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Review Article

Integration of Artificial Intelligence into Chest Computed Tomography

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Abstract: The integration of Artificial Intelligence (AI) in radiology, especially for chest computed tomography (CT) scan analysis, marked a significant advancement in medical diagnostics, aiming to improve patient care and streamline the workflow for radiologists. This review article examined the role of current AI technologies, including machine learning (ML), deep learning (DL), convolutional neural networks (CNN), and radiomics, in enhancing the detection and characterisation of lung diseases. These technologies are instrumental in identifying complex patterns within imaging data and constructing more informed decisions regarding disease severity, progression, and potential treatment options. Deep learning and CNN have demonstrated effectiveness in analysing the intricate details present in chest CT scans, offering a high degree of accuracy. Radiomics complements these methods by extracting quantitative features from medical images, providing deeper insights into disease characteristics that are not visible through standard imaging techniques. The application of AI has shown promise in improving the diagnosis and management of interstitial lung diseases and lung cancers, contributing to the development of personalised treatment plans. However, this review also highlights limitations, such as small sample sizes in studies, which may impact the generalisability of AI applications in this field. Despite these challenges, the ongoing incorporation of AI into radiological practices is anticipated to significantly enhance the accuracy and efficiency of lung disease diagnostics, setting a foundation for future research and improvements in clinical practice.

Keywords: Radiology, respiratory, artificial intelligence, machine learning, deep learning, convolutional neural networks, radiomics.

INTRODUCTION

Artificial intelligence (AI) is the engineering and deployment of computational frameworks that emulate human cognitive functions by integrating computation methodologies including machine learning (ML), deep learning (DL) and convolutional neural network (CNN) (Saba *et al.*, 2019). In recent years, there has been increasing research into the integration of artificial intelligence into the imaging chain and radiology reporting process, with the goals of improving patient care and radiologist workflow (Hanada *et al.*, 2022. Gandhi *et al.*, 2023. Cobo *et al.*, 2023). These improvements were achieved through the ability of AI to identify subtle and complex nodule or interstitial patterns in imaging data, which provided insights into disease severity and progression. As a result, the patient received earlier intervention, personalised treatment plans, and ultimately, better lung oncological outcomes (Avanzo *et al.*, 2020).

Machine Learning

Machine learning is a subset of artificial intelligence focused on developing systems that learn from data, identify patterns, and make decisions with minimal human intervention. This involved algorithms and statistical models that allowed computers to perform specific tasks by generalising from trained models. Machine learning is categorised into supervised and unsupervised learning. In supervised machine learning, the model learnt from a dataset that included both the inputs and the desired outputs. Whereas in unsupervised learning, the datasets do not have labelled responses and the model identified inherent patterns (Saba *et al.*, 2019).

Deep Learning

Deep learning is a subset of machine learning that mimics the human brain in processing data and creating patterns for use in decision-making (Saba *et al.*, 2019). This utilised artificial neural networks with multiple layers that allowed the model to learn from unstructured data. Likewise, deep learning algorithms can learn and improve from experience with minimal human input. This enabled deep learning models to

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handle complex tasks such as image recognition in radiology.

Convolutional Neural Network

A convolutional neural network (CNN) is a class of deep learning algorithms primarily used in processing structured array data. CNN simulated the biological processes of the visual cortex in recognising patterns and structures in radiological images. One or multiple convolutional layers adaptively learn spatial hierarchies of features of lung disease pathology (Saba *et al.*, 2019). These layers involved learnable filters that scan the image to capture specific features of lung nodules or interstitial changes and identify pathology by comparing images to the training model. This enabled the algorithm to have visual perception or "computer vision" (Escotta *et al.*, 2022). CNN can be integrated into radiomics to extract large amounts of quantitative features from medical images using data-characterisation algorithms. Radiomics attempts to uncover disease characteristics, such as shape, intensity, texture and surrounding environment, that are difficult or impossible to detect through standard image interpretation. Consequently, radiomics allowed radiologists to gain a comprehensive understanding of tumour behaviour, and disease progression and predict response to treatment outcomes. Radiomics is comprised of several steps, starting with image acquisition and followed by image segmentation; identifying a region of interest, feature extraction; applying filters to extract features of the disease and analysis; prediction is made about patient outcomes or response to therapy (Papanikolaou *et al.*, 2020).

Computer Vision

Computer vision utilises deep learning algorithms and convolutional neural networks to analyse images of chest CT (Choi *et al.*, 2022). The algorithm employed multiple filters to process images, detecting and learning different features by systematically scanning the entire image. A filter, moving across the image from left to right and top to bottom, is used to search for specific patterns. When a feature matching the filter's pattern is found, it is recorded in a feature map (Iglesias *et al.*, 2021).

Notable algorithms included AlexNet and ResNet. In 2012, AlexNet a DL algorithm won the ImageNet Large Scale Visual Recognition Challenge, it demonstrated a 61% improvement in error rate compared to the previous year's winning algorithm (Chassagnon *et al.*, 2023). Additionally, in 2015, ResNet the winning algorithm of the competition achieved an impressive error rate of 3.6%, surpassing human-level performance (Hwang *et al.*, 2020). Scalable Open Framework for Integrated Analysis (SOFIA) is a framework designed for integrated analysis, used in radiology to manage and analyse imaging data, particularly assessing fibrotic lung disease patterns in HRCT (Walsh *et al.*, 2022). In 2022, a study performed by Walsh *et al.*, assessed the SOFIA-PIOPED deep learning algorithm's prognostic utility in forecasting transplant-free survival for patients with fibrotic lung disease, using a dataset from a national IPF registry. The algorithm, designed to detect UIP-like features from HRCT scans, was tested on a novel imaging dataset from various institutions, showing uniform prognostic significance across different patient subgroups, regardless of the CT pattern or underlying disease cause. Specifically, the SOFIA-PIOPED UIP probability categories were the only predictors of transplant-free survival in bivariable analysis with radiologist PIOPED UIP probability categories (Hazard Ratio [HR], 1.45; P < 0.0001; 95% Confidence Interval [CI], 1.33–1.59) and remained significant when adjusted for total interstitial lung disease (ILD) extent (HR, 1.31; P < 0.0001; 95% CI, 1.19–1.44). In multivariable analysis adjusting for age, sex, and total ILD extent, these categories persisted as significant predictors. Adjustments for disease severity measures, including percent predicted Forced Vital Capacity (FVC), Diffusing Capacity for Carbon Monoxide (DlCO), composite physiologic index, and gender-age-physiology stage, did not alter the outcome, emphasising the algorithm's robust prognostic capability. The goal of computer vision is to enhance diagnostic accuracy and provide objective assessments of fibrotic lung diseases, such as idiopathic pulmonary fibrosis (IPF), by identifying patterns.

Deep Learning Image Reconstruction

Deep learning algorithms are being employed in reconstruction methods of ultra-low dose CT (ULD-CT) chest imaging to overcome image noise associated with traditional methods. The absorbed doses of low-dose CT scans are 1-2 mSv and use iterative reconstruction which significantly lowers image noise and enhances over image quality compared to filtered back projection. Whereas ULD CT reduces radiation levels to 0.13-0.49 mSv while utilising DLIR. This is comparable to single chest radiography which the dose ranges 0.03-0.1mSv. Jiang *et al.*, 2022 demonstrated deep learning image reconstruction (DLIR) performed better than adaptive statistical iterative reconstruction-V (ASIR-V) in noise levels, lung nodule detection rates, and measurement accuracy. DLIR showed the lowest noise at 51 HU ± 4, achieving a 13.8% noise reduction from the baseline of filtered back projection (FBP) level. This surpassed ASIR-V-80% noise reduction of 11.3% from the baseline of FBP level. Likewise, the air background noise was lowest for DLIR-H reduction of 34.7% which greater reduction than ASIR-V-80% (16.6% [P > .001]), and nearly matching the CECT level's noise reduction (36.0% [P > .99]). DLIR demonstrated an enhanced lung nodule detection rate over FBP (75.8% compared to 62.5%; P < .001) and ASIR-V (73.3%; P = .18). It also surpassed ASIR-V in nodule size accuracy for both lengths (6.2% versus 9.2%; P < .001) and volume measurements (14.4% versus 21.0%; P < .001). Additionally, DLIR identified a greater number of nodule features associated with malignancy than ASIR-

V did, capturing 81.5% (225 out of 276 features) versus ASIR-V's 77.5% (214 out of 276 features); P = .04.

Radiomics

By describing the characteristics of lesions through the extraction of medical images, radiomics can predict the growth rate of nodules help prognostic analysis distinguishing benign from malignant nodules and predict the nodule's response to treatment, based on the gene expression pattern and the microenvironment. The radiometric model can be combined with a clinical model to provide a more accurate predictor model. Sun *et al.*, 2023 investigated the prediction of the growth of persistent ground glass nodules (GGN) in a retrospective study where CT images were randomised into training (70%) and validation sets (30%) which helped develop models. They concluded the predictive model that integrates radiomics with clinical characteristics (such as size, location, and age) achieved the highest Area Under the Curve (AUC) scores in both training and validation datasets (AUC = 0.843 and 0.824, respectively). This radiomics-based model surpassed the performance of the clinical-only model in both datasets (AUC scores of 0.836 vs 0.772 and 0.818 vs 0.735, respectively). Additionally, the radiomics signature's performance closely matched that of the combined nomogram model, as indicated by the Delong test results for the training (P = 0.09) and validation (P = 0.37) sets. These results were consistent with Zhang *et al.*, who developed and validated a predictive model for preoperative differentiation of pulmonary nodular mucinous adenocarcinoma (PNMA) from pulmonary tuberculoma (PTB) in retrospectively analysed. They determined that combined radiomics and clinical model provided the best performance in the prediction model to differentiate PNMA from PTB, with ROC-AUC of 0.940, 0.990 and 0.960 in training, test and external validation group respectively.

CONCLUSION

The integration of artificial intelligence into medical imaging and diagnostics marks a significant advancement in enhancing patient care and optimising radiologist workflows. Through sophisticated analysis of medical images, AI techniques such as radiomics and deep learning image reconstruction can improve precision in detecting and differentiating interstitial lung diseases and lung cancer. Additionally, innovations like DLIR have been demonstrated to improve the accuracy and efficiency of ultra-low-dose CT imaging in demonstrating superior noise reduction and nodule detection rates. Combined radiomic and clinical models performed better than radiomic or clinical models alone. However, there are limited studies investigating the application of AI models in detecting lung diseases. Most of the research employed limited participant numbers in their training and validation groups which restricts the applicability of their findings. Despite AI models in their infancy stages, this research contributes to the ever-growing database of AI applications in chest computed tomography. They set a precedent for future research into integrating AI to improve patient care.

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