AN IMPROVING THE PERFORMANCE OF RADIOLOGY APPROACH USING ARTIFICIAL INTELLIGENCE WITH DEEP LEARNING TECHNIQUES

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ABSTRACT

Rapid developments made in AI and Deep Learning Technologies has explored the growth of real time applications in the medical field. Machine learning and artificial intelligence to fight the leading cause of cancer death in the US among both men and women. Entrants were challenged to use a dataset of thousands of high-resolution pulmonary CT images to create new lung cancer detection algorithms. These algorithms were made to improve diagnosis and reduce false positive rates. Artificial intelligence (AI) has recently made substantial strides in perception (the interpretation of sensory information), allowing machines to better represent and interpret complex data. Deep learning is a subset of machine learning that is based on a neural network structure loosely inspired by the human brain. Such structures learn discriminative features from data automatically, giving them the ability to approximate very complex nonlinear relationships. There are many image analysis tools and enhancement techniques that can improve image interpretation. Many of these systems use imaging techniques which are not being used in medical radiology departments. Many of the image adjustment tools in the radiology field which may help in improving image recognition . In this paper we proposed SVM Method for representing correlation between Features. The Correlated dataset is classified by using the K-Nearest-Neighbors (KNN) classification technique. Finally we have to implementing the AI with Deep Learning techniques for measured the performance of radiology.

Keywords: Classification, Machine learning, Support Vector Machine(SVM), K-Nearest-Neighbors (KNN), Artificial intelligence, Deep Learning.

1. INTRODUCTION

The ultimate guide to AI in radiology provides information on the technology, the industry, the promises and the challenges of the AI radiology field. Currently, we are on the brink of a new era in radiology artificial intelligence. AI has had a strong focus on image analysis for a long time and has been showing promising results. Therefore, there are great expectations around applying AI to radiological images. To build an algorithm you (almost) always need a dataset, the training data, to get started. This dataset will be a batch of the type of data you want your algorithm to analyze. In radiology, this would be image data. Depending on the type of algorithm used, you may need additional information as well. This may be information on what you see in the image (e.g. a segmentation) or other patient information. Depending on the context, several definitions for artificial intelligence can be used. Many of these definitions link human behavior to the (intended) behavior of a computer. In the case of radiology these definitions do not quite cover the scope of AI as there are many situations where AI exceeds human capabilities. In radiogenomics, for example, we link genetic information to what we see on medical images, enabling us to predict the presence or absence of genetic mutations in a tumor which can be used to determine further diagnosis and management. Another example is applying deep learning (DL) to image reconstruction in MRI or CT, called deep imaging. Image quality can be boosted by using DL algorithms that translate the raw k-space data of an MRI scan into an image. A definition for AI that fits these criteria could be

“a branch of computer science concerning the simulation of intelligent human behavior in computers”.

Refining this definition of AI even further to the context of radiology results in

“a branch of computer science dealing with the acquisition, reconstruction, analysis and/or interpretation of medical images by simulating human intelligent behavior in computers”

There is a wide range of methods within the field of artificial intelligence. As discussed previously, machine learning covers part of this field and deep learning is one of the methods within machine learning (frankly, there are numerous ways to implement deep learning too, but we will come to that later). In this section we will discuss a few methods that are within the realm of AI, but do not belong to ML or DL. This plot outlines the performance levels of artificial intelligence (AI) and human intelligence starting from the early computer age and extrapolating into the future. Early AI came with a subhuman performance and varying degrees of success. Currently, we are witnessing narrow task-specific AI applications that are able to match and occasionally surpass human intelligence. It is expected that general AI will surpass human performance in specific applications within the coming years. Humans will potentially benefit from the human-AI interaction, bringing them to higher levels of intelligence.

Machine learning (ML) work flow

Machine learning algorithms are a subset of artificial intelligence methods, characterized by the fact that you do not have to tell the computer how to solve the problem in advance. Instead, the computer learns to solve tasks by recognizing patterns in the data.

Supervised and Unsupervised learning

Machine learning techniques can be divided into supervised and unsupervised algorithms. This categorization has to do with the type of data used to develop the algorithm. Supervised methods use a dataset that is labeled, meaning a ground truth is available in the database. In the case of medical imaging this can be for example a (manually obtained) segmentation of brain tissue, a yes/no to the question whether the patient has a fracture, or a Kellgren-Lawrence-score for scoring osteoarthritis on X-ray images of the hip.

