

Artificial Intelligence (AI) And Deep Learning (DL) In Medical Diagnosis Process Such As SPECT And PET

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Abstract

AI has been defined as an area of study in computer science concerned with “the development of computers to engage in human-like thought processes such as learning, reasoning and self -correction”. Artificial intelligence has typically been used to solve logical and rational challenges. Due to significant advancements in AI-driven picture segmentation and interpretation, research on more current deep learning (DL) improvements has increased. These studies have been published in radiology and nuclear medicine journals. Abolishing careers in medicine was a prediction made by critics and AI scientists as early as 1976. In this article, we have tried to study the Medical image diagnosis method (SPECT and PET) using artificial intelligence. In order to increase the quality of nuclear medicine imaging, we would want to draw the landscape of AI technological breakthroughs. Top four above mentioned methods were the four primary areas on which we primarily concentrated. After learning is finished, using AI for prediction will be quicker than using conventional techniques. The potential of AI technology to enhance nuclear medicine imaging quality and its use in the clinic is still being actively researched.

Keywords: Artificial Intelligence, deep learning, SPECT, PET

Introduction

AI has been defined by Dilsiziand & Siegel (2014) as an area in Information Technology concerned with “the development of computers to engage in human-like thought processes such as learning, reasoning and self -correction”. At a conference held at Dartmouth College in 1956, the term "artificial intelligence" is thought to have been first used (Patel et al., 2009). AI enables users and programmers to get over the various limitations of rule-based systems and other traditional decision support methods, including the difficulties in creating new rules and changing existing ones. Although they were developed

with the help of experts, these traditional systems lack human traits like self-improvement, reasoning, and ongoing learning. The use of AI hasn't yet reached its full potential in the field of medicine, despite significant efforts and initial excitement. But in recent years, non-medical applications of AI have seen something of a rebirth.

The last 50 years have seen an increase in the usage of artificial intelligence (AI) in nuclear medicine and radiology (e.g., auto-contouring). Artificial intelligence has typically been used to solve logical and rational challenges. Due to significant advancements in AI-driven picture segmentation and interpretation, research on

more current deep learning (DL) improvements has increased. These studies have been published in radiology and nuclear medicine journals. Abolishing careers in medicine was a prediction made by critics and AI scientists as early as 1976. (Maxma, 1976). Despite the fact that Geoffrey Hinton's predictions about AI putting radiologists out of work have received a lot of attention (Liew, 2018), his more cautious outlook anticipated significant changes to the way that healthcare is delivered and how medicine is practiced. (Hinton, 2018). If ignored, AI might be an extinction-level rival as well as the means of transportation into the next century of sustainable medical imaging. Understanding and utilizing AI's potential in nuclear medicine while mastering the skills that are only available to human health professionals will be the key to achieving lasting coexistence (Figure 1).

With the reengineering of clinical and research capabilities, precision nuclear medicine ushers in an exhilarating era. The use of computer algorithms to carry out operations often linked to human intellect (such as learning or problem-solving) was first referred to as artificial intelligence (AI) in 1955 (Tang et al., 2018, McBee et al., 2018 and Langlotz et al., 2019). The use of incidental finds in visual recognition is an intriguing application given the improved capabilities of AI. The well-known "gorillas in our midst" experiment on intentional blindness (Simons & Chabris, 1999) demonstrated how people could become blind to a person in a gorilla suit walking through the middle of a complex scene if they were concentrating on a single task (counting the number of times a ball was passed). An artificial gorilla was introduced into many CT slices to investigate this later during the interpretation of a chest CT (Drew et al., 2013). Expert radiologists missed the artefact 83% of the time, and eye tracking technology revealed that 60% of them had focused on it. Intentional blindness may make it harder to spot results in

more challenging datasets related to SPECT, PET, and co-registered pictures, even when accidental findings in general nuclear medicine studies are easily discernible—possibly a job for AI. Understanding and utilizing AI's potential in nuclear medicine while mastering the skills that are only available to human health professionals will be the key to achieving lasting coexistence. In general, algorithms created for thinking and problem solving are referred to as artificial intelligence (AI). There is a wealth of information about applications in nuclear medicine and radiology.

