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Enhancing Pulmonary Care: The Pivotal Role of Segmentation and Automated Analysis in Advanced Pulmonary Imaging

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Abstract

English:

In the field of medical imaging, techniques like computed tomography (CT), magnetic resonance imaging (MRI), and X-rays are essential for diagnosing and monitoring diseases, particularly in pulmonary pathology. A significant development in this area is the application of automated segmentation and machine learning, enhancing the accuracy in diagnosing lung diseases, such as lung cancer. However, there remains a knowledge gap in fully understanding the potential and limitations of these technologies, especially across diverse clinical conditions and datasets. To address this gap, the paper delves into the integration of artificial intelligence with conventional imaging techniques, focusing primarily on the use of convolutional neural networks (CNNs) and transformer-based models in automated segmentation. This approach is pivotal in improving the detection rates and accuracy of diagnoses in complex pulmonary diseases. Findings indicate that AI-enhanced imaging significantly advances the early detection of pulmonary diseases, notably lung cancer, and reduces the time until diagnosis. Yet, challenges such as the necessity for diverse and comprehensive training data and the generalizability of algorithms, persist. Moreover, ethical considerations in the deployment of AI technologies in healthcare are crucial. In conclusion, while these technologies mark substantial progress in pulmonary imaging, it is essential to find the balance between technological advancements and ethical considerations. This balance is key to ensuring effective and equitable healthcare, maximizing the benefits of AI in medical imaging while maintaining patient trust and privacy.

Keywords

pulmonary imaging • automated segmentation • machine learning • convolutional neural networks • artificial intelligence in medicine

Avansul în îngrijirea pulmonară: Rolul cheie al segmentării și analizei automate în imagistica pulmonară de vârf

Rezumat

Romanian:

În domeniul imagisticii medicale, tehnici precum computer tomografia (CT), imagistică prin rezonanță magnetică (IRM) și radiografiile sunt esențiale pentru diagnosticarea și monitorizarea bolilor, în special în patologia pulmonară. O dezvoltare semnificativă în acest domeniu este aplicarea segmentării automate și a machine learning-ului, ceea ce sporește acuratețea diagnosticării bolilor pulmonare, cum ar fi cancerul pulmonar. Cu toate acestea, rămâne o lacună de cunoaștere în înțelegerea completă a potențialului și limitărilor acestor tehnologii, în special în condiții clinice diverse și pentru seturi de date. Abordând această lacună, articolul investighează integrarea inteligenței artificiale (IA) cu metodele tradiționale de imagistică, concentrându-se pe rețelele neuronale convoluționale (CNN) și modelele bazate pe transformatori pentru segmentare automată. Această abordare este esențială în îmbunătățirea ratelor de detecție și a acurateței diagnosticelor în bolile pulmonare complexe. Rezultatele indică

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faptul că imagistica îmbunătățită cu IA avansează semnificativ detectarea timpurie a bolilor pulmonare, în special a cancerului pulmonar, și reduce timpul de diagnosticare. Totuși, provocări precum necesitatea unor date de instruire diverse și cuprinzătoare, precum și generalizabilitatea algoritmilor, persistă. Mai mult, considerațiile etice în implementarea tehnologiilor IA în domeniul sănătății sunt cruciale. În concluzie, deși aceste tehnologii marchează un progres substanțial în imagistica pulmonară, este esențial să existe un echilibru între avansurile tehnologice și considerațiile etice. Acest echilibru este cheia pentru asigurarea unei îngrijiri medicale eficiente și echitabile, maximizând beneficiile IA în imagistica medicală, menținând în același timp încrederea și confidențialitatea pacientului.

Cuvinte-cheie

imagistică pulmonară • segmentare automată • machine learning • rețele neuronale convoluționale • inteligență artificială în medicină

Introduction

The term “medical imaging” encompasses a variety of techniques that enable the visualization of internal body structures to diagnose or track the progression of diseases. This field includes numerous digital imaging methods like computed tomography (CT), magnetic resonance imaging (MRI), X-rays, ultrasound (US), and positron emission tomography (PET) scans. While some techniques, like retinal photography, are specialized for specific organs, others, such as CT and MRI scans, are capable of examining multiple organs simultaneously (1).

