Revolutionizing Pulmonary Embolism Care: The AI Advantage

The evolving role of artificial intelligence in pulmonary embolism diagnosis and management, current challenges, and future directions.

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Acute pulmonary embolism (PE) poses a severe and potentially life-threatening cardiovascular condition, necessitating prompt diagnosis and intervention.[1] CT pulmonary angiography (CTPA) has become the cornerstone for PE detection, yet its increasing utilization, coupled with time-intensive interpretation, challenges timely patient care.[2-4]

In response, artificial intelligence (AI) integration into PE diagnosis has emerged as a transformative frontier. AI, particularly using convolutional neural networks (CNNs), exhibits notable capabilities in enhancing diagnostic efficiency and accuracy. This synergy between advanced technology and clinical care addresses critical issues such as prolonged wait times, missed incidental PE cases, and the urgency for rapid risk stratification.

This article delves into AI's evolving role in PE, encompassing applications in diagnosis, risk stratification, mortality prediction, and multidisciplinary patient care through PE response teams (PERTs). Beyond immediate clinical impact, AI serves as a dynamic platform for ongoing research, promising continuous advancements in diagnostic precision and efficiency. The intersection of AI and PE management aims not only to optimize current practices but also revolutionize cardiovascular health care, paving the way for personalized, data-driven, and timely interventions. This narrative navigates the significance of PE, challenges in current diagnostic paradigms, and the transformative potential that AI holds in reshaping PE patient care.

DETECTION AND DIAGNOSIS OF PE

Acute PE, a common and potentially life-threatening condition, demands an efficient evaluation approach for prompt therapy initiation. CTPA, the preferred diagnostic method, offers noninvasive and rapidly acquired imaging.[2,3] CTPA not only serves as a diagnostic tool but also aids in risk stratification and assessing illness severity in PE patients by evaluating right ventricular dysfunction (RVD), a parameter linked to both all-cause and PE-related mortality.[5] However, the diagnostic process using CTPA is time-intensive and reliant on radiologists' expertise, posing a risk of errors and delayed diagnosis. The growing utilization of CTPA for diagnosis observed in recent years places additional strain on the health care system, potentially resulting in delays in the care of patients who could benefit from timely medical and/or surgical interventions.[4]

Current Challenges in Diagnosing PE

Bach et al found that patients with a time to diagnosis of > 12 hours after a PE event had a higher incidence of death within 30 days.[6] The time to diagnosis was defined as the duration between placing a CTPA order and the actual diagnosis. In a related study, Kline et al reported that every seventh patient diagnosed with PE experienced a time to diagnosis exceeding 48 hours.[4] These challenges are exacerbated during periods of restricted staffing, particularly at night.[6] This highlights a critical need for developing algorithms and pathways to improve efficiency and reduce the time to diagnosis, facilitating prompt intervention. In response to this imperative, AI technology is emerging as a promising tool to address these challenges and enhance the management of acute PE.

ROLE OF AI IN PE

AI and PE Diagnosis

To diagnose PE, AI utilizes CNN, a specific type of deep neural network designed for image recognition and processing.[7] In each layer, CNNs apply convolutions to every pixel of an image, allowing them to effectively extract important features. This capability makes CNNs highly proficient at detecting patterns, objects, and abnormali-