A neural network, which analyses images by layering connected nodes, is used in medical imaging (Currie, 2019). There may be hundreds of thousands or millions of nodes, and they mimic the connections between neurons in the human brain (Tang et al., 2018). Nodes gather data from clusters of nodes or from other nodes. When a threshold is crossed, communication between nodes happens, and the outputs of those nodes are weighted (McBee et al., 2018). For the modifications to be made during the training phase of creating an ANN, hundreds or thousands of iterations may be necessary. It is obvious that the inference phase will be more accurate the more data that are utilized to train the ANN. A mathematical solution converges to a more accurate answer by each iteration and subsequent adjustment of the nodes, just like we might imagine iterative reconstruction of SPECT and PET data.

Artificial intelligence (AI)-based technology is rapidly being implemented into a variety of different fields (Litjens et al., 2017, Mont et al., 2019 and Ting et al., 2019, Subramian et al., 2020 and Adir et al., 2020). AI has also focused on how to use imaging data in nuclear medicine (Nensa et al., 2019). Machine learning is a key branch of artificial intelligence (ML). Naive Bayes, SVMs, and random forests have all been utilised widely in the field of medicine for a very long time. PET

(Duffy et al., 2019), SPECT (Magesh et al., 2020 and Martin-Isla et al., 2020), SPECT prognosis (Toyama et al., 2020), PET (Moazami et al., 2020), SPECT lesion classification (PET; Moazami et al., 2020), and PET (Moazami, 2020)

are examples of applications of machine learning (Wang et al., 2020).

In this article, we have tried to study the Medical image diagnosis method (SPECT and PET) using artificial intelligence.

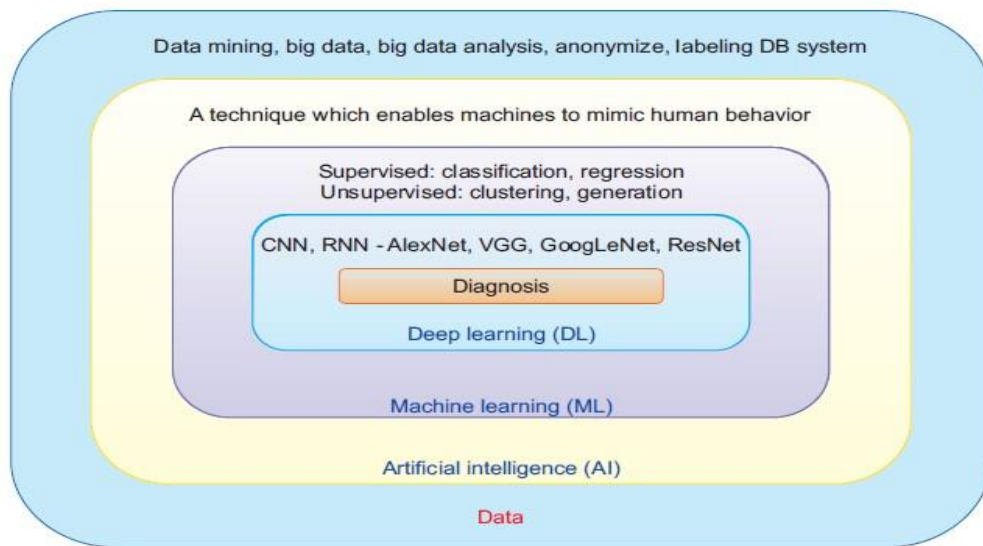


Figure 1. Medical image diagnosis method using artificial intelligence (AI) (Yoo et al., 2019)

Principles of machine learning and deep learning

The two main subcategories of deep learning algorithms are supervised and unsupervised techniques. In supervised learning, the desired outputs or ground truth associated with the inputs are provided during training, when a specific end-to-end transformation and/or connection is established to forecast the required outputs for new inputs. Because overfitting is a wasteful learning process that mostly depends on recollection of the example data, it should be avoided at all costs. Due to the overfitting issue, several research have found that when using deep learning algorithms on a specific dataset, there are comparatively few errors (highly accurate conclusions) Sahiner et al. 2019), and for that

such a favorable outcome is less probable to occur.