The realm of pulmonary imaging has become an indispensable component in the diagnosis and monitoring of respiratory diseases. Pulmonary imaging incorporates a wide array of techniques and methodologies, each contributing uniquely to the understanding, diagnosis, and management of respiratory conditions. The advent of advanced imaging technologies has significantly enhanced the ability of clinicians to diagnose and monitor various lung diseases, ranging from cystic fibrosis or chronic conditions like COPD to acute infections and malignancies such as lung cancer (2-5).

Imaging techniques, including conventional modalities like chest X-ray, computed tomography (CT), and magnetic resonance imaging (MRI), have traditionally played a crucial role in the differential diagnosis of lung diseases. This is particularly important given the overlap of symptoms among various pulmonary conditions, which can become distinct only at more advanced stages, impacting the prognosis. A rather small progress was documented in AI driven ultrasound (US) diagnosis, in spite of the central role of US in real life medicine. Point of care lung ultrasound (POCUS) is the most often used approach in clinical practice because of low cost, nonionizing mechanism and ease of portability, but AI-povered diagnosis is still gaining expertise. A 2019 survey on deep-learning applications in ultrasound (6) is presenting some hope. New publications from 2023 present AI-assisted ultrasound equippment with robotic arms dedicated to emergency and disaster medicine (7) or deep learning-based approach for abdominal wall segmentation that outperformes previous applications (8).

The evolution of molecular imaging, for instance, has opened new roads in understanding the pathophysiology of lung diseases, as well as in the early detection and accurate diagnosis of these conditions. The development of artificial intelligence (AI) and automated pulmonary imaging analysis further augments these traditional techniques’ capabilities. AI algorithms, when used in conjunction with human expertise, have shown promising results in improving the detection rates of pulmonary nodules, offering more precise measurements, and enabling the extraction of additional clinically relevant information from CT scans (9, 10). There is a strong need for AI to improve oncologic care because cancer prediction can diminish the rate of mortality (11, 12).

In lung cancer, which is a leading cause of cancer-related death globally, imaging plays a critical role. The primary issue in computerized lung segmentation, a process often necessary for accurate diagnosis, is the presence of specific lung diseases like pulmonary nodules and pneumonia, which can significantly impact the accuracy of these computerized methods (13, 14). Cancer diagnosis involves three key predictive elements: assessing cancer risk, predicting cancer recurrence, and forecasting cancer survivability. The process begins with evaluating the likelihood of cancer development, followed by anticipating the chances of its recurrence. The final phase encompasses predictions about factors such as disease progression, life expectancy, tumoral drug sensitivity, and overall patient survivability (15). Zhang et al. conducted a comprehensive study on the use of automated methods for detecting lung nodules in CT scans. They discussed the most effective techniques for identifying lung nodules and highlighted both general and specific challenges in this area, noting that nodules differ in type, size, texture, location, and associated clinical history. Their review covered various stages such as data gathering, preprocessing, segmenting the lung, detecting nodules, and reducing false positives. While many approaches achieved high sensitivity, they often came with a high rate of false positives. The study frequently referenced the LIDC-IDRI dataset and found that while traditional methods were effective, AI-based methods, especially deep learning, outperformed them, expanding future expectations in this field (16).

Automated segmentation

The advent of automated segmentation (Figure 1) in pulmonary imaging marks a significant advancement in the diagnosis and treatment of respiratory diseases. This technology involves using advanced algorithms to automatically identify and isolate specific lung structures in medical images. This methodology allows for precise differentiation of structures such as pulmonary lobes, bronchi, nodules, or fibrotic areas, thereby enabling more accurate diagnosis and personalized treatment plans (17,18).

