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A SUMMARY OF THE CURRENT DIFFICULTIES AND AI APPLICATION IN RADIOLOGY

Uma Srivastava*[1], Navneet Kumar Verma[2], Shashikant Singh[3], Ankur Srivastava[4], Ankita Malviya[2]

[1*]Department of Mathematics and Statistics, DDU Gorakhpur University, Uttar Pradesh, India.
[2]Buddha Institute of Pharmacy, Gida, Gorakhpur, Uttar Pradesh, India.
[3]Faculty of Pharmaceutical Sciences, Mahayogi University, Gorakhpur, Uttar Pradesh, India.
[4]Institute of Pharmacy, Dr. Ram Manohar Lohia Avadh University, Ayodhya, Uttar Pradesh, India.

ABSTRACT

DL and AI techniques have led to substantial advancements in the field of picture analysis. Radiologists and doctors will both profit from artificial intelligence-based procedures, even though they won't completely replace them. Rather than being used for decision-making, these methods will probably be employed for consultation and decision support. Radiologists, however, need to understand these tools and how the medical industry employs them. Studies have shown that AI algorithms are very accurate, resilient, fast and useful in medical imaging; nevertheless, the majority of these algorithms, especially DL algorithms, are still in the experimental stage and have not yet been developed further or applied to clinical settings. There are many barriers that prevent modern AI technology from being widely used in therapeutic settings. First off, using very large data sets to train these algorithms is frequently impractical. Furthermore, all institutions must use the same study methods prior to the implementation of DL algorithms. Improving algorithm accuracy and performance is a difficult, complex problem.

KEYWORDS

Radiology, Artificial intelligence-based techniques, AI algorithms and Medical imaging.

Author for Correspondence:

Uma Srivastava,
Department of Mathematics and Statistics,
DDU Gorakhpur University,
Uttar Pradesh, India.

Email: umasri.71264@gmail.com

INTRODUCTION

Before we discuss artificial intelligence (AI), it is crucial to define it. We could begin by defining intelligence more precisely. One view put out by Simmons and Chappell states that intelligence is the ability to solve problems both implicitly and explicitly, as well as the capability to naturally acquire solutions for problems that arise[1]. Based on this, we can define artificial intelligence (AI) as a machine's capacity to solve issues and learn new approaches to problem-solving. This suggests that the object needs to be able to sense its environment, which includes detecting input data and its parameters, looking for patterns and recognizing them, which entails figuring out what the characteristics of the problem are, organizing and executing the best course of action, and applying inductive reasoning to derive general principles, which entails picking up knowledge from experience[2]. Hardware or software designed to carry out a specific task is referred to in this study as artificial intelligence (AI). The goal of artificial intelligence (AI), an applied science, is to develop computer systems to the point where they can perform activities just as well as or even more effectively than humans[3]. For many years, artificial intelligence has been researched and applied in the medical industry. These days, it is widely employed in vital clinical tasks such as the interpretation of arterial blood gas and computerized ECG analysis[4]. It would be difficult for a radiologist in practice in 2018 to have missed the constant talk about artificial intelligence (AI). For example, a renowned AI researcher has advocated for the abolition of radiology education[5]. One president used the departure of radiologists as proof of the economic impact of artificial intelligence. AI's prominence is evident, as evidenced by[6] and the numerous pieces in books and the public domain[7]. It may therefore come as a surprise to some readers that artificial intelligence has been discussed in radiology since at least 1994[8]. Within machine learning, supervised and unsupervised learning are frequent subcategories. Annotated data, also referred to as "ground truth" data, is fed to the algorithm in supervised learning so that it can improve. Giving the system unlabeled input allows it to classify the data on its own, without the need for supervision[9]. A particular kind of supervised machine learning that has garnered the most attention recently is deep learning, and more especially deep convolutional neural networks, or CNNs. Multi-layer neural networks, often known as deep CNNs, are supervised learning techniques that use an algorithmic structure inspired by neural networks[10]. The scalability of this technology and the ability of neural network architecture to automatically extract relevant features from data with no additional instruction beyond labeled input data are its main strengths.

