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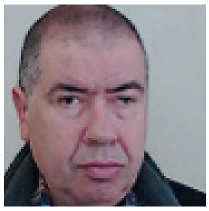
Artificial Intelligence in Radiology: From Image Processing to Diagnosis

Inteligência Artificial em Radiologia: Do Processamento de Imagem ao Diagnóstico



João Miranda Lemos

Jorge S. Marques[ab], Catarina Barata[b], J. Miguel Sanches[ab], Patrícia Figueiredo[ab], J. Miranda Lemos[ac]

[a]Instituto Superior Técnico, [b]Instituto de Sistemas e Robótica - Lisboa, [c]INESC-ID, Portugal

Introduction

The objective of this article is to present a view on the potential impact of Artificial Intelligence (AI) on processing medical images, in particular in relation to diagnostic. This topic is currently attracting major attention in both the medical and engineering communities, as demonstrated by the number of recent tutorials [1-3] and review articles [4-6] that address it, with large research hospitals, as well as engineering research centers contributing to the area. Furthermore, several large companies like General Electric (GE), IBM/Merge, Siemens, Philips or Agfa, as well as more specialized companies and startups are integrating AI into their medical imaging products. The evolution of GE in this respect is interesting. GE SmartSignal software was developed for industrial applications to identify impending equipment failures well before they happen. As written in the GE prospectus, with this added lead time, one can transform from reactive maintenance to a more proactive maintenance process, allowing the workforce to focus on fixing problems rather than looking for them. With this background experience from the industrial field, GE developed predictive analytics products for clinical imaging, that embodied the Predictive component of P4 medicine (predictive, personalized, preventive, participatory). Another interesting example is the Illumeo software from Philips that embeds adaptive intelligence, i. e. the capacity to improve its automatic reasoning process from its past experience, to automatically pop out related prior exams for radiology in face of a concrete situation. Actually, with its capacity to tackle massive amounts of data of different sorts (imaging data, patient exam reports, pathology reports, patient monitoring signals, data from implantable electrophysiology devices, and data from many other sources) AI is certainly able to yield a decisive contribution to all the components of P4 medicine. For instance, in the presence of a rare disease, AI methods have the capacity to review huge amounts of prior information when confronted to the patient clinical data.

Medical Image Processing

For the purpose of computer processing, an image is described as a table of numbers, with image elements called pixels for 2 dimensional images, or voxels for 3 dimension pictures. A plethora of technologies to visualize inside the human body are available and generate image data. Examples include ultrasound (US), computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single photon emission computed tomography (SPECT). The use of a specific sensing device depends on the medical field of application.
Processing medical images comprises two broad classes of problems: Obtaining enhanced images and providing them to the clinician through a suitable man/machine interface, and automatic generation of diagnostic decisions (possibly involving the clinician). The first problem is the realm of image processing methods that comprise image reconstruction (build images from sensor data), image filtering (separation of image useful information from "noise"), and image segmentation (isolation of single elements of interest in the image), that may refer to single images or to video sequences. The second class of problems is related to computer-aided diagnosis and is tightly related to AI. Computer aided diagnosis (CAD)[10] systems based on multimodal information, that is to say, clinical information from different sources, are commonly used today to support therapeutic and surgical decisions in several medical fields.[11] The diagnosis and characterization of the atherosclerotic disease of the carotid is a paradigmatic example where this type of systems has been successfully used in support decision-making of endarterectomy, the surgical approach for atherosclerotic plaque removal. This is a critical surgical procedure on the neck with significant medical risks that should be avoided when the risk of plaque disruption and carotid stenosis are small. In[12] a new score is proposed to assess the stability of the plaque and indirectly quantify the risk of stroke mainly in asymptomatic patients. The novelty of the method relies on putting together automatic textural and morphological features extracted from ultrasound images of the plaque with traditional clinical information provided by the medical doctor. This diagnosis strategy has also proven to be very useful in the diagnosis of chronic liver disease[13] where sophisticated and complex image

processing algorithms coexist harmoniously with the classic, sometimes subjective, techniques used in clinical practice producing more accurate tools for diagnosis.

While in the classical architecture the work of the image processing engineer is to define handcraft features, conveying information about the decision to be made (e.g., color or texture histograms), the end-to-end approach does not require this intermediate step and attempts to produce the decision directly from the input image. This approach is much more difficult since, instead of using a few hundred features to produce the decision, it considers the full image with thousand or millions of pixels/voxels, and relies on deep neural-networks with thousands of coefficients. On the other hand, the end-to-end approach does not depend on the ability of the engineer to reduce the input image into a "small" set of feature but, instead, the image features are internal variables that are trained from the data.[7,8,9]

Artificial Intelligence

Artificial Intelligence includes many problems and paradigms. The class of problems addressed in this article fits into the scope of supervised data-based learning that consists of using known data and past decisions to learn how to predict the decision for new data.

AI decision algorithms comprise many methods, including statistical [14] or neuronal methods such as

- Bayes classifier
- Linear classifiers (Logistic regression, linear discriminant analysis)
- Support vector machines
- Decision trees (often used in Medicine because they provide a justification for the decision)
- Random forests. An extension of decision trees that uses multiple trees, trained under different conditions. It has the advantage over decision trees of improving the decision process, but the drawback of loosing the justification.
- Neural networks (based on a collection of simple processing units inspired in the human brain; these units are nonlinear, highly interconnected and they are often organized in processing layers). When the number of layers is higher then three, the network is called a deep neural network and the learning phase is called deep learning.