Automated segmentation is crucial in the efficient evaluation of pulmonary CT images, especially in cases of lung cancer and other complex pulmonary pathologies. A notable example is the detection and measurement of pulmonary nodules in lung cancer screening programs. AI algorithms can detect nodules that human radiologists might miss, thereby increasing the overall nodule detection rate (19). However, the widespread implementation of these automated systems faces challenges, particularly in diseases that share manifestations with other conditions (20).

Recent studies have demonstrated that automated algorithms for the detection, segmentation, and measurement of mediastinal structures in computed tomography pulmonary

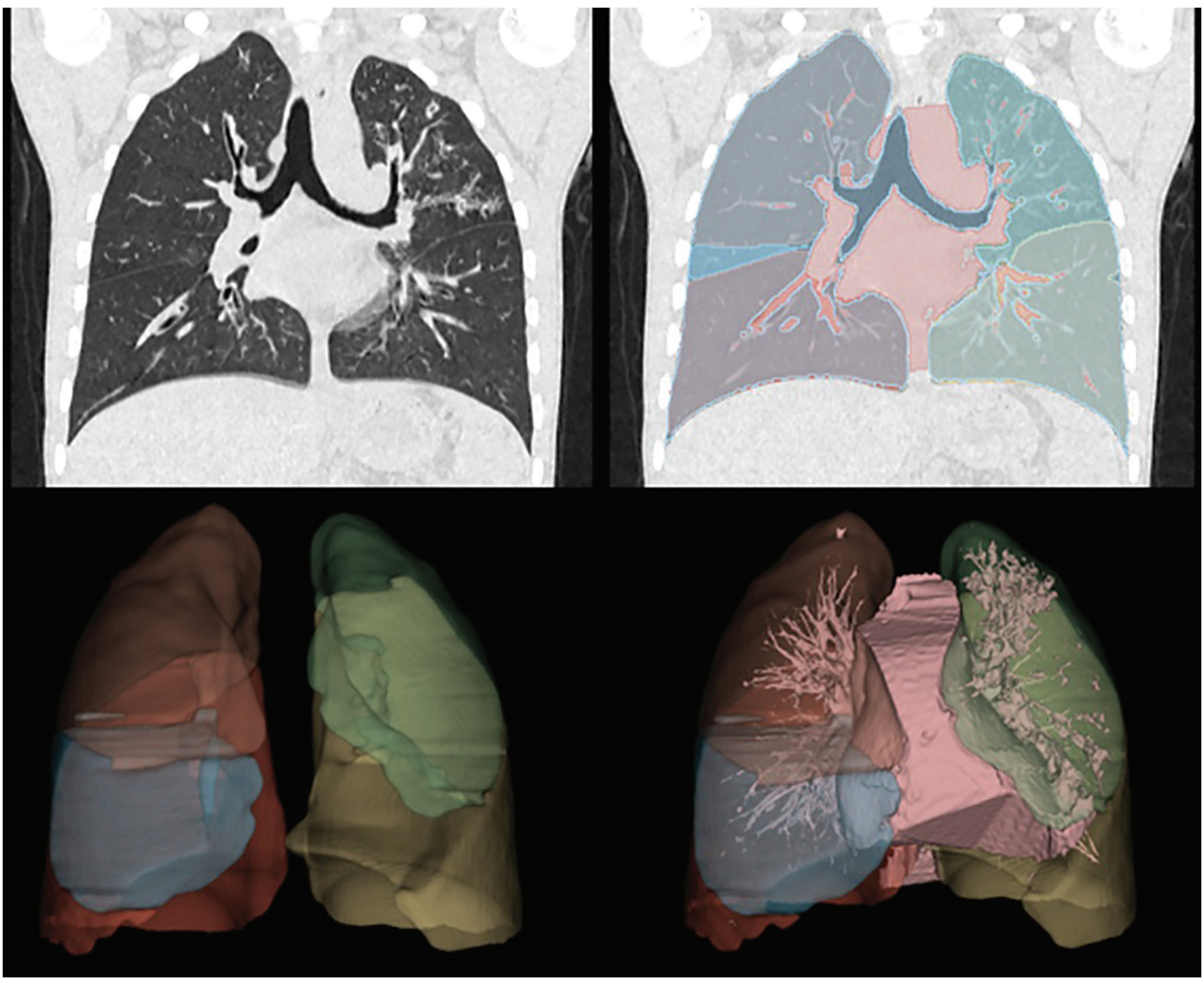

Figure 1. Examples of lung segmentation applied. Deep learning lung and lobe segmentation is realized by implementation of 'Lungmask' AI models and algorithms (38).

angiography (CTPA) are as accurate as radiologists, underscoring the potential of these systems to save time and provide consistent evaluations (21). Cases that are challenging to segment without a co-registered PET scan enable deep learning networks to distinguish tumors from other lung irregularities, such as atelectasis and tumors with mediastinal involvement. This, combined with the precise segmentation of the 3D tumor volume, makes it suitable for clinical use in radiotherapy settings and for extensive data radiomics research, as well as potentially other areas of study (22).

To overcome these challenges and improve accuracy, the development of robust schemes capable of efficiently handling these issues is necessary, especially when analyzing a large number of CT examinations (23).

Techniques and technologies used

Automated segmentation in pulmonary imaging increasingly employs advanced machine learning techniques, with current methods being broadly classified into three categories: convolutional neural networks (CNNs), transformer-based approaches, and various other deep learning techniques. CNNs, known for their proficiency in processing and analyzing extensive image data sets, are especially relevant in medical imaging applications. They excel in pattern recognition, allowing for the identification and delineation of intricate structures within pulmonary images, such as nodules, bronchi, and fibrotic areas. While transformer technology has also seen significant growth and success in a variety of domains, its application specifically in pulmonary nodule segmentation is still in a developmental phase and warrants