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REVIEW ARTICLE

Advancements in Neuroradiology via Artificial Intelligence and Machine Learning

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Abstract

Neuroradiology is significantly showing the broad impact in field of Artificial intelligence research and Machine learning. Neuroradiology includes methods such as neuro-imaging which simply diagnose and characterize disorders of the CNS and PNS. Artificial Intelligence (AI) is one of the main attributes in the field of computer science generally focusing on creating "algorithms" which can be used to solve any arbitrary desired problem. AI has several applications in the field of Neuroradiology and one of the most common and influencing application is machine learning. Machine learning is a data science approach that allows computers to learn without being programmed with specific rules. Some of the factors which shows neuroradiological impact on AI research are, (a) neuroimaging comprising rich, multicontrast, multidimensional, and multimodality data which fit themselves well to machine learning tasks; (b) consideration of well-established neuroimaging public datasets of various neural diseases such as Alzheimer disease, Parkinson disease, tumors, different forms of sclerosis etc. (c) quantitative neuroimaging research history which proves clinical practices. Another major application is Deep learning which is useful in management of information content of digital pictures that a human reader can only identify and use partially. Except these various limitations also come in the picture such as adoption in neuroradiology practice etc. Till now several research has been done which connects the concepts of Neuroradiology and Artificial intelligence and yet more to be done to overcome the limitations of AI in Neuroradiology.

Key Words: *Neuroradiology; Machine learning; Artificial intelligence; Algorithm; Neuroimaging*

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1. Introduction

Neuroradiology involves neuro-imaging methods to diagnose and characterize disorders of the central and peripheral nervous systems, and image parenchymal consequences of vascular disease and their etiological causes. It is one of the emerging sub-specialities of radiology which is the widespread application of AI [1]. Artificial Intelligence (AI) can be attributed as a field of computer science that focuses on creating sophisticated functions or "algorithms" that may be used to solve any arbitrary desired problem. By easing 3D reconstructions and segmentation, recognizing tiny new lesions, and assessing longitudinal changes, AI technology has the potential to alleviate the burden of time-consuming and monotonous operations.

AI, particularly deep learning (a subset of machine learning), is currently gaining attention as a disruptive breakthrough in medicine, especially neuroradiology, with the potential to change entire sectors and therefore increase the value of quantitative imaging techniques. Neuroradiology on AI research has gained much significance due to number of causes including multi-dimensional and complex neuro-imaging data sets which lend itself properly to machine learning (ML) tasks and remaining unsolved problems related to neuroscience and neuro-developmental diseases [2].

Though AI and machine learning promise to provide neuroradiology, a powerful and emerging tool to ease transformation in imaging systems, but its potential pitfalls and complex ethical and societal issues raises a limitation over its applications.

2. Neuroradiology

Neuroradiology is critical for the first examination of patients having clinical suspicion of a brain or spine disorder using cross sectional imaging such as PET, CT and MRI which leads to a significant change in clinical practices of neuroradiology [3]. Imaging technological advancements allows a better knowledge of neurological diseases and transforms neuroimaging from a purely anatomical to a functional assessment of the nervous system. Despite all these accomplishments, one of the most difficult questions in neuroradiology [4] is estimating/forecasting the results and/or benefits of a therapy before conducting it [5]. Nevertheless, the discovery of a reliable mechanism for predicting success rate of single therapy for a specific patient might eliminate needless and ineffective treatments and interventions, lowering healthcare expenditures and substantially lowering risk. It also considers the practice of examining patient's demographic and pathologic features before the therapy may impact treatment efficacy, which can then be assessed using post-treatment assessments [6]. Breakthroughs in neuroimaging in recent years which paved the way for the advancements in neuroradiology studies are:

2.1. Advances in CT scan

The most recent 64 multi-detector CT imaging technology produces pictures with a minimum isotropic spatial resolution of 0.6mm. This means that brain scans may be recreated in any plane without introducing substantial artifacts. The brain may be scanned in a matter of seconds and rebuilt in any plane with a slice thickness of less than 1mm if necessary. Because of the high spatial and temporal resolution, CT brain perfusion and CT angiography of the cerebral arteries are now possible. CT cerebral perfusion allows the stroke physician to quantify the size and extent of the cerebral infarction while doing the initial CT scan. The primary drawback of CT perfusion and CT angiography is that the patient receives a significantly greater radiation dosage, particularly to the lens of the eye and the thyroid gland. Despite recent negative press in the United States over CT radiation doses, there is little question that the cautious use of CT imaging with current X-ray tube dose regulation techniques has resulted in a significant breakthrough in neuroimaging over the last decade.