What Is AI? A Brief Overview

Although the word artificial intelligence (AI) has several meanings, in the medical industry, it usually refers to systems or equipment that can recognize something about their environment and use that information to achieve a predefined goal[11]. Most medical use cases are classified as "weak" or "narrow" AI, which means that they need the completion of a single task or set of related tasks. Machine learning, in particular, is an area of artificial intelligence that focuses on developing computer algorithms without explicitly incorporating decision-making principles[12]. Within machine learning, supervised and unsupervised learning are frequent subcategories. The system is trained on annotated data, sometimes known as "ground truth" data, in supervised learning. Giving the system unlabeled input allows it to classify the data on its own in an unsupervised learning environment[9]. Deep learning and more especially deep convolutional neural networks, or CNNs for short, are the aspect of supervised machine learning that has attracted the most attention lately. Deep neural networks, or DCNNs, are a kind of supervised learning that employs an algorithmic structure based on multi-layered neural networks[10]. This method's strength lies in its scalability and neural network architecture's capacity to identify pertinent features on its own from data without guidance other than labelled input data.

Why is AI needed for imaging?

In addition to being expert diagnosticians, radiologists also serve as gatekeepers for a valuable service and as guardians of patient safety, among other roles. AI seeks to replace this diagnostic function. The diagnostic role of radiologists has gained more attention due to technological advancements in AI and imaging. This position essentially consists of two steps: first, analysing images, and second, interpreting the results. These require the ability to perceive images visually and the mental ability to recognize patterns in order to differentiate between normal and abnormal[12]. This is a difficult endeavour since human interpretation of images often overlooks crucial information and results in inaccurate interpretations. Since Garland discovered in 1949 that human errors in radiography are, in fact, ubiquitous, many academics have attempted to quantify the incidence and impact of these errors[13]. The 2004 RADPEER study, which looked at 20,286 cases with over 250 radiologists, indicated a 3-4% mistake rate, which is consistent with earlier data[14]. In a 2014 study, Kim and Mansfield reviewed 656 imaging cases with postponed diagnosis and discovered 1269 errors[15]. Notably, they noted that in 196 out of 656 cases (30%), follow-up radiologic testing had failed to identify the correct diagnosis. Additionally, they classified the most common types of errors as incorrect reasoning, under reading, search satisfaction, and location discovery. This study, however, can be criticized for omitting to account for the years of expertise of the radiologists, the intricacy of the cases, or the therapeutic significance of each error. The reason this last point is so significant is that it has been suggested that in incredibly complex situations, so-called errors could be seen as legitimate differences of opinion[16]. Growing case numbers, fatigue, anatomical diversity, and incorrect patient placement can all lead to misdiagnosis[17,18]. It is clear that the complexity of radiological misinterpretation is reflected in the frequency of errors. Errors happen, but what impact do they have on patients in a medical setting? In a 1995 investigation, two experienced radiologists compared 100 body MRI data, and 39 of the results showed disagreements. Of them, 23 represented significant deviations that required a significant adjustment to the way patients were managed[19]. A follow-up retrospective research found that 49(19%) of 259 patients with non-small cell lung cancer who had a nodular lesion on a chest X-ray had the lesions missed[20-21]. Due to the delayed diagnosis, 21 patients (43%) out of these 49 were able to move from stage T1 to T2, which caused the 5-year survival to drop from 60-80% to 40-50%.

Using AI to Improve Radiology Workflow

The most vulnerable to sudden disruptions is probably the management of AI work lists. Classifiers have been developed for aberrant chest radiographs in order to expedite the evaluation of an abnormal exam[22]. Additionally, classifiers for cerebral haemorrhage and stroke on noncontract head CT as well as acute stroke on diffusion weighted MRI have been developed[23,24]. Similar techniques could be used to find studies that might not be diagnostic, such as cross-sectional exams that reveal mobility degeneration or radiographs that are positioned wrongly. If the technologist found difficulties throughout the scanning process, they might retake the exam or speak with the radiologist to minimize issues with patient call backs and treatment delays. Another stage of reinterpretation that AI can assist with is creating sensible and intuitive hanging protocols. Hanging protocols are the specifics of how a research and relevant prior studies are exhibited when opened in a PACS. According to a poll taken by radiologists, automated hanging techniques accounted for the majority of their enhanced output[25]. Currently, hanging operations review images from several scanners at one workstation using Digital Imaging and Communications in Medicine (DICOM) data, which is inherently non-uniform and unpredictable. Ongoing research towards this goal leverages AI's ability to identify structures inside the image and merge that information with image metadata to show photos in a way that can shorten the time between exam loading and interpretation.