further research to match the effectiveness of CNNs in this field (24, 25). By 2017, there was a significant surge in interest within the field. A comprehensive review by Merjulah and Chandra on medical image processing segmentation methods highlighted the most effective techniques. Their findings showed that convolutional neural networks (CNNs) were superior in accuracy compared to non-deep learning methods. Furthermore, the review emphasized that CNNs not only excel in detection and segmentation tasks but also in performing classification. However, their effectiveness varies based on the specific problem at hand and the appropriateness of the chosen CNN architecture (26).

Labaki and Han explored the potential of deep learning in enhancing chest imaging techniques. They highlighted the significant impact of applying these methods on a larger scale. Due to the impracticality of analyzing every slice in a CT scan, they utilized images consisting of four cuts. The performance of their model improved with a larger number of scans, indicating the need for more extensive training and consideration of different imaging protocols. They also noted the importance of incorporating clinical data into predictive models, emphasizing the relevance of clinical outcomes like airway disease. Additionally, they recommended focusing on the compatibility of these models with established clinical workflows (27).

One of the key strengths of using machine learning in pulmonary imaging is its ability to continually learn and improve from a growing database of images (28). This adaptability is crucial in handling the wide variability seen in pulmonary diseases. Recent studies have shown that AI algorithms can detect pulmonary nodules with a higher accuracy rate compared to traditional methods, significantly aiding in the early diagnosis of conditions like lung cancer. However, these algorithms do face challenges, particularly in diseases with overlapping symptoms or similar radiographic presentations (29).

Despite these advancements, there are obstacles in the widespread application of these technologies, such as the presence of specific lung diseases and anatomical variations that can lead to segmentation errors (30). A significant challenge in integrating AI into pulmonary imaging is its assimilation into clinical workflows, requiring radiologists and clinicians to become more familiar with AI's potential applications. Understanding the efficient use of AI in initial evaluations, diagnostics, disease severity assessment, and decision support is pivotal (31).