2.2. Advances in MRI

The development of MR tractography of the brain and spinal cord, as well as functional MR imaging (f MRI), have been the most interesting research topics in neuroradiology. Diffusion weighted imaging is now standard practice in stroke and spinal cord imaging. Neuroradiologists are increasingly imaging the nervous system using 3 Tesla high field MR devices which with the introduction of cerebrospinal fluid motion nulling software, can now perform spinal cord tractography. MR spectroscopy quantifies key metabolites in the brain and their relative amounts as a ratio to an internal standard of creatine. This has enabled researchers to look at a variety of mental and cognitive diseases, such as Alzheimer's disease and schizophrenia. Spectroscopy, in conjunction with CT-PET scans, can identify tumor recurrence following surgery or chemotherapy.

3. Artificial Intelligence and Neuroradiology

The term "artificial intelligence" (AI) refers to computational algorithms that can execute activities that are regarded typical of human intellect, with partial to total autonomy, in order to generate new useful outputs from specified inputs. The evolution of AI is primarily dependent on the advent of artificial neural networks (ANN), which enabled the ideas of "computational learning models," machine learning (ML), and deep learning to be introduced (DL) [7,8]. Since beginning, it was obvious that computers might be beneficial in aiding the radiologist with routine detection and diagnostic duties. More complicated activities, such as sorting or comparing, are also possible using artificial intelligence systems. They also allow to emphasize information that isn't visible.

Artificial intelligence has the potential to change the practice of neuroradiology, thanks to novel procedures, computational tools, and increased availability of imaging data. The use of artificial intelligence approaches to improve workflow, diagnosis, and treatment, as well as to increase the utility of quantitative imaging techniques, is gaining traction [9]. The use of AI in neurosciences demands a greater knowledge of the intelligent functioning of the biological brain, which proves to be a contradiction. The growing availability of healthcare data and the fast advancement of analytical tools are causing a paradigm change in healthcare. AI helps physicians make better decisions by discovering clinically important information hidden in huge amounts of data [2,10]. AI can be programmed with learning and self-correction capabilities to improve its accuracy in response to feedback. To improve patient care, an AI system can aid doctors by delivering up-to-date medical knowledge from journals, textbooks, and clinical practices.

However, it should be emphasized that the use of lower degrees of AI in medical image processing has been integrated since this discipline's inception. The confluence of improved technical performance and increased data volume to process has promoted the development of more sophisticated processes, such as Machine Learning (ML) [11]. ML is a subset of AI that enables computers to learn from data without the need for explicit programming. ML-based algorithms might vary depending on the strategy, data type, and task. This includes both supervised and unsupervised learning (Figure 1). The latter technique does not employ criteria or ground truth to train the algorithm. Deep Learning is therefore a supervised machine learning approach that employs a certain architecture, mostly a type of neural network, to extract important information automatically [7]. The structure of the brain influenced the design of these neural networks.

3.1. Machine learning: essentials

Machine learning is a data science approach that allows computers to learn without being programmed with specific rules. ML enables the development of algorithms that can be learned and predicted. Machine learning, as opposed to rules-based algorithms [12], benefits from increased exposure to vast and fresh data sets and has the capacity to grow and learn with experience. ML is based on the "reverse training" technique, in which computer systems concentrate on certain pathological traits found during the training stage [13,14].

