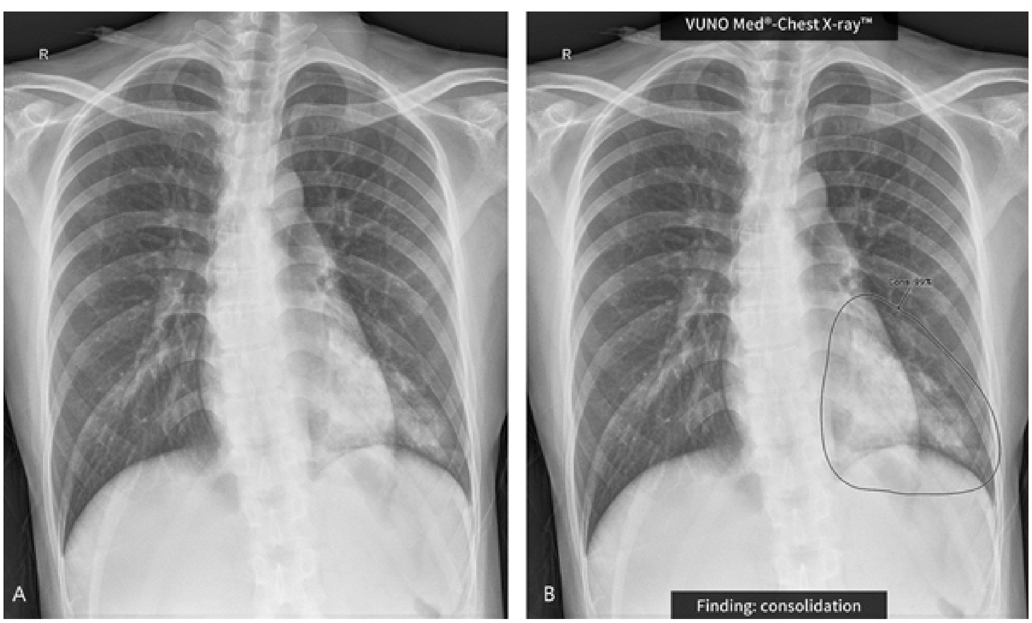

Figure 2: Case 1 patient with pneumonia with concurrent infection of S. pneumonia and COVID-19(A). Clear and prompt delineation of consolidation area with 99% probability after VUNO-med software application(B).

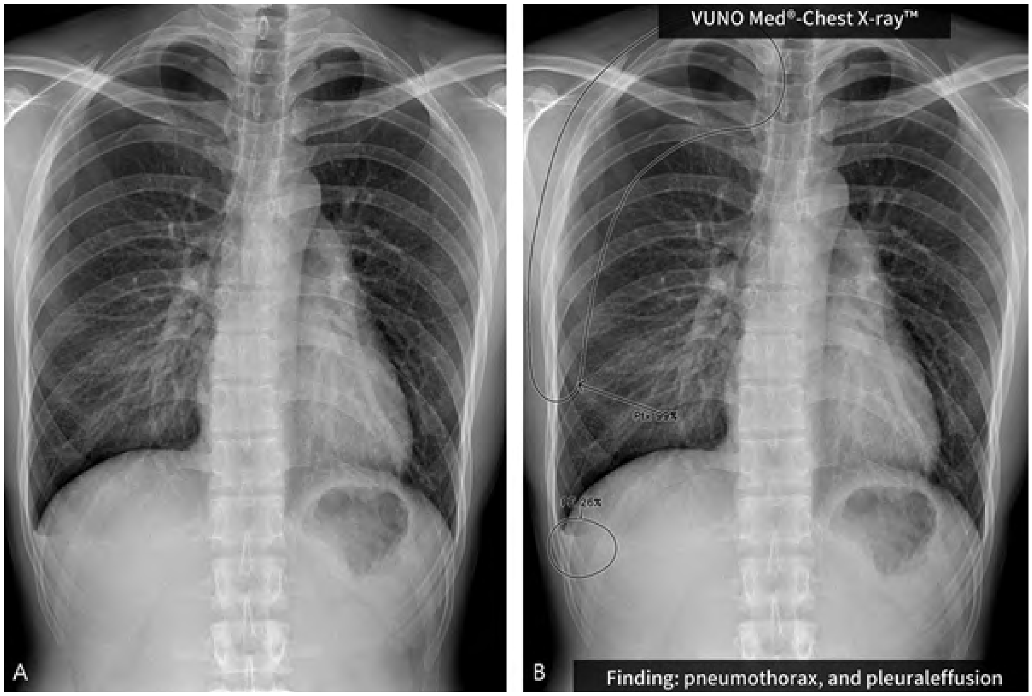

Figure 3: Case 2 patient with pneumothorax(A). Med-Chest X-Ray system delineates apparent appearance of pneumothorax with suggested 99% probability(B).