Unsupervised methods on the other hand, use a dataset without labels. These algorithms are typically developed by presenting it with a large stack of data in which the algorithm on its own will find correlations between features present in the images, i.e. it will start recognizing patterns. Based on these patterns the algorithm will divide the dataset into separate groups, for example brain scans with metastases and those without.[4] An advantage of unsupervised learning is that these methods can find patterns that are hidden to the human eye. For example, an unsupervised trained algorithm might be able to recognize tumors in MRI scans of the brain, which are not yet discernible for radiologists.

A third option between supervised and unsupervised methods are the semi-supervised methods. This approach uses a smaller set of labeled data combined with a bigger set of unlabeled data. The labeled dataset is used to create the algorithm and guides it in the right direction after which it refines itself using the unlabeled data. This technique can be the go-to method when it is clear what type of outcome you want, but a dataset with good quality labels is hard to get. For example, brain scans with manually segmented white matter hyperintensities are very labor intensive to create and must meet a very high quality standard, hence creating a large labeled dataset to perform fully supervised learning can be a lengthy and therefore expensive process.[6] Instead, a semi-supervised strategy can be used with a subset of manually labeled images (e.g. with a segmentation of white matter hyperintensities), which can be combined with a bigger unlabeled dataset.

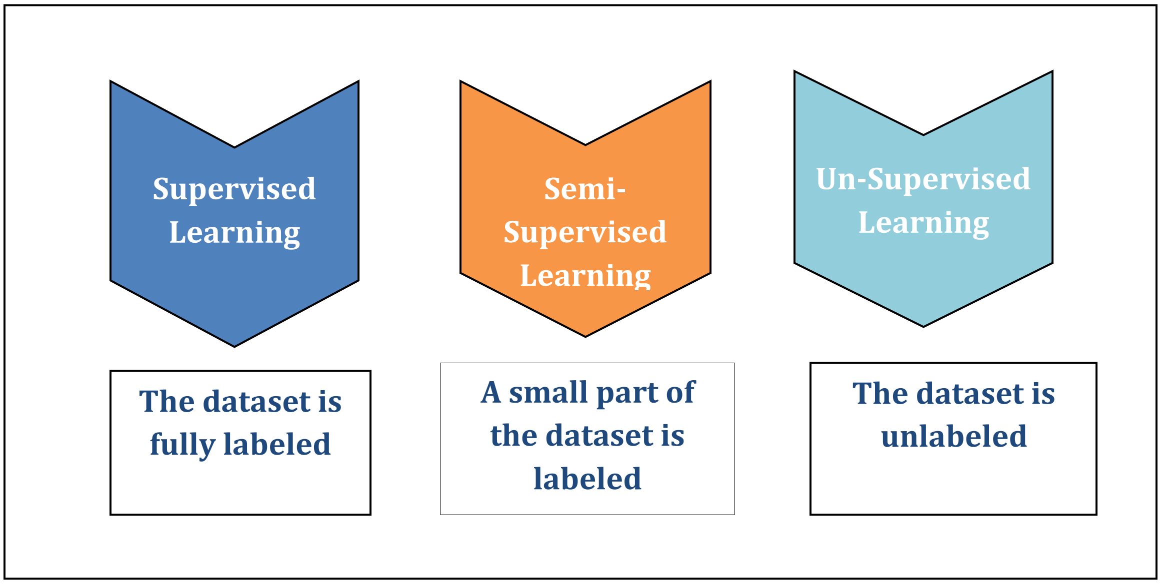

Figure 1: All machine learning methods can be divided into three groups: supervised learning, semi-supervised learning and unsupervised learning, with the data being fully labeled, partly labeled or fully unlabeled.

2. EXPERMENTAL

Classification techniques

Classification algorithms classify the input they get. For example, whether a brain tumor is an oligodendroglioma or an astrocytoma, along with the certainty of this classification. Classification algorithms are typically created using labeled images. Because we know exactly in which classes we want to categorize our input, it is a supervised method.

Example of a classification technique: Support Vector Machine

An example of a basic classification algorithm is a support vector machine, or SVM for short. The idea of an SVM is simple. First, we select specific (image) features on which we want to train the algorithm. These features are, for example, the distribution of gray values in the image, or the presence of certain shapes. Most importantly, these features should be known for all images we use to develop the algorithm. Secondly, this training data is plotted in feature space. Because an SVM is a classification algorithm, it will attempt to sort the data in multiple classes. In our example, there are two classes depicted as green and dark blue circles. To sort the data, it should be known to which class each data point belongs, i.e. the dataset should be