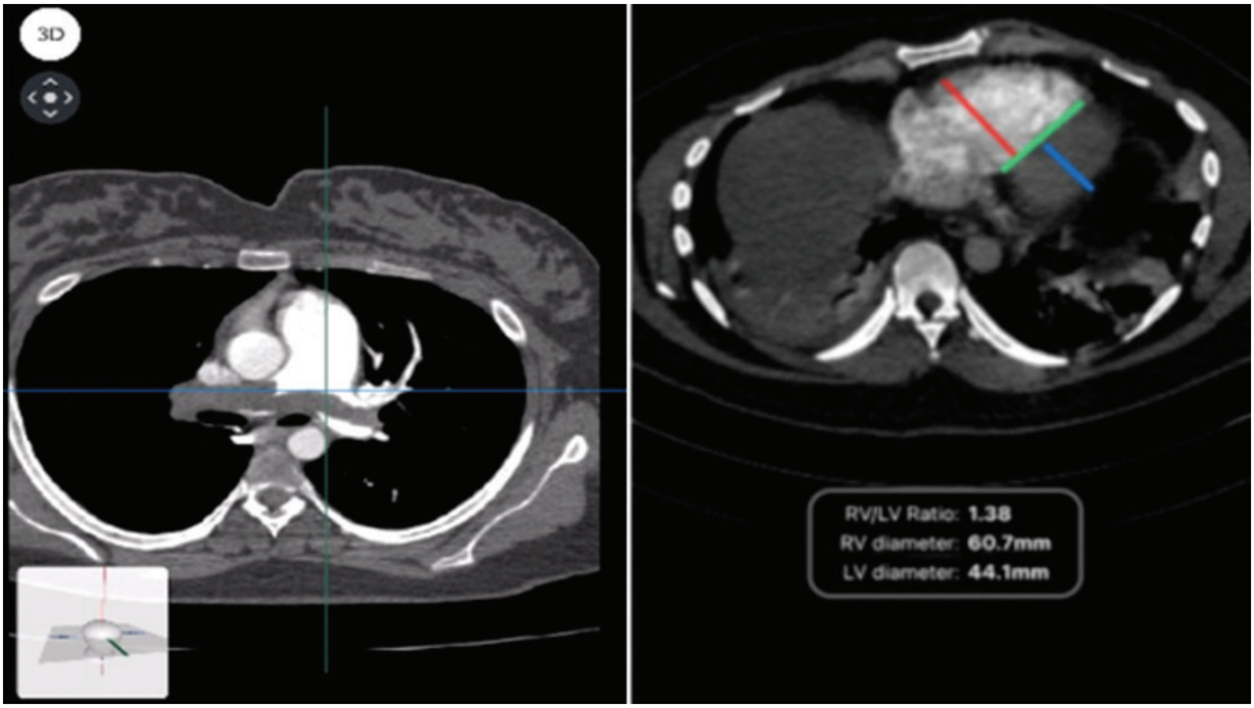

Figure 1. Automatic detection of the radiodensity and automatic calculation of RV/LV ratio.

ties in visual data, enhancing their utility in medical image analysis for conditions like PE.[8] Weikert et al pioneered the evaluation of an AI-powered algorithm for automatic PE detection in chest CTPAs on a large data set of 1,499 patients. The algorithm demonstrated a sensitivity of 92.7% and specificity of 95.5%, showcasing its accuracy in identifying both positive and negative PE cases.[9] Since then, multiple studies have reported high sensitivity and specificity of AI algorithms for the detection of PE on CTPA.[7,10-22] Even among patients with COVID-19 and parenchymal disease, the sensitivity and specificity of AI algorithms remained high.[23] Furthermore, a study confirmed that AI maintained both sensitivity and specificity when interpreting suboptimal CTPA examinations.[24] AI tools are not confined to conventional CT scans, as a recent study revealed comparable sensitivity (77.5% vs 85%) and specificity (96% vs 94.6%) between conventional polychromatic CT images and virtual monochromatic images.[10]

AI and Incidental PE Diagnosis

Although prompt detection and management of PE are crucial, the issue of missed incidental PE on routine venous contrast-enhanced chest CT scans is equally pressing. According to the literature, the frequency of missed incidental PE diagnoses can be as high as 44%.[25] Research indicates that AI algorithms exhibit significantly higher sensitivity for detecting PE in these routine scans as compared with radiologist-driven initial reports (95.5% vs 62.7%).[26] Similarly, studies have shown enhanced detection of incidental PE using AI algorithms.[25,27-29] Noteworthily, Topff et al showcased that collaboration with AI significantly reduced the missed rate of incidental PE by radiologists, plummeting from 44.8% without AI to 2.6% with AI.[25] Similarly, Wildman-Tobriner demonstrated that incorporating AI into scans obtained for reasons other than PE diagnosis significantly improved the detection of incidental PE.[29] This highlights the symbiotic relationship between AI tools and radiologist-driven reads.[25]

AI Reduces Wait Times for PE Diagnosis

Rothenberg et al effectively showcased the impact of AI tools in reducing time to diagnosis. Their study demonstrated that implementing an AI triage system for the detection of PE in CTPA studies resulted in significant improvements in the time it took from the completion of the study to its interpretation by a radiologist.[30] Batra et al similarly demonstrated the efficacy of AI software in radiology worklist reprioritization, reducing the wait time to one-third for routinely ordered CTPA studies (15 vs 44 minutes).[13] Another study demonstrated at the implementation of AI-guided triage and prioritization in the radiologic workflow was linked to a substantial reduction in the length of stay (2 days) for patients diagnosed with PE.[31]