In 2020 Hofmanninger and colleagues discuss the use of deep learning models for lung segmentation in CT scans. The focus is on the impact of training data diversity on the performance of these models. They trained the models on a dataset that included a wide range of lung diseases, which significantly differs from standard public datasets. This approach demonstrated the crucial role of diverse, real-world clinical data in improving the accuracy and reliability of lung segmentation techniques in medical imaging (32).

Benefits and clinical applications

One of the primary benefits of automated segmentation in pulmonary imaging is the enhancement of diagnostic accuracy. Machine learning algorithms, especially those based on convolutional neural networks, have shown a remarkable ability to detect and delineate pulmonary structures and abnormalities with high precision. This improved accuracy is particularly significant in the early detection and diagnosis of lung diseases, including lung cancer, where early intervention can drastically alter patient outcomes (29).

Another significant advantage of automated analysis is the reduction in analysis time. Traditional manual analysis of pulmonary images is time-consuming and subject to inter-observer variability. Automated systems, on the other hand, can process images rapidly and consistently, thereby reducing the time from imaging to diagnosis. This efficiency is not only beneficial for patient care but also helps in managing the large volumes of imaging studies that radiology departments handle daily (25).

Automated segmentation also opens the door for conducting longitudinal studies on large image databases. This capability allows for the tracking of disease progression over time, providing valuable data for clinical research and patient monitoring. By analyzing changes in pulmonary structures over multiple imaging sessions, clinicians can gain insights into the effectiveness of treatments and the progression of diseases (33).

According to Primakov et al., automated systems are more accurate and efficient than manual methods when it comes to segmenting CT scans of non-small cell lung cancer (NSCLC). They also found that automated segmentations are preferred in 56% of cases, and the process is significantly faster. Its clinical relevance is highlighted in radiotherapy and radiomics, where accurate segmentation is key for treatment planning and personalized medicine. The methodology involves a three-step workflow, achieving high sensitivity and specificity. The automated segmentations offer more insightful prognostic data and hold promise for future clinical trials. This advancement in AI-driven medical imaging significantly enhances lung cancer detection and management (34).

Automated algorithms might also represent a tool for diagnosis or an aid to other clinicians in remote areas where access to imaging specialists is reduced, especially in countries with increased medical exodus rates such as Romania.

Challenges and perspectives

A major hurdle in this field is the necessity for high-quality training data. Deep learning and other machine learning algorithms depend on extensive and diverse datasets for learning and accurately recognizing patterns in pulmonary imaging. These datasets must encompass a broad spectrum of pulmonary conditions, imaging techniques, and patient demographics to ensure algorithmic robustness and generalizability across varied patient groups and imaging situations. Moreover, it's increasingly important to address challenges such as diseases with similar symptoms and the development of algorithms robust enough to handle a wide array of clinical conditions (30).

Another significant challenge is the generalization of algorithms. While machine learning models can perform exceptionally well on the datasets they are trained on, their performance can vary when applied to new, unseen datasets (35). This issue is particularly relevant in medical imaging, where variability in imaging protocols, machine types, and patient populations can be substantial. Overcoming this challenge requires extensive and diverse training data and sophisticated algorithmic approaches that can adapt to different conditions and maintain accuracy. Looking to the future, there is significant potential for growth and improvement in the field of automated segmentation in pulmonary imaging. As AI and machine learning technologies advance, we should anticipate seeing algorithms grow more skilled at managing the complexities of pulmonary imaging. Future developments may include more advanced multimodal learning approaches that integrate different types of data (e.g., clinical, radiological, and pathological) to provide a more comprehensive understanding of pulmonary diseases (30).

Some experts are concerned about accountability when AI systems generate diagnostic or treatment plans, without human input. The responsibility for errors in such cases may become unclear, making it essential to define clear lines of accountability and ensure patient safety (36).

