White paper

Assisted Multi-Organ Image Interpretation in the Age of Artificial Intelligence

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SIEMENS Healthineers

While a number of useful stand-alone artificial intelligence (AI) algorithms already are in clinical use for the interpretation of medical images, the broader implementation of the technology in everyday radiology requires versatile AI platforms that support and augment image reading and reporting for multiple organs and can be easily integrated into existing workflows and IT architectures. Such intelligent assistance systems with increasing degrees of autonomy promise to make radiology as a whole more efficient and precise, thereby absorbing the growing workload, and reducing diagnostic errors.

An exemplary application is chest imaging, which often involves the evaluation of several organs and anatomical structures. Integrated AI platforms can be used here to automate a wide variety of biomarker-based measurements, to highlight and characterize suspicious lesions, and to prepare structured reports. This should also significantly reduce the number of missed pathological findings. Likewise, the interpretation of whole-body scans may increasingly benefit from multi-organ, multimodal AI assistance systems in the future.

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Introduction

Toward a comprehensive use of AI in radiology

The interpretation of medical images with the aid of artificial intelligence (AI) is becoming a clinical reality. While the technology ranks undoubtedly among the most visionary topics at medical congresses and in media reporting, a number of specific AI algorithms have already proven their practicality and benefits.

Accordingly, the question is no longer whether AI can in principle be advantageous for image analysis. Most experts already take this for granted. The challenge today is rather to promote the work of radiologists in an everyday context with intelligent software and thus to achieve a significant increase in added value for the entire discipline. Indeed, AI in medical imaging promises to help improve the physician's experience and prevent burnout, thereby safeguarding the important fourth component of the "quadruple aim" in healthcare (Bodenheimer & Sinsky 2014). Some specialists speak of radiology being "augmented" with AI (Liew 2018).

"The mainstream market will require end-to-end AI-powered solutions, with proven productivity gains."

Source: Harris 2018

This requires software platforms that support imaging in an easy way for a wide variety of organs and modalities. While existing AI applications are usually specialized stand-alone solutions for individual tasks, the broader implementation of the technology will be based on versatile assistance systems that can be seamlessly integrated into existing workflows and IT architectures. "When considering AI in medical imaging, a deep-learning algorithm on its own is not the total solution, merely a component. The mainstream market will require end-to-end AI-powered solutions, with proven productivity gains," emphasizes a recent analysis by healthcare technology consulting firm Signify Research (Harris 2018).

Strategies are now emerging to use such integrated AI platforms to, for example, assess multiple anatomical structures on a chest CT more quickly and precisely, or to evaluate whole-body scans in the future. This would make AI a cross-sectional technology in radiology – and would make AI support a self-evident aspect of image interpretation.

AI is already a partial reality in medical image interpretation today

Case studies from various fields of application show that AI can bring tangible advantages. AI-powered image interpretation is already partly reality.

A well-known example is bone age assessment in children based on X-rays of the hand. For example, Danish researchers have developed image-analysis software that has been approved in Europe for some time and is now routinely used for this purpose in around 100 clinics (Thodberg et al. 2009, Thodberg 2017). According to a recent study with a deep-learning system, automated analysis can indeed provide age results as accurately as a time-consuming image reading by a radiologist (Hyunkwang et al. 2017). Another algorithm has been proven to detect wrist fractures, thereby bringing the expertise of an orthopedic surgeon to the emergency department. (Deep neural network improves fracture detection by clinicians Robert Lindsey, Aaron Daluiski, Sumit Chopra, Alexander Lachapelle, Michael Mozer, Serge Sicular, Douglas Hanel, Michael Gardner, AnuragGupta, Robert Hotchkiss, Hollis Potter, Proceedings of the National Academy of Sciences Oct 2018, 201806905; DOI:10.1073/pnas.1806905115).

No less remarkable is AI-supported tuberculosis screening, especially in regions with limited medical resources and few radiologists.
In a number of developing countries today, machine analyses of chest X-rays are efficiently used to identify people who have an increased likelihood of disease and need to undergo further testing (Philipsen et al. 2015).

A related approach to TB detection is that radiologists only examine chest radiographs that cannot be clearly classified by artificial neural networks (Lakhani & Sundaram 2017).

Likewise, AI applications for other imaging modalities have proven their value under everyday conditions. As a three-month clinical implementation phase in a U.S. healthcare network has shown, head CTs can be evaluated in seconds using an intelligent algorithm to detect unknown intracranial bleeding and prioritize the scans for rapid interpretation by a radiologist, which in some cases could even save lives (Arbabshirani et al. 2018). Many other AI applications – for example, for the analysis of lung or liver cancers – are at a practical development stage, and a growing number of algorithms are now approved for clinical use by authorities such as the U.S. Food and Drug Administration.