Deep-learning[4,8,9,15] is solving problems in a scale that was not conceivable up to 5 years ago, but has the drawback of requiring large amounts of annotated data (many thousands of annotated examples). Tackling this problem is easy in areas where data is freely available through the internet but it is much more difficult in areas such as medical diagnosis where annotated data is scarce. In such areas, either it is possible to develop new algorithms that are able to achieve similar performance with a smaller amount of data or one has to rely on conventional decision methods with hand-crafted features, or a mixture of both.

Selected Future Prospects

Although the application of AI to Radiology is manifold, only two possible developments are considered hereafter, that have been selected because of their relevance.

Deep learning in relation to clinically inspired decision systems

Clinically Inspired Decision Systems are systems that provide explanations for the final decision that are similar to the ones yielded by a human expert medical doctor. The interest for this type of systems stems from the fact that medical doctors are reluctant to accept unjustified decisions. Currently, the diagnosis based on medical images partially relies on the existence of text reports that describe the exams and highlight the most relevant findings (e.g., the identification and sizing of nodules on chest X-rays). This makes one wonder what will be the real acceptability of the deep learning based systems, which lack these descriptive properties and are usually perceived as "black-boxes" among clinicians and patients.[16] This section addresses the previous issue and the possibility to develop deep learning systems that yield explanations and decisions similar to that of human experts.

One of the simplest strategies is to go beyond simply diagnosing a 2D or 3D scan using a deep learning architecture, and extend it to the localization of relevant organs, regions or lesions (e.g., nodules, tumors, and micro-bleedings).[17] Such modification provides the clinicians with visual cues to understand the diagnosis. In some cases, it is possible to refine the location of the relevant structure, leading to its segmentation, that in turn allows a quantitative analysis of useful shape and volumetric clinical parameters. Among the segmentation-based convolution neural network architectures, the most popular is the U-net, that was proposed by Ronneberger et al.[18] to segment cells in light microscopy images.

The main limitation of the aforementioned systems is the lack of a large amount of data, namely segmentations, to train the deep learning models. Some researchers tackled this issue using text reports to train deep learning architectures in a weakly supervised fashion. In this case, the models try to associate key words in the reports with specific regions of the medical images. An example is the work of Hwang et al. that used this framework to detect nodules in chest X-rays and lesions in mammography.[19] The generation of reports, such as the prediction of BI-RADS for breast lesions,[20] has also been investigated. These works rely on methods developed for image caption generation[21] and use two types of deep learning architectures: a convolution neural network for image analysis and a recurrent neural network for text generation. The production of automatic reports may be useful to understand what the network is responding to.

Another interesting line of research is applying deep learning to perform content-based image retrieval. The idea is to discover similar cases in databases, i.e., make use of previous knowledge, as would happen with clinicians that are exposed to several cases through their years of practice. In this case, deep learning architectures may be used to obtain suitable image representations.[22]

It is important to bear in mind that medical images convey only part of the useful information. Clinicians also rely on a set of medical covariates, such as the gender, age, patient and familial history, as well as demographics to complement the diagnosis procedure. Although recent works have shown that incorporating this information in a deep learning system improves the performance,[23] combining such distinct information is not trivial and few works have explored this possibility.[4]

Brain imaging

Artificial intelligence is playing a rapidly expanding role in brain imaging, including clinical applications in neurology and psychiatry as well as new tools for neuroscience research. Magnetic resonance imaging (MRI) is by far the most important modality for brain imaging, not only allowing the visualization of cerebral anatomy with exquisite detail, but also providing information on cerebral micro-structure (using diffusion-weighted imaging) as well as multiple physiological and functional parameters (such as blood perfusion and oxygenation, cerebrovascular reactivity and neuronal activity).[31,32] The availability of the latter advanced techniques opens the applicability of MRI to subtle brain pathology that eludes macroscopic structure. This is the case of cerebrovascular and microstructural changes preceding white matter lesions in cerebrovascular disease (e.g.[24]), or functional changes preceding brain atrophy in dementia (e.g.[25]). Physiological imaging is also needed to monitor brain tumors and evaluate their response to treatment (e.g.[26]), while alterations in functional brain networks are a hallmark of psychiatric diseases such as schizophrenia and depression where no morphological changes are observed (e.g.[27]).

The remarkable developments in MRI technology over the past decade have pushed brain imaging to unprecedented levels of sensitivity and spatial resolution, attainable with previously unimagined speed, which offers extraordinary possibilities for the application of AI methods. On the one hand, the development of increasingly faster acquisition schemes motivates the use of machine learning for image reconstruction from under-sampled or noisy data (e.g.[28]). On the other hand, AI methods can be employed at various levels of image post-processing, including artifact correction, image registration or lesion segmentation, as well as parameter quantification (e.g.[29]). Moreover, AI is clearly needed for the identification of imaging biomarkers of brain disease, that can be used to support early diagnosis and outcome prediction as well as to monitor disease progression and assess response to treatment, including the evaluation of novel therapeutic approaches in clinical trials (e.g.[30]) – this is the field of radiomics.

Conclusion

AI software is permeating the field of Radiology with commercial products already available. This fact does not mean that the progress is towards a situation in which the medical doctor is no longer needed, but instead that he will have an enhanced role, free from repetitive tasks, and able to concentrate on the core clinical decisions. Indeed, future applications of AI to Radiology will provide an enhancement of the quality of diagnosis combining multiple data and integrating the clinician as a crucial element. The progress in this area will rely on a deep cooperation between medical doctors and engineers to develop complex computer aided diagnostic systems.

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