Current Challenges with AI Application in Trauma and Emergency Radiology

There are several challenges that need to be solved before the above mentioned potential advantages of AI deployment can be realized. The majority of these difficulties are associated with three main issues: technological adoption, education, and ethics. The largest barrier to the use of AI in medicine is the requirement that radiologists put together a multidisciplinary team and spend two or three years building the network before they can develop an algorithm for a particular task. A trauma and emergency radiologist needs a variety of things, including adequate video card infrastructures, accurate labelling and outcome data, and more. In fact, an emergency radiologist may achieve 98% accuracy if they can correctly put everything together after the method is tested! Although a researcher's dream, this level of accuracy raises the question of how to have all the necessary elements in place as quickly as feasible[28]. The training, validation, and testing of an AI algorithm depend on the proper data collection being assembled. Examine the variables-diseases, modalities, different body parts, and scanners-that are being added to the data gathering. These complicate the process of gathering and validating data. The more variations there are, the harder it is to cover every dimension. In addition, it is critical to consider the presence of clinical heterogeneity, which encompasses distinct outcomes, patient demographics, and geographic regions. It is challenging to cover them all because each issue and circumstance requires a validated dataset[26]. Therefore, from the beginning of an AI development project, goals for an AI system must be realistic in order to minimize difficulties in gathering sufficient data sets. Because of its scalability, the technique offers specific benefits when the data is gathered by an emergency radiologist. However, because of the heterogeneity found in the huge datasets, it also has significant drawbacks. This needs to be recognized. An accurate algorithm, the newest technology, and a successful business plan are necessary for scaling an AI product. The issue is money. Tesla and self-driving cars are good examples, as they have gone through a rigorous training procedure. When combined, these are all incredibly safe. It has taken them a while to arrive at this. For any major research endeavour to succeed, funding and persistence are necessary. Underneath seemingly straightforward activities is a great deal of hidden depth. When creating an algorithm, a large amount of data, processing power, and the ideal combination of code are required to accomplish the task. This explains why a certain condition is the focus of every algorithm or breakthrough. Algorithms do not generally generalize well, especially when used to distinct data sets. It's possible that a radiology-developed method can't be generalized. In one hospital setting, it might work well, but not in another[27]. How can we implement it at hospitals across the nation and maybe even abroad? It is worthwhile to consider this. Regarding the impact of artificial intelligence in radiology, there are numerous theories. When faced with tedious tasks, they might be a godsend or an indication that radiologists are close to retirement[27]. Some well-known AI specialists projected that radiography, despite being an emergency specialty, would be among the first occupations to be automated in 2016[28].

The future of AI in Imaging

As a result, AI's potential as a second reader in imaging software has been shown; nevertheless, this potential is currently limited by the noticeable but dropping high FP rate. However, IBM is confident about the future of imaging AI as evidenced by its $1 billion investment in the Watson Health Project, which is an algorithm that has been evaluated in the medical field. Watson will be able to learn from 30 billion photos thanks to this investment, which will enable it to develop[29] its algorithm to pull data from the greatest knowledge base to date. Watson will also have access to patient-supporting information, including medical history, blood tests, imaging results, and genetic sequencing. Artificial intelligence (AI) technology in the future might be able to utilize algorithms that are much more productive and accurate, addressing problems with high recall and FP rates as well as the capacity to detect abnormalities on any imaging modality, including the diagnosis of challenging and unusual circumstances that might go missed in other circumstances[30]. The computerized diagnosis programs that were once designed to replace radiologists in the 1980s may wind up being revived as a result of this. However, IBM's project is still in its infancy, thus its future potential is yet unknown. Another area of ongoing research that has been mentioned is artificial swarm intelligence. This technology expands upon the notion that "many minds are better than one" by providing radiologists with an international online platform to collaborate and integrate decision-making in complex cases. It also enhances an individual's knowledge base and problem-solving abilities. Preliminary study suggests that this type of collective intelligence is advantageous and may create new potential for artificial intelligence in radiology[31,32].

CONCLUSION

Adaptive intelligence, a component of continuous learning AI, offers a workable strategy for making AI applications in radiology viable. Unlike many of its "turnkey" predecessors, continuous learning AI systems cannot be used in a passive manner. Rather, radiology departments need to take a more active role in the development of continuous learning AI by supplying accurate and timely data feeds, taking part in quality control for continuous learning AI, analyzing results for continuous learning AI, and continuously challenging the effectiveness of continuous learning AI. We should realize that, for the time being at least, people tolerating subpar AI output poses a greater risk than AI outsmarting humans. We need to learn how to collaborate with "self-improving machines" if we are serious about using them to enhance healthcare. In order to do this, we must completely reframe AI solutions from the adversarial, distant "machines replacing humans" to the cooperative, integrated, and "machines augmenting the work of humans".

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CONFLICT OF INTEREST

We declare that we have no conflict of interest.

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