Implementing AI on a broader basis:

the need for integrated routine solutions

While these examples underscore the enormous potential of artificial intelligence for radiology, its broader implementation in routine imaging is still pending. One of the challenges lies in the nature of the algorithms themselves, which usually only perform single tasks, such as the segmentation of a particular organ. "The traditional view of machine learning and neural networks is that a given system can only solve one well-defined problem," Bradley Erickson and his colleagues from Mayo Clinic write in an article on the state of deep learning (Erickson et al. 2018). However, they continue, "it is rare for an examination to have only one question." For example, the interpretation of a thoracic CT can involve multiple questions about several organs. This presents radiologists with the dilemma of either restricting the use of AI to specific cases, or integrating various algorithms from different developers into their IT systems, which in turn can compromise practicability and raise compatibility problems.

"Ultimately, the driver of clinical adoption may reside in the implementation and availability of AI applications integrated into the PACS system at the reading station."

Source: Tang et al. 2018

A crucial prerequisite for advancing the implementation of AI and fully exploiting its benefits is therefore the availability of easy-to-use, comprehensive solutions for clinical routine. This applies in particular to the large number of radiologists who generally welcome AI but do not see themselves as tech pioneers. "The early-majority customers expect total solutions for a given business or clinical problem, rather than discrete products and technologies. These solutions must seamlessly integrate into their existing infrastructure," underscores a current market assessment (Harris 2018).

In particular, compatibility with existing picture archiving and communication systems (PACS) is key to the successful use of AI in healthcare organizations. "Ultimately, the driver of clinical adoption may reside in the implementation and availability of AI applications integrated into the PACS system at the reading station," confirms a technology white paper from the Canadian Association of Radiologists (Tang et al. 2018). In other words: AI should not reinvent workflows, but instead improve and accelerate what radiologists do every day in as many different ways as possible.

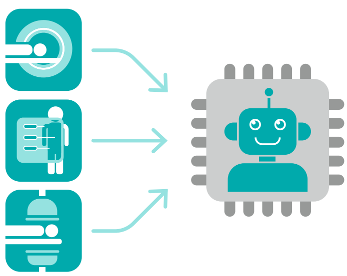
In the meantime, various strategies for such a comprehensive implementation of AI are emerging. On the one hand, many software providers enter into cooperations in order to coordinate their AI applications or to bundle them into market places. These "AI app stores" give hospitals access to curated algorithm libraries with applications for a wide variety of radiological issues (Harris 2017, Signify Research 2018).

On the other hand, it is particularly suitable for larger companies to design integrated AI assistance systems from the outset that cover entire areas of imaging and provide multifunctional support – a strategy that Siemens Healthineers also pursues on the basis of its extensive AI research and expertise (Ghesu et al. 2017, Liu et al. 2017, Yang D et al. 2017) (Fig. 1).

Conceptual framework

for an integrated AI platform assisting multimodal multi-organ imaging

1 Multi-Modal Input

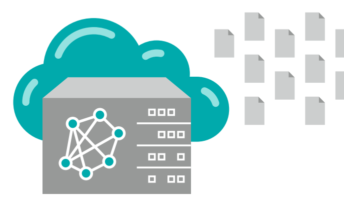


All data produced by any modality for any examination is automatically sent to an integrated AI assistant.

2 Intelligent Dispatching

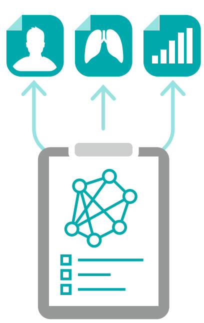
The algorithms to be executed are automatically selected from a global library depending on the data content.

3 Automated Results Generation



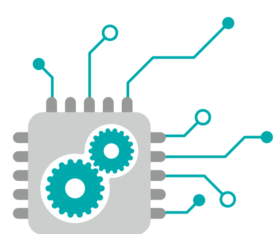
AI-powered image analyses (e.g. measurements) are performed and structured reports are generated.

4 Multi-Channel Output



Results are dispatched to the appropriate target systems (e.g. PACS, RIS, EMR).

5 Continuous Improvement



web-based infrastructure and plug-ins in partner systems enable user feedback and continuous improvements of algorithm functionality.

Figure 1: The system, which comprises a collection of continuously learning algorithms, integrates itself into the existing image-processing IT environment and can be cloud-based or installed locally. (PACS: Picture archiving and communication system; RIS: Radiology information system; EMR: Electronic medical records)

Tangible benefits of AI assistance:

chest imaging – and beyond

An exemplary case for AI-supported multi-functional image analysis is chest imaging, which is one of the most important radiological fields of work. In the U.S., for example, approximately 900 chest X-ray examinations and 90 chest CTs are performed per 1,000 Medicare beneficiaries every year (Kamel et al. 2017). Lung cancer screening with low-dose CT in particular could further increase the need for fast and reliable image interpretation in many countries worldwide in the coming years.