Figure 4: Case 3 patients who had acute alcoholic hepatitis without pulmonary symptom. An incidentally found lung nodule(arrow) was analyzed by CAD software. In the follow-up observation after the patient refused tissue biopsy, no significant change in the size was observed.

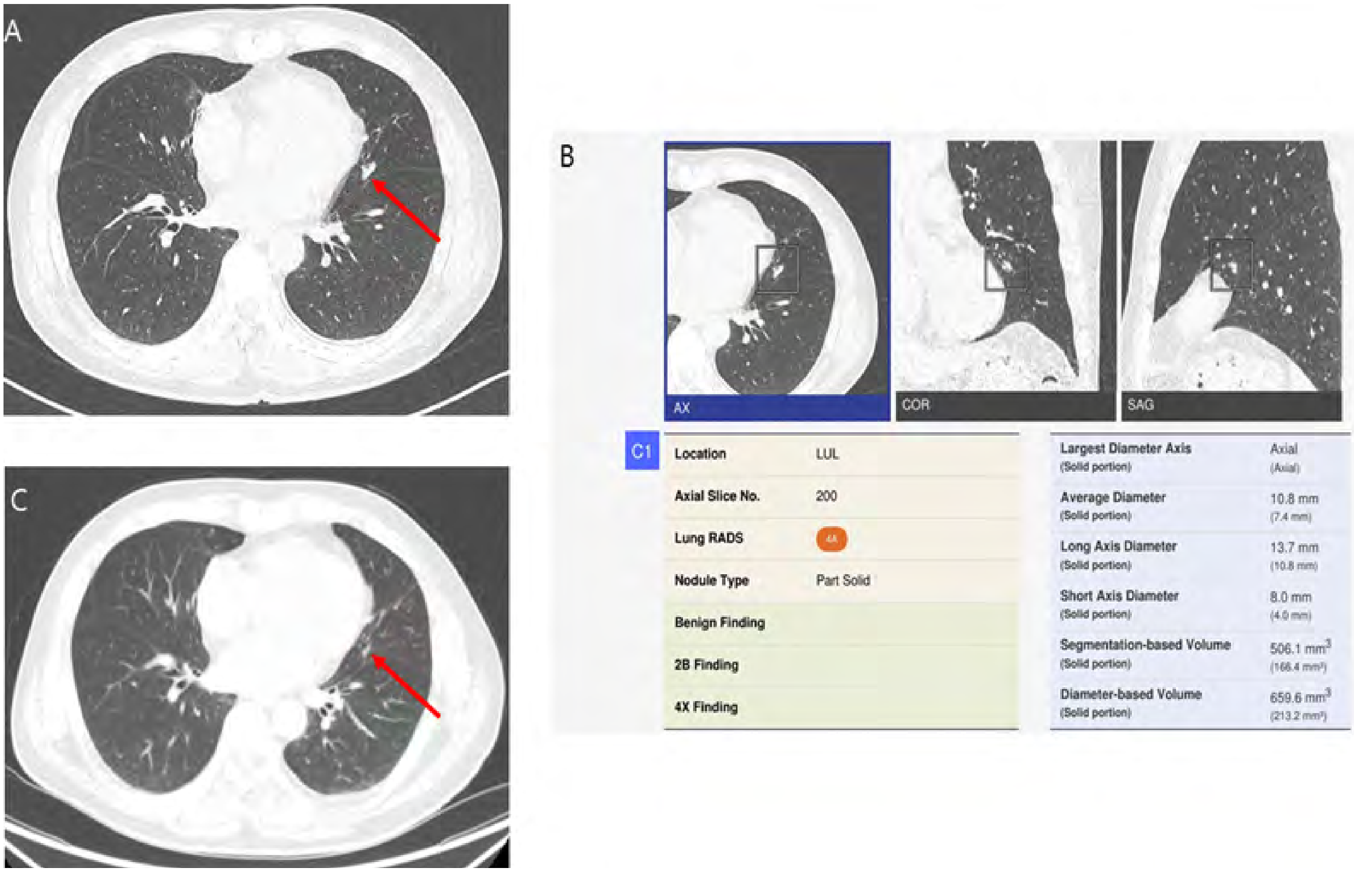

Figure 5: In the case of patient 4, A lung nodule in the left upper lobe (LUL) was observed(A) and analyzed using CAD software(B). This nodule was overlooked in a CT scan conducted two years ago(C), which was performed without the assistance of CAD software. Since then, it has shown an increase in size. Subsequent surgical pathology confirmed the diagnosis of adenocarcinoma.

6. Conclusion

We showed four patients with commonly encountered lung diseases, demonstrating the clinically significant impact by the deep learning-based CAD software installed in our hospital. This commercially available CAD systems can detect a range of lung lesions, including subtle nodules that might go unnoticed, while enhancing reading efficiency. In the future, these systems could potentially take over a significant portion of diagnostic radiologists' workload, leading to reduced labor costs.

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