Ethical considerations and data privacy

In addition to the technical and clinical advancements in pulmonary imaging, the ethical considerations associated with the deployment of AI and automated analysis are of paramount importance. Herington et al. stated that the successful integration of AI in medical imaging relies not only on technological proficiency but also on earning the trust of both clinicians and patients. The AI Task Force of the Society of Nuclear Medicine and Molecular Imaging emphasizes the critical ethical challenges, including respecting patient and clinician autonomy, ensuring transparency in clinical performance, upholding fairness, especially for marginalized populations, and maintaining accountability among physicians and developers. Addressing these ethical risks is essential for realizing the full potential of AI in pulmonary imaging, and it requires a balanced approach that considers health justice and equitable distribution of benefits and burdens, thereby aligning technological advancements with core medical ethics and patient rights (37).

Conclusions

The advancement of pulmonary imaging through automated segmentation and machine learning has markedly improved the diagnosis and treatment of lung diseases, particularly lung cancer. These technologies offer enhanced accuracy in detecting pulmonary abnormalities and reduce the time from imaging to diagnosis. Despite these benefits, challenges like the need for diverse training data and algorithm generalization remain. Future developments are expected to refine these tools further, integrating more comprehensive data for better disease understanding. However, it's crucial to balance these technological advancements with ethical considerations and data privacy to ensure patient and clinician trust. Overall, these innovations represent a significant step forward in pulmonary imaging, promising more personalized and effective patient care.

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Informed Consent Statement

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Data Availability Statement

Data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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Glossary

Artificial intelligence (AI): AI involves building machines to do tasks that usually require human intelligence, like learning, problem-solving, and understanding language and images.

Automated analysis: Using algorithms for efficient data interpretation, especially in medical imaging, without manual intervention.

Automated segmentation: The use of advanced algorithms to automatically identify and isolate specific lung structures in medical images, allowing for precise differentiation and more accurate diagnosis and personalized treatment plans.

Computed tomography (CT): An imaging technique that uses X-rays to create detailed cross-sectional images of the body, providing valuable information about internal structures and abnormalities.

Convolutional Neural Networks (CNNs): A subset of AI, excel at tasks mimicking human vision, especially in recognizing patterns in images. They use specialized layers for efficient visual data processing.

Deep learning: A subset of machine learning involving neural networks with multiple layers (deep neural networks), capable of learning complex representations and patterns, commonly applied in medical imaging tasks.

LIDC-IDRI: The Lung Image Database Consortium image collection consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions.

Machine learning (ML): A subset of artificial intelligence that allows for improved performance without the need for explicit task programming.

Magnetic resonance imaging (MRI): A medical imaging technique that uses strong magnetic fields and radio waves to generate detailed images of the internal structures of the body, especially useful for soft tissues.

Medical imaging: The visualization of internal body structures for diagnostic or monitoring purposes, encompassing various digital imaging methods such as computed tomography (CT), magnetic resonance imaging (MRI), X-rays, ultrasound (US), and positron emission tomography (PET) scans.

Multimodal learning: Combining insights from diverse data sources for a comprehensive understanding in machine learning.

Molecular imaging: The visualization and measurement of biological processes at the molecular and cellular levels, offering insights into the physiopathology of lung diseases and aiding in early detection and accurate diagnosis.

Pattern recognition: The ability of algorithms, especially CNNs, to identify and interpret patterns within data, a key strength in automated segmentation for recognizing intricate structures in pulmonary images.

Pulmonary imaging: A field integral to the diagnosis and monitoring of respiratory diseases, involving diverse techniques contributing uniquely to the understanding, diagnosis, and management of respiratory conditions.

Positron emission tomography (PET): A nuclear medicine imaging technique that produces 3D images of functional processes in the body, often used in conjunction with CT for comprehensive imaging.

Radiomics: An advanced method for extracting quantitative data from medical images and transforming visual information into mineable, numerical features. It enables comprehensive analysis of tissue characteristics and aids in the identification of subtle patterns for improved diagnostic and prognostic insights.

Segmentation: The methodical partitioning of images, precisely delineating object boundaries. It employs pixels in 2D or voxels (3D pixels) in 3D, facilitating focused analysis of specific image regions.