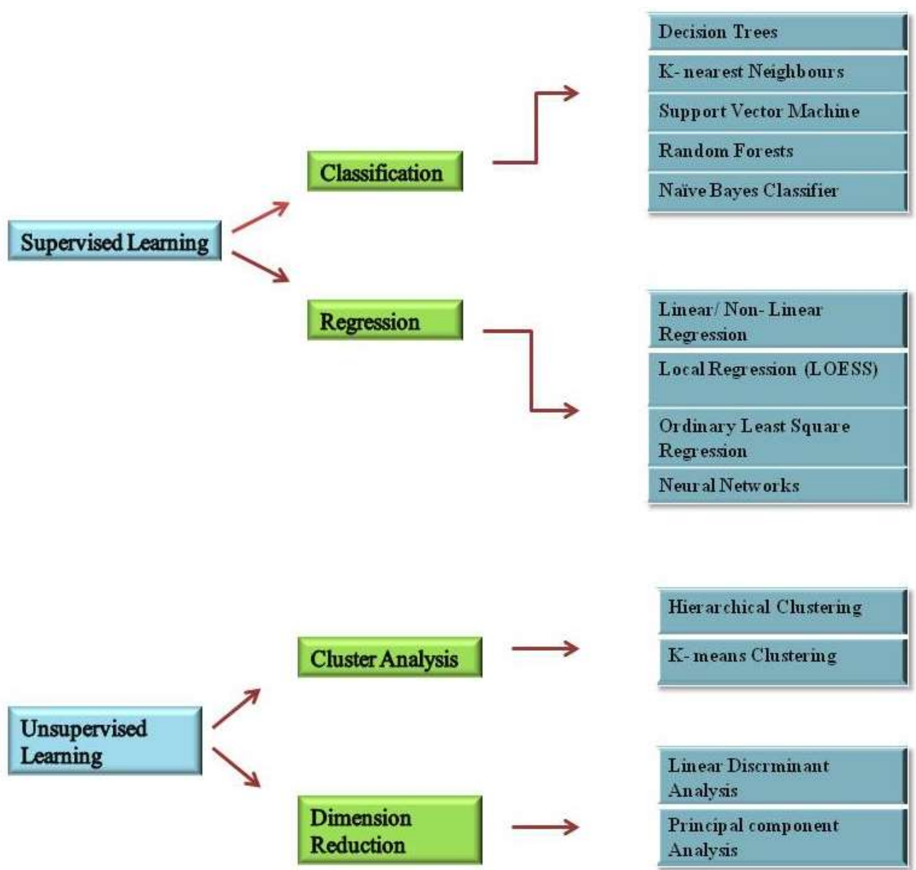

Figure 1: *Supervised and unsupervised machine learning.*

3.2. Why machine learning in neuroradiology?

Machine learning is fundamentally strong because it is not "brittle." When exposed to the actual world, a rules-based method may fail because the real world frequently provides examples that are not captured inside the rules that a programmer employs to create an algorithm [13,15]. Machine learning is adaptable since it merely utilizes statistical approximation to respond most effectively based on its training set. Furthermore, machine learning is a valuable tool since it is general, which means that the same ideas are utilized for self-driving vehicles as they are for medical imaging interpretation [15]. Typical ML tasks in neuroradiology include identifying particular patterns/conditions and image segmentation, which is defined as the representation of a digital picture by splitting it into meaningful portions (i.e., pixels or segments) for interpretation.

Machine learning technologies are adept at combining huge data into a cohesive algorithm. These algorithms can be used to predict outcomes by combining non-invasive imaging with clinical and laboratory measurements [16]. This will broaden the scope of neuroradiologists' work and bring up new avenues for the detection and treatment of neurologic illnesses, such as neuropsychiatric disorders, for which imaging has previously played a limited role.

3.3. Artificial neural networks: a hidden layer

Artificial neural networks are statistical and mathematical approaches referred as a subset of machine learning. An artificial neural network is a network of interconnected processing units that is comparable to the network of neurons in the brain. Each processing element is referred to as a cell (also called neuron or node). Numerous hidden layers with nodes enable multiple mathematical computations to be performed to create outputs. The steps of ANN model development include training, validation, and verification. During the training phase, the network is supplied with a large collection of data with known outcomes, whereas validation (or testing) refers to the process of model selection. Verification is used to report the predictive capacity of models and should be conducted on an independent set of data [17]. Fully connected neural networks are computationally costly due to the huge number of weights, particularly with pictures of common matrix size [18]. A completely linked layer requires 4 billion weights even with just one slice. As a result, most of the research in image-based deep learning has shifted to more computationally efficient architectures, especially convolutional neural networks (CNNs).

The existence of many neural layers between input and output, as well as the application of various methods (most frequently known as convolutional neural networks-CNN) [19], add to the flexibility of Deep Learning (DL) and provide the ability to replicate human brain functions throughout the training process. The exposure of CNN to data, namely pictures that may be processed during "training" is critical to the method's effectiveness (supervised or unsupervised). The kernels are filter components that make up the convolution layer. The method is based on the mathematical action of convolution. To achieve the final output layer, 1 completely linked layer is generally added for categorization [17]. Up-sampling layers are employed in image prediction to "re-form" the lower dimension hidden layers back into the original size of the input picture. An "encoder-decoder" architecture is so named because it represents the picture in terms of increasing abstraction (encoding) in the hidden layers and then utilizes them to reconstruct (decode) the image (Figure 2).

