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Editorial

Artificial neuroradiology: Between human and artificial networks of neurons?

Increasingly widespread application of advanced image processing and Artificial Intelligence (AI) in the field of neuroradiology highlights changing trends in the availability of emerging technologies. In the past 10 years, publications on AI in radiology have increased from 100–150 to 700–800 per year and neuroradiology appears as the most involved subspecialty, accounting for about one-third of articles [1].

But it should be noted that the application of lower levels of AI through medical image processing [2] has been integrated since the birth of our discipline. The convergence of better technological performance and higher volume of data to process has favored the development of more advanced processes, such as machine learning (ML).

AI can be attributed to any machine performing a task normally claiming human cognition. ML is a type of AI that allows computers to learn from data without explicit programming (not by programming it for a specific domain, but by designing a system that can learn from several examples to solve a problem, such as classification algorithms: clustering, support vector machine...). ML-based algorithms may differ depending on the approach, the type of data, and the task. Supervised and unsupervised learning are part of this. In this latter approach neither criteria nor ground truth are used to train the algorithm. Deep learning is therefore a supervised machine learning method that uses a specific architecture, mainly a form of neural network to automatically extract relevant features. These neural networks are inspired by the structure of the brain.

Early attempts of brain modeling even precede the computer age. In 1943, McCulloch (neurophysiologist) and Pitts (logician) proposed the first notions of formal neuron. This concept was then networked by Rosenblatt in 1959 to simulate retina functioning and to recognize forms, thus giving birth to the perceptron. This so-called "connectionist" approach reached its technological limits given the computing power in the early 1970s. The simple perceptron algorithm had a significant disadvantage when applied to real-life cases: its linearity. The passage from a simple perceptron (a layer of neurons) to a multi-layer perceptron is one of the answers to this problem, leading to the emergence of deep neural networks. The connectionist approach was then supplanted by a symbolic approach that promoted knowledge-based expert systems, whose objective was to automate the principle of human expertise by combining a knowledge base (logical propositions using quantifiers), a fact base (observations of the case), and an inference engine (apply the expert rules). Technological development and some theoretical advances at the beginning of the 80s allowed to revive the connectionist approach [3].

Today in neuroradiology, many applications have been developed or are under development. Several studies focus on the field of emergencies to provide a tool for diagnostic assistance in the case of stroke or hematoma detection, using for example automated deep neural network surveillance of cranial images for acute neurologic events [4], or deep neural network-based algorithm to detect cerebral aneurysms in MR angiography (computer-assisted detection) [5]. Projects on tumor characterization are also underway. As the previous study of Uthoff et al. published in the *Journal of Neuroradiology* that explored whether objective, quantitative radiomic biomarkers derived from MR, PET and CT, may be useful in reliably distinguishing malignant peripheral nerve sheath tumors from benign plexiform neurofibromas, and suggested that imaging features can be used to distinguish malignancy in NF1-related tumors [6].

ML has been applied to imaging data for several decades by researchers. However, it is only recently, that radiologists have made better use of the quantitative data contained in their images [7].

Radiomics convert radiological regions of interest, such as brain meningiomas or hemangiopericytomas in the recently published article of Li et al. [8], into a collection of metrics. These metrics could be markers of tumor heterogeneity through quantitative descriptors, such as histogram-based methods (first-order), texture features (second-order) or methods that impose filter grids (high-order). Here Li et al. have included pathologically confirmed cases of rare brain tumor processes to apply a radiomics algorithm. This is particularly relevant because the treatment principles highly differ between angiomatous meningiomas and hemangiopericytomas; and the radiological differential diagnosis based on classic imaging features remains difficult.

One of the major advantages of radiomics extraction of metrics before applying a classic machine learning classifier such as support vector machine, is the possibility to train the model faster with better performance than with deep learning algorithms when data are sparse and the number of patients small or with high interindividual variability. In other words, in "real-world" clinical data (like Li et al. who compared 24 malignant hemangiopericytomas and 43 angiomatous meningiomas), radiomics can provide excellent results in distinguishing tumor subtypes, potentially leading to better patient care. It should be emphasized that radiomics can be used to include clinical and various imaging modalities markers in the same model.

However, the high number of extracted features compared to the comparatively smaller number of patients is challenging to apply classification and regression algorithms. Richard E. Bellman has defined this problem as "the curse of dimensionality", requiring a first step of dimensionality reduction [9].

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Instead of using linear or nonlinear feature extraction algorithms to do so, researchers usually perform reproducibility studies of biomarkers to select those with high scores [10], demonstrating the need for various MRI sequences/markers to build the best models. Besides the choice of non-redundant clusters of features, the most critical point to expand the radiomics concept into clinical care is probably results variability following the algorithm choice. For example, Choi et al. have recently tested the influence of various radiomics algorithms on chest CT features [11]. They have demonstrated a dramatic fall of concordance correlation coefficients between readers when using different kernels of reconstructions. Fortunately, they have proposed in the same article to associate radiomics with deep learning, not to perform a direct concomitant analysis of the lung cancers, yet to improve the robustness of radiomics features reproducibility using different algorithms.

With this regard, while the study of Li et al. [8] can be considered as interesting in neuroradiology clinical research, further studies of technical validation are needed to ensure the usefulness in various imaging centers. Radiomics standards exist, yet there are still gaps in the algorithm choice requiring public sharing of the raw data and source code.

The strengths of the *Journal of Neuroradiology*'s papers are the choice of features, all extracted form routine MRI sequences, and the comparison with neuroradiologists for diagnostic accuracy. Healthcare algorithms require a high degree of interpretability for clinical decision making. By demonstrating the role of support vector machine classifiers on texture features alongside the presence of larger sizes and serpentine-like intratumoural vessels in cases with hemangiopericytomas, Li et al. [8] enhance both the expertise of neuroradiologists and the added value of the machine. Better exploitation of quantitative characteristics of brain tumor processes is inevitable in the future, keeping in mind the need for precision medicine. The development of methods such as synthetic MRI may promote the use of parametric mapping and exploitation of these quantitative characteristics [12].

While the development of artificial intelligence algorithms requires a large amount of data, rigor in data manipulation, standardization and sharing will be an asset. Considering the variability introduced by the actual variety of equipment and imaging protocols, there may be a need to validate any AI process (in particularly radiomics biomarkers) in prospective multicenter studies, to allow these approaches to be used in a broader manner [13].

In addition, for information to be diagnostically or prognostically analyzed, patient data (clinical, biological...) are often essential. In this context, it is important that information systems as PACS/RIS/XDS integrate more patient information into more comprehensive databases. These last ones may evolve to support research and processing on larger (clinical and radiological) dataset.

AI will surely induce a future transformation of our profession. Its primary role of may be to reduce redundant tasks, allowing us to focus more on studying complex issues, to improve the quality of the report, or to spend more time with the patient [14]. Artificial intelligence algorithms also allow for more complex tasks, such as categorizing or comparing. They also make it possible to highlight information that is not visible. AI does not have the role of replacing our profession but rather of being at our service [1].

To take part of this future, the *Journal of Neuroradiology* invite manuscripts that would have an impact in the field of neuroradiology using AI or innovative computational methodologies to handle information, diagnose and decide, optimize imaging workflow [15]. AI and neuroradiology cannot coexist side by side, they must be gathered to advance knowledge. AI must be a human-driven activity that shapes but does not replace the future for the neuroradiology and neuroradiologists, by extending our human abilities to provide the best possible medical care.

Disclosure of interest

The authors declare that they have no competing interest.

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