Machine Learning in Medical Imaging

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Abstract

Advances in both imaging and computers have synergistically led to a rapid rise in the potential use of artificial intelligence in various radiological imaging tasks, such as risk assessment, detection, diagnosis, prognosis, and therapy response, as well as in multi-omics disease discovery. A brief overview of the field is given here, allowing the reader to recognize the terminology, the various subfields, and components of machine learning, as well as the clinical potential. Radiomics, an expansion of computer-aided diagnosis, has been defined as the conversion of images to minable data. The ultimate benefit of quantitative radiomics is to (1) yield predictive image-based phenotypes of disease for precision medicine or (2) yield quantitative image-based phenotypes for data mining with other -omics for discovery (ie, imaging genomics). For deep learning in radiology to succeed, note that well-annotated large data sets are needed since deep networks are complex, computer software and hardware are evolving constantly, and subtle differences in disease states are more difficult to perceive than differences in everyday objects. In the future, machine learning in radiology is expected to have a substantial clinical impact with imaging examinations being routinely obtained in clinical practice, providing an opportunity to improve decision support in medical image interpretation. The term of note is *decision support*, indicating that computers will augment human decision making, making it more effective and efficient. The clinical impact of having computers in the routine clinical practice may allow radiologists to further integrate their knowledge with their clinical colleagues in other medical specialties and allow for precision medicine.

Key Words: Machine learning, deep learning, radiomics, computer-aided diagnosis, computer-assisted decision support

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Advances in both imaging and computers have synergistically led to a rapid rise in the potential use of artificial intelligence in various radiological imaging tasks, such as risk assessment, detection, diagnosis, prognosis, and therapy response, as well as in multi-omics disease discovery. Although computer-aided detection (CADe) has been proposed, developed, and clinically used since 1966, especially in thoracic and breast imaging [1-5], the widespread progress in multiple clinical decision-making tasks and multiple disease sites has only advanced in the past decades with the corresponding access to large computational resources, including computer power, storage, and digital imaging, as well as increased electronic access to information at the time of interpretation (eg, clinical history, laboratory data, prior examinations).

A brief overview of the field is given here, allowing the reader to recognize the terminology, the various subfields, and components of machine learning, as well as the clinical potential. Figure 1 shows the number of publication counts in PubMed for searches on computer-aided diagnosis (CADx) in radiology, machine learning, and deep learning from 1972 to middle of 2017. Note that in each of these areas, there are numerous review publications; however, the aim of this article is to elucidate the concepts and generalities. The range in presentation of various subtle disease states, the need for large annotated clinical data sets, and the complex structure of many machine learning methods signify much need for continued research and development before full clinical incorporation and use.

CADe, CADx, AND DECISION SUPPORT

Medical image interpretation is the main undertaking of radiologists, with the tasks requiring both good image quality and good image interpretation. Image interpretation by humans is limited by the presence of structure noise (camouflaging normal anatomical background), incomplete

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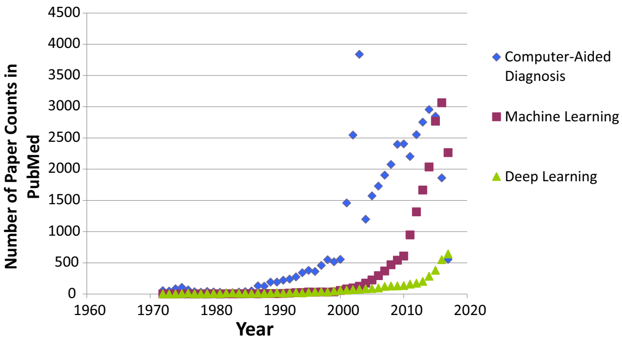

Fig 1. Number of paper counts in PubMed for searches on computer-aided diagnosis in radiology, machine learning, and deep learning from 1972 to middle of 2017.

visual search patterns, fatigue, distractions, the assessment of subtle or complex disease states, vast amounts of image data, and the physical quality of the image itself.