In general, experts assume that completely independent diagnostic algorithms will find their way into radiological routines only in the medium to long term and that AI will, in the near future, rather serve to accelerate workflows and facilitate image interpretation (Loria 2018). Indeed, many supporting functions can already be integrated into AI systems today, for example, to perform biomarker-based measurements for various organs on a thoracic CT automatically, to highlight anatomical and pathological structures, or to prepare reproducible structured reports. In this way, readily actionable information is provided (Fig. 2).

Numerous current software developments aim, for instance, to facilitate detection and classification of lung nodules, thereby potentially improving cancer screening and diagnosis and minimizing false positive findings (Yang Y et al. 2018). The mere ability to automatically locate suspicious lesions using AI-powered lung segmentation (Humphries et al. 2018) and to measure their size in 2D and 3D could save an enormous amount of time.

Equally promising are algorithms for determining airway obstructions in COPD and the extent of emphysema (Das et al. 2018) or for quantifying the severity of pulmonary fibrosis on CT scans (Humphries et al. 2017). Last but not least, AI-supported 3D visualizations such as cinematic renderings can simplify the reading process and make it more intuitive (Dappa et al. 2016).

> *"Radiologists tend to overlook the heart while interpreting a routine chest CT."*
>
> Source: Kanza et al. 2016

Siemens Healthineers is currently developing software platforms that integrate many of these algorithms for assisted multi-organ image interpretation. An envisioned advantage of

Exemplary benefits

through comprehensive AI assistance in chest CT reading and reporting

Accelerating reading and reporting workflows

Making patient care more effective and efficient[1]

- Guideline- and biomarker-based automatic measurements of multiple structures, such as aorta, lung nodules, heart, coronary tree, and vertebrae
- Automated consideration of prior studies, as well as progression quantification e.g. for lung nodules and aortic aneurysms
- Automated transfer of results into structured reports and export to appropriate IT systems, e.g. PACS, RIS, and EMR
- Highlighting of lung lobes and detected nodules, airways, heart structures, or vertebrae through cinematic rendering
- Characterization and classification of bone mineral density, vertebral fractures, emphysema, coronary plaque, cardiomegaly, and aortic aneurysms
- Integration of reference values and risk scores, such as Lung RADS, calcium score, or bone mineral density score, as a guidance for reading and reporting

Figure 2: Exemplary benefits through comprehensive AI assistance in chest CT reading and reporting

[1] medcitynews.com/2018/04/how-radiologists-will-use-ai/

such an organ-spanning AI system is that, for example, cardiopulmonary diseases are easier to assess and incidental findings are less often missed. Due to their high spatial and temporal resolution, modern scanners enable comprehensive cardiothoracic evaluations even on non-ECG-synchronized, non-contrast-enhanced thoracic CTs (Marano et al. 2015). However, "radiologists tend to overlook the heart while interpreting a routine chest CT," as Canadian radiologist René Kanza and his colleagues comment (Kanza et al. 2016). Indeed, up to two-thirds of incidental cardiac findings detectable on a noncardiac CT, such as coronary calcifications or aortic dilatation, remain unmentioned in the radiological report (Secchi et al. 2017, Balakrishnan et al. 2017). This could probably be largely avoided by automated image analysis and AI-supported reporting.

The same is true for thoracic bone tumors or metastases, which are by no means rare or unexpected findings on chest CTs but still tend to slip through the diagnostic net, with potentially serious clinical consequences (Jokerst et al. 2016).

For metastasis detection in particular, it is desirable to have assisting AI platforms available in the future to evaluate not only images of individual body areas such as the chest, but also whole-body scans. For example, in advanced stages of breast or prostate cancer, metastases typically occur in the skeleton, or in the lungs, liver, or brain. The reliable detection and quantification of such tumor lesions is of enormous importance for therapy and prognosis, but it is also labor-intensive and prone to errors. Here, further developed, integrated AI systems may significantly improve whole-body evaluation in the coming years.

Leveraging a learning system

Artificial intelligence is a learning technology. On the one hand, AI as a whole has great development potential. New architectures of artificial neural networks have made possible remarkable progress in image analysis in recent years and will most probably continue to do so in the future. On the other hand, it is in the nature of intelligent algorithms themselves that they learn by processing large amounts of data and adjust and optimize their internal parameters. This optimization process is key, in particular when AI applications are used with different scanners or imaging protocols, or in different patient populations.

It is therefore obvious that AI systems need regular, well-planned updates to take full advantage of the technology. The FDA in the U.S., for example, is currently developing a regulatory framework to take into account this dynamic character of artificial intelligence, and at the same time to be able to implement incremental technological developments safely and on the basis of their clinical benefit (Petro & Lyapustina 2018, Miliard 2018).

For AI-supported image interpretation, this means that solutions that are already tangible and feasible today are poised for expansion and improvement in the future. Cloud-based infrastructures and user feedback will allow algorithms to be adapted at a fast pace, and new applications to be integrated into AI systems. Assisted multi-organ image interpretation thus constitutes a key milestone on the path to comprehensive, AI-powered whole-body imaging.

Additional Resources

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