Artificial intelligence and cardiovascular computed tomography

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Cardiovascular computed tomography (CT) routinely acquires volumetric datasets with large numbers of axial slices. While review of the axial slices remains an important part of the image analysis, a critical step is detailed reconstruction of multiple oblique planes and volumes on an advanced 3D workstation (1). This is performed by a combination of manual and (semi)-automated reconstruction along oblique planes, vascular centerlines, and volumes. This analysis results in a large number of discrete qualitative and quantitative data-points and is increasingly supported by dedicated, "smart" software.

In the traditional clinical diagnostic approach, the pattern of findings/data-points is analyzed by the Imaging Specialist/Radiologist and, based on accumulated knowledge and experience, summarized into a dictated impression. In traditional dictated reports, the datapoints cannot easily be extracted from narrative text blocks, because sensitivity and accuracy of natural language processing algorithms are still limited (2). However, the data-points have value in itself, and in structured reports are entered into data-fields as machine readable discrete data, allowing processing with intelligent algorithms or extraction for further evaluation. These data-points are combined with other data derived from history, clinical examination, laboratory tests, etc. collected and stored in an electronic medical record (EMR).

In addition to these data currently stored in the EMR, there are emergent novel data-sources, including data collected directly by the patient, e.g., with wearable sensors and smart phone-based applications. These data appear valuable in understanding an individual's health status and variations in patient outcomes and will increasingly supplement a traditional clinical diagnostic approach (3,4).

Modern "smart" computer systems allow collection and automated data analysis of large data sets, using artificial intelligence (AI)/machine learning (ML). Examples of data generation are computer-aided detection (CAD) systems in diagnostic imaging/radiology, e.g., for lung nodules identification (5,6). For data analysis, ML techniques are increasingly applied to large data sets in healthcare in order to build predictive models, both for individual patients and for larger populations (7,8). ML uses algorithms to identify expected and unexpected patterns in complex data sets analyzing large numbers of variables. Deep learning neural networks can automatically incorporate new data, using it to update and optimize its algorithm, with improvement of its predictive performance over time (9,10).

An example in the field of cardiovascular imaging is a paper by Motwani *et al.* describing the application of ML to predict 5-year all-cause mortality in >10,000 patients (745 died during the 5-year follow-up) undergoing coronary computed tomographic angiography (CCTA) (9). The model used 25 clinical and 44 CCTA parameters. Compared with the performance of existing clinical or CCTA metrics, the ML algorithm exhibited a higher area under the curve for predicting all-cause mortality. The authors caution that research using such large, complex data sets is still limited by the fact that current statistical methods are not optimized.

There are other, technical limitations. The large amount and complexity of patient-related data accumulating in large healthcare institutions requires advanced software and hardware and a dedicated group of IT professionals for maintenance. Data have to be available without downtime at multiple locations and data safety has to be maintained. A significant challenge is unequivocal patient identification, in particular if data are shared across large healthcare systems and with other institutions. Complex issues related to data security, patient consent and ownership have to be addressed. Because of the complexity and associated cost of maintaining such data, healthcare systems may consider external "data cloud" providers for data analysis, management, and storage further complicating oversight and regulation (11,12).

It is likely that AI will become increasingly integrated into routine clinical workflows in both cardiovascular imaging and cardiovascular medicine in general (13). However, decision-making in medicine is significantly influenced by various humanistic factors that play a role in the physician-patient relationship. These human aspects of the doctor-patient relationship are not necessarily logical and therefore not yet easily described by a computer code. Physicians will have to learn to integrate computer-generated analytic results into established workflows to benefit individual patients. Data analysis will likely be used to develop and adjust clinical pathways and monitor impacts on outcome measures of large patient populations within healthcare systems. The availability of data-points in discrete form created by the clinicians and enhanced with AI has the potential for faster and more precise diagnostic decision making.

In summary, the combination of large EMRs and automated analysis with ML algorithms allows information gathering, data analysis, and feedback to individual practitioner and to healthcare systems. Similar to the impact of data technology in many aspects of daily life, these changes will impact current models of doctor–patient relationships, with potential benefit for the individual patient and also larger patient populations. It may also have impact on the work of specialists including radiologists, but clearly not substituting them. It will enhance their diagnostic workflow, allowing faster and more precise diagnosis. The role of the future imaging specialist will likely increasingly include generation and management of imaging data, providing access to discrete data beyond the traditional report. This requires close collaboration with IT specialists. Future studies will be necessary to define the role of these tools in clinical practice.

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References

1. Schoenhagen P, Numburi U, Halliburton SS, et al. Three-dimensional imaging in the context of minimally invasive and transcatheter cardiovascular interventions using multi-detector computed tomography: from pre-operative planning to intra-operative guidance. Eur Heart J 2010;31:2727-40.
2. Bresnik J. Health IT Analytics. Available online: https://healthitanalytics.com/features/what-is-the-role-of-natural-language-processing-in-healthcare
3. Rumsfeld JS, Joynt KE, Maddox TM. Big data analytics to improve cardiovascular care: promise and challenges. Nat Rev Cardiol 2016;13:350-9.
4. Huynh QL, Negishi K, Blizzard L, et al. Predictive Score for 30-Day Readmission or Death in Heart Failure. JAMA Cardiol 2016;1:362-4. Erratum in: Errors in Table and Text. [JAMA Cardiol 2016].

5. Liang M, Tang W, Xu DM, et al. Low-Dose CT Screening for Lung Cancer: Computer-aided Detection of Missed Lung Cancers. Radiology 2016;281:279-88.
6. Bogoni L, Ko JP, Alpert J, et al. Impact of a computer-aided detection (CAD) system integrated into a picture archiving and communication system (PACS) on reader sensitivity and efficiency for the detection of lung nodules in thoracic CT exams. J Digit Imaging 2012;25:771-81.
7. Deo RC. Machine Learning in Medicine. Circulation 2015;132:1920-30.
8. Singal AG, Mukherjee A, Elmunzer BJ, et al. Machine learning algorithms outperform conventional regression models in predicting development of hepatocellular carcinoma. Am J Gastroenterol 2013;108:1723-30.
9. Motwani M, Dey D, Berman DS, et al. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. Eur Heart J 2017;38:500-7.
10. Mjolsness E, DeCoste D. Machine learning for science: state of the art and future prospects. Science 2001;293:2051-5.
11. Bakkar N, Kovalik T, Lorenzini I, et al. Artificial intelligence in neurodegenerative disease research: use of IBM Watson to identify additional RNA-binding proteins altered in amyotrophic lateral sclerosis. Acta Neuropathol 2018;135:227-47.
12. Blog IEEE Future Directions: "Congrats Xiaoyi. You are now a medical doctor." Available online: http://sites.ieee.org/futuredirections/2017/12/02/congrats-xiaoyi-you-are-now-a-medical-doctor/
13. Schoenhagen P, Roselli EE, Harris CM, et al. Online network of subspecialty aortic disease experts: Impact of "cloud" technology on management of acute aortic emergencies. J Thorac Cardiovasc Surg 2016;152:39-42.

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