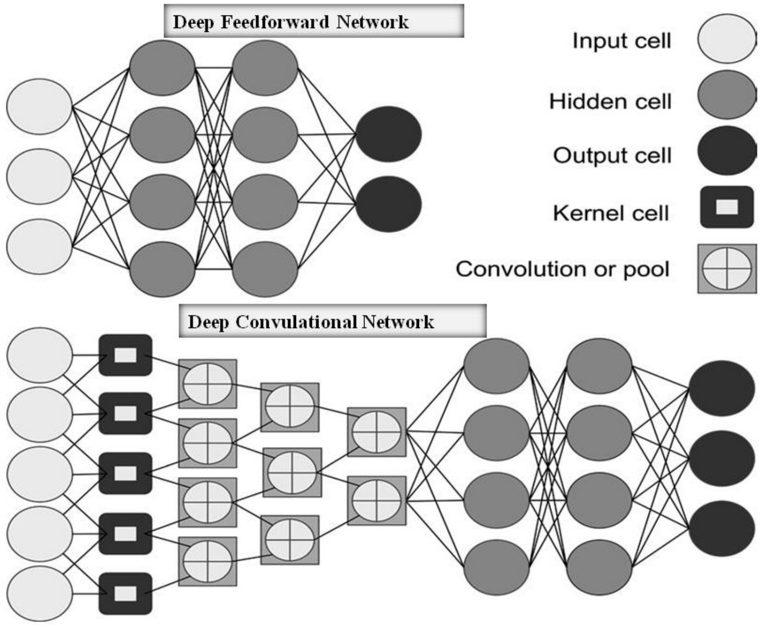

Figure 2: *Artificial neural networks.*

3.4. Deep learning: a broader context of AI

Deep learning (DL), also known as deep structured learning, hierarchical learning, or deep machine learning represents a significant step forward, based on the implementation of a large number of ANN layers (subset of artificial neural network algorithms), allowing for the determination of more complex relationships (similar to neuronal networks) and more sophisticated performance, attributes that are particularly suited for imaging.

DL can perform higher level classification tasks [20] as well as automatically extract and learn features, which is useful for managing the information content of digital pictures that a human reader can only identify and use partially. This approach demonstrates DL's exceptional potential as compared to traditional image management [21].

Many areas of neuroradiology may be addressed using deep learning. The general flow of development in neuroradiology provides a good foundation for considering various applications.

This process begins with referring doctors ordering investigations and progresses to image capture. The pictures are then shown to radiologists, who are tasked with duties such as lesion identification and segmentation, as well as differential diagnosis.

A deep learning approach has the potential to benefit each link in this chain. Deep learning algorithms for interpreting natural language are already established, making protocol automation a viable option. In principle, this is essentially a classification issue, with the multiple protocols serving as the classes to forecast and the order itself and patient information serving as the input.

Because of the massive amount of training data already available, the protocolling application is excellent for deep learning; any past research that have been protocolled by humans may be used for training.

Deep learning algorithms may be used to rebuild images and enhance picture quality. Deep learning frameworks can "learn" common MR imaging reconstruction [22] approaches including Cartesian and non-Cartesian acquisition strategies.

Combining deep learning with k-space undersampling [23,24] and model-based/compressed sensing reconstruction methods [22] has the potential to transform imaging research by improving picture data collection.

Deep learning algorithms might be used to increase image quality. If low- and high-resolution pictures are available, a deep network can be used for super-resolution [19]. If you have matched picture sets of poor and high quality, you might consider learning the best nonlinear transformation between them. This has already been used to CT imaging and shown to be useful on a dataset of normal-dose and simulated low-dose CT.

Deep learning also offers advantages for segmenting normal brain regions because present approaches are time-consuming and may not generalize to younger or older people as well. Automated segmentation of brain tumors, encompassing not only their enhancing margins but also other characteristics like as areas of enhancement and necrosis, would be beneficial for a variety of reasons, including diagnosis, pre-surgical planning, and follow-up.

Deep Machine Learning has the potential to make imaging systems smarter. Data processing approaches based on machine learning have the potential to reduce imaging time. Furthermore, intelligent imaging systems have the potential to decrease needless imaging, enhance placement, and aid in the characterization of results [12]. For example, an intelligent MR image [25] may identify a lesion and recommend changes to the sequence to ensure optimal lesion characterization.

3.5. Advances in neuroradiology via artificial intelligence

In present scenario artificial intelligence (AI) is significantly a leading technological innovation in healthcare which represents all those technologies which are involved in machine development for performing different tasks of human intelligences [26]. Neuroradiology is studied broadly in field of AI as it has various applications (Figure 3) such as automated identification of stroke [27] and the automated volumetric measurement of multiple sclerosis lesions by artificial neural networks [28]. There are different factors which shows that neuroradiology has great impact in AI research. Some of these factors are (a) neuroimaging which includes rich, multicontrast, multidimensional, and multimodality data which fit themselves well to machine learning tasks; (b) presence of well-established neuroimaging public datasets of various neural diseases such as Alzheimer disease, Parkinson disease, tumors, etc. (c) quantitative neuroimaging research history which proves clinical practices [2].