CADe and CADx have been under development for decades [1-5]. In fact, CADe systems have already been commercialized and have been in clinical use since the turn of the century [6]. In addition, over the past few decades, various investigators have been developing image analysis methods for CADx, such as the computer-assisted quantitative characterization of breast lesions on clinical images, as well as in the assessment of cancer risk [4].

There is no one-size-fits-all when it comes to computer algorithms and specific radiological interpretation tasks. Each computerized image analysis method requires customizations specific to the task as well as the imaging modality. For example, in breast cancer risk assessment, computer-extracted characteristics of breast density or breast parenchymal pattern are computed and related to breast cancer risk factors [7-12]. CADe methods involve a localization task and serve as a second opinion to radiologists in their task of finding suspicious regions within images, as in screening mammograms, leaving subsequent patient management decisions to the radiologist. CADx involves the characterization of a region or tumor, initially indicated by either a radiologist or a computer, after which the computer characterizes the suspicious region or lesion or estimates its probability of disease, again leaving the patient management to the physician [4].

RADIOMICS AND IMAGING GENOMICS (RADIOGENOMICS)

Effective diagnosis and treatment of disease rely on the integration of information from multiple patient tests involving clinical, molecular, imaging, and genomic data (ie, various "-omics"). Radiomics, an expansion of CADx, has been defined as the conversion of images to minable data [13-15]. Obtaining radiomic data may involve computer segmentation of a tumor from its background followed by computer extraction of various tumor features. The ultimate benefit of quantitative radiomics is to (1) yield predictive image-based phenotypes of disease for precision medicine or (2) yield quantitative image-based phenotypes for data mining with other -omics for discovery (ie, imaging genomics).

Radiomic features can be described as handcrafted or engineered, with intuitive features or deep-learned features. In this section, the focus is on handcrafted features for which computer algorithms are developed based on some analytical feature-extraction approach, such as the calculation of geometric shape of a tumor. For example, Figure 2 demonstrates a computer-aided design or radiomics pipeline for the computer extraction of various characteristics of breast tumors on dynamic

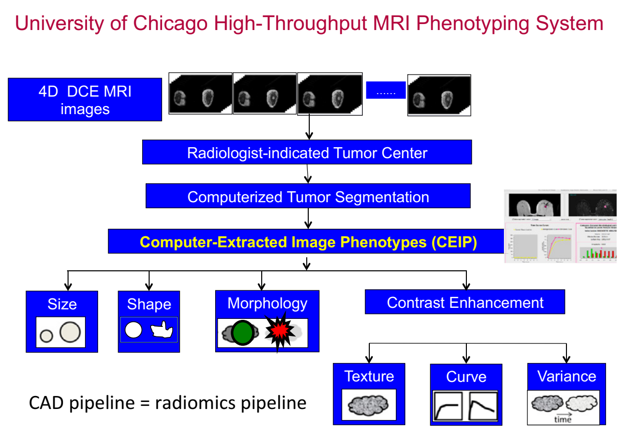

Fig 2. Schematic flowchart of a computerized tumor phenotyping system for breast cancers on DCE-MRI. The computer aided diagnosis (CAD) radiomics pipeline includes computer segmentation of the tumor from the local parenchyma and computer-extraction of "handcrafted" radiomic features covering six phenotypic categories: (1) size (measuring tumor dimensions), (2) shape (quantifying the 3-D geometry), (3) morphology (characterizing tumor margin), (4) enhancement texture (describing the heterogeneity within the texture of the contrast uptake in the tumor on the first postcontrast MRIs), (5) kinetic curve assessment (describing the shape of the kinetic curve and assessing the physiologic process of the uptake and washout of the contrast agent in the tumor during the dynamic imaging series, and (6) enhancement-variance kinetics (characterizing the time course of the spatial variance of the enhancement within the tumor) [16-21]. CAD = computer-aided diagnosis; DCE-MRI = dynamic contrast-enhanced MRI.