By deciphering the information's distinctive structures and patterns, the computer can learn directly from the input data in contrast to supervised learning. When developing paired datasets (input/label), which are expensive to produce in many clinical scenarios, unsupervised training may provide practical answers. However, the majority of research that has been written about in the literature has used supervised training since it is reasonably easy to train (but requires no data preparation) and evaluation is simple because the ground-truth labels are readily available (Sahiner et al. 2019). Additionally, a hybrid strategy that uses both supervised and unsupervised learning was proposed for situations where it is impossible to gather enough labelled data for supervised training. Unlabeled

data and photos are frequently easily accessible; however, annotated data and images need a significant time investment and professional expertise to produce. It would typically not

produce sufficient results to build a model using a tiny sample of annotated data or photos (Chen et al. 2019).

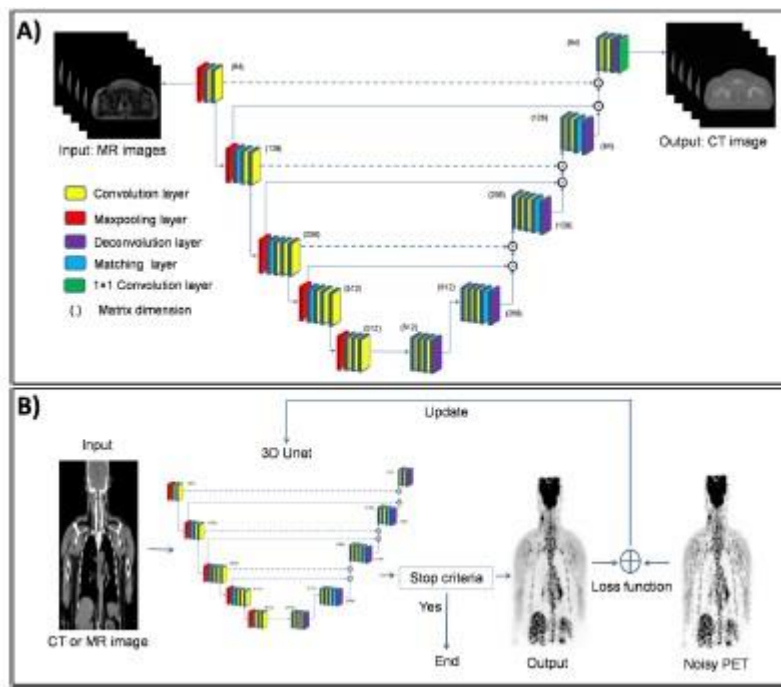


Figure 2. Examples of (a) supervised and (b) unsupervised deep learning approaches employed in molecular imaging (Arabi & Zaidi, 2020)

Image reconstruction

Reconstructing an image from raw projection data is a problem in reverse. Analytical filter back-projection (FBP), algebraic reconstruction techniques (ARTs), the maximum likelihood algorithm (MLEM), ordered subset expectation maximization (OSEM), and the maximum a posterior (MAP) algorithm are the four algorithms that make up the reconstruction algorithm used in nuclear medicine (Chen et al., 2019 and Gedik et al., 2017). The maximum likelihood approach provides a better control over reconstruction quality and can duplicate physical attributes during data collection, but it will take more time and money. As AI technology has

developed, researchers have used it to recreate nuclear medicine images, primarily in PET reconstruction (Qi et al., 2006). The inverse problem is intractable with AI technology. It fundamentally provides a mapping link to address several crucial reconstruction challenges using a data-driven strategy. The advancement of AI technology has made it possible to some extent to improve photographic quality without having to pay more for hardware. Reader et al 2020.'s paper provided a clear summary of the fundamental theory underlying PET reconstruction as well as the substantial paradigm shift brought about by DL in PET reconstruction. The only focus was on raw PET data. The search was focused on PET/SPECT (NUCLEAR MEDICINE), thus we applied AI to three distinct systems shown below.

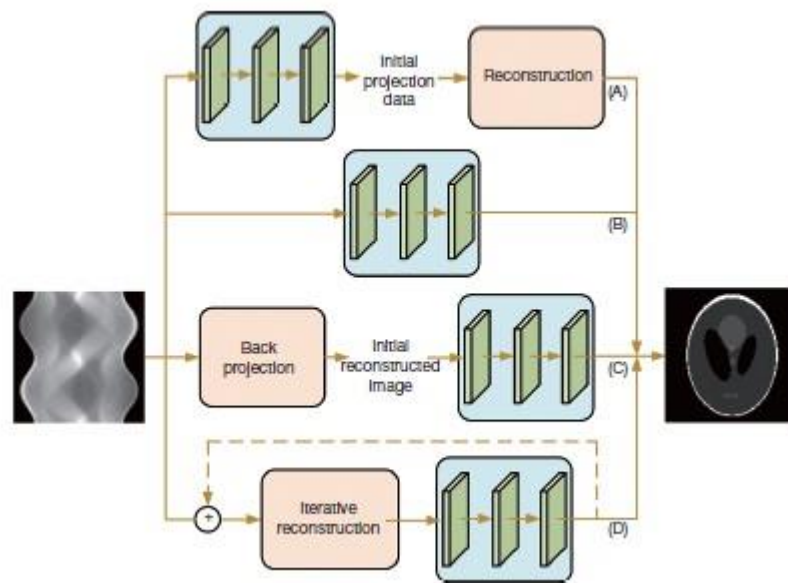


Figure 3: Method for reconstructing static nuclear medicine images. To complete sonogram data or generate more continuous sinogram data, (A) AI technology is utilized in the projection domain. B) Using AI technology, sinogram data is used to directly generate PET/SPECT images. To immediately improve the back-projection data and produce PET/SPECT images, artificial intelligence technology is used (C). (D) Iterative reconstruction methods mixed with artificial intelligence (Cheng et al., 2021)

Discussion and conclusions

The following factors need to be taken into consideration for the therapeutic application of AI. What form of network structure is suitable for various themes, first? According to Zeng et al. (2017), a neural network's structure is superfluous. Pairs of training data sets are utilized as the input and output for black-box AI systems. Most algorithms have variables that must be changed based on the job. This method is performed numerous times until the outcome is good by continuously to obtain the ideal factors for learning. The structure's design is a factor in current study when determining how practicable

a performance is. They all require sufficient data sets to function as dependents, which is what unites them. It will therefore continue to need development to figure out how to overcome the limitations of network structure and offer an interpretable network structure. Larger photos are challenging to manage due to memory and time constraints as well as the network's enormous weight. When making pure predictions, in particular, one should think about whether such a technique is meaningful if training data are limited. Problematic is how to prevent training's unpredictable nature.

The data pairs used for training do not necessarily comprise nearly all scenarios, hence we cannot guarantee this. Research in this area should concentrate on promoting data integration and sharing. Additionally, utilizing a small sample size to support an argument is not always effective, therefore we must be aware of unusual data. Gathering training data is more crucial in this case than training the network structure since it can result in results that are more accurate depictions of the desired effect. This is a popular topic right now. This problem is present almost everywhere in research on AI, not just in one particular field.

Thirdly, we should consider carefully if we should use the promising results of the AI technology in clinical practice; as a result, the next thing to consider may be how to validate the suggested method in everyday practice. The quality of composite images is typically evaluated using metrics like RMSE, PSNR, and SSIM, although studies have shown that the interpretation of these indicators may not necessarily be equivalent to clinical job evaluation (Yu et al., 2020). Professional evaluations are particularly crucial in addition to the generally used evaluation indications. The majority of AI applications in use today were created with a specific purpose in mind. Even while the use of contextual information increases AI's intelligence, it is unfeasible to let it replace doctors entirely and carry out activities on its own. Inadequate model and technique interpretation is one of AI's shortcomings, along with a lack of accurate baseline data and label data. In comparison to more established techniques, the research community still appears to be investigating the best ways to apply AI technology, which ought to cover a wider range of circumstances. The success of these strategies has to be evaluated using more assessment indicators in practical applications.

Fourthly, hybrid imaging can provide greater training knowledge during network training compared to independent system imaging. We discovered that multimode imaging and prediction may be new areas for investigation. The training technique used in conjunction with unpaired data may be the right course of action. In the case of the brain, there is still a chance for head drift between the acquisition time windows of various modal systems. Additionally, using numerous multi-mode images as inputs to the network would undoubtedly add more parameters, making it more difficult for the network to converge and lengthen training times,

necessitating additional care in the network design.

In order to increase the quality of nuclear medicine imaging, we would want to draw the landscape of AI technological breakthroughs. Top four above mentioned methods were the four primary areas on which we primarily concentrated. After learning is finished, using AI for prediction will be quicker than using conventional techniques. The potential of AI technology to enhance nuclear medicine imaging quality and its use in the clinic is still being actively researched.

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