CLINICAL APLLICATIONS OF MACHINE LEARNING IN RADIOLOGY
Order Scheduling and patient Screening
Automated Clinical decision support and examination protocoling
Image Acquisition
Automated detections of finding and features
Automated interpretations of findings
Image management, display and archiving (Eg, picture archiving and communication systems)
Image quality analytics
Postprocessing- - image segmentation, registration and quantification.
Radiology reporting and analytics.
Automated dose estimation.

Figure 3: *Clinical applications of Machine learning in radiology.*

3.6. Limitations and challenges

Artificial intelligence in neuroradiology is not only in the development and testing stages, but it is already accessible for clinical use. Despite their relevance, thorough reviews of the capabilities of AI applications on the market are rare [29]. It is also critical to understand the kind of effects that AI may have in order to properly design reaction strategies for dealing with AI. A thorough analysis of existing AI applications and their radiology workflow features helps us determine whether and how AI will affect neuroradiologists' daily operations [30]. Deep learning applications are nevertheless constrained by the need for huge quantities of annotated training datasets [20], as well as the difficulty of keeping models current when source data and practice patterns change. It is currently unclear whether applications are backed by sufficient clinical necessity to encourage widespread adoption among those that are susceptible to disruption. As a result, it is critical that radiologists continue to collaborate with artificial intelligence scientists in order to grasp the capabilities of present approaches and to intelligently lead future research.

The scarcity of well-curated imaging datasets is a key impediment to high-quality medical imaging AI research and development. To address training data biases and build tools in an ethical and responsible manner, the quality and variety of datasets will be critical [31].There is a need to be conscious of health inequities that may be created or worsened accidentally by AI algorithms or data curation.

The major hurdles facing machine learning adoption in neuroradiology practice are the collection of high-quality ground truth data, the development of generalized and diagnostically accurate methods, and workflow integration. Confounders in source data may cause machine learning algorithms to fail. Rare discoveries or characteristics may also be potential vulnerabilities for neural networks due to a lack of high volume of a specific feature, making them prone to errors. High variance can lead an algorithm to learn the data too well and begin fitting random noise (over-fitting) [8], which is a significant issue in machine learning, especially when a model is overly complicated.

Appropriate artificial intelligence tool development involves the definition of standardized use cases and annotation tools. These use cases must be congruent with clinical practice as well as the regulatory, legal, and ethical problems that come with artificial intelligence in medical imaging. Machine learning algorithms must be updated on a continual basis depending on potential changes in the model as a result of increased data exposure.

Despite the compelling notion of AI applied to imaging and the rapid rise of research, widespread clinical application of AI algorithms remains delayed [16]. Indeed, a number of challenges must be addressed before AI technologies may be successfully implemented in therapeutic settings. These include not just the assessment of such tools' correctness, but also ethical issues such as prejudice and practical aspects such as information technology integration with other systems.

4. Conclusion

AI applications appear promising for radiology scenarios, undoubtedly enhancing lesion detection, segmentation, and interpretation, with a current algorithms and applications also for interventional radiology (IR) practice, including the ability of AI to offer prognostic information to both patients and physicians about neuroradiology procedures.

The increasing role of AI may provide the possibility to better personalize treatment to patients based on "big data" that can be processed quickly, revealing novel insights that would otherwise need decades of prospective trials. As a result, this novel method is expected to result in a paradigm shift in the near future, decisively altering the existing conventional treatment algorithms of tumor therapy and giving patients with improved truly customized care. The applications created are extremely useful for neuroradiology [8] in terms of supporting the radiologist and expanding the radiologist's ability to bring value to patient care. The identification and interpretation of aberrant picture findings are the primary functions that assist radiologists. The key functionality that expands radiologists' capabilities is the supply of quantitative data.

With the introduction of AI algorithms into normal clinical practice [9,32], the emergence of artificial intelligence provides another once-in-a-lifetime chance for neuroradiologists' to be leaders and change agents. There are several possibilities, ranging from improved operational efficiency to lower health-care costs and increase access to genetic prediction using brain MR data. Thus, AI will give neuroradiologists' with augmented intelligence rather than artificial intelligence, making it increasingly important to their patients and the clinical teams with which they collaborate.

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