AI and PE Risk Stratification

RVD is a prognostic indicator for adverse outcomes in individuals with PE. Although echocardiography is the established reference for RVD assessment, various studies propose an elevated RV/left ventricular (LV) diameter ratio (RV/LV > 1) on CTPA as a surrogate marker for RVD. This ratio has been identified as a predictor of short-term mortality and adverse clinical events in acute PE patients, establishing it as a significant reportable finding.[32] Recent studies indicate that the RV/LV ratio on CTPA can be consistently measured automatically in the majority of acute PE cases, demonstrating excellent reproducibility with the use of AI tools (Figure 1).[17,33] The integration of this automated analysis into routine clinical practice could provide crucial prognostic information for patients with acute PE.

AI and Mortality Prediction

AI's role in PE care extends beyond diagnosis and risk stratification; it also holds promise in disease prognosis. Sadegh-Zadeh et al demonstrated that machine learning can effectively predict mortality in patients with acute PE.[34] Similarly, Wang et al demonstrated that machine learning models can effectively predict low risk of mortality, suggesting its potential in helping with judicious allocation of critical care resources.[35]

PE CARE AND PERTs

The care of PE patients is intricate and requires a multidisciplinary approach. Although radiology reporting of a positive PE finding on CTPA is crucial, equally critical is the activation of a PERT. A typical PERT includes critical care pulmonologists, cardiologists, cardiac surgeons, and vascular specialists. The AI-driven rapid detection of a positive PE scan, particularly one with high-risk features, and its swift communication to the PERT through automated software prove to be invaluable tools. High-risk features include, but are not limited to, radiographic evidence of RV dysfunction and an RV/LV ratio of > 1. This approach has demonstrated improvements in both time to diagnosis and management. Moreover, the swift interhospital transmission of AI-driven analyses of CTPA scans enables the early identification of patients with high-risk features. This timely recognition facilitates the efficient transfer of these individuals to tertiary care centers equipped with advanced vascular and surgical interventions, ensuring that they receive appropriate medical attention when necessary.

EVOLVING PARAMETERS AND FUTURE DIRECTIONS

Recent data highlight ongoing advancements in using deep learning networks for the detection and segmentation of PE,[36] identifying important features associated with PE risk[37] and indicating continuous progress in improving diagnostic accuracy and efficiency. A recent study demonstrated the ability of deep learning methods to detect chronic PE on CTPA, emphasizing its potential to distinguish between acute and chronic clots.[38]

The dynamic evolution of PE management presents a promising frontier, particularly with the integration of AI capabilities. AI stands as a substantial data repository, streamlining data mining and refinement within the PERT registry. This transformative potential has the capacity to revolutionize both research and clinical medicine.

AI's ability to track patient scans offers unprecedented insights, enabling the observation of therapeutic responses, clot resolution, and disease progression. Moreover, it facilitates the seamless transition of care as patients leave the hospital and provides postacute phase follow-up. In ongoing trials within the dynamic PE landscape, AI-driven automated reads emerge as a transformative tool, addressing the urgency of patient enrollment. By swiftly and accurately diagnosing individuals, AI broadens the pool of eligible participants, fostering active contribution to and benefit from evolving medical trials. This not only accelerates research progress but also holds the promise of uncovering novel insights, ultimately improving overall patient outcomes in the field of PE management. An excellent example of this is the ongoing PE-TRACT study, which investigates whether up-front thrombus removal with catheter-directed therapy reduces the incidence of these post-PE impairments. This study uses AI-driven patient recruitment, allowing for efficient and swift identification and recruitment.

CONCLUSION

The integration of AI into the realm of PE diagnosis and management represents a transformative and promising frontier in health care. The studies discussed underscore the remarkable capabilities of AI, from enhancing diagnostic accuracy in detecting acute PE to significantly reducing wait times for critical interventions. The symbiotic relationship between AI tools and health care professionals, particularly in the context of a PERT, showcases the potential for AI to streamline multidisciplinary care and improve patient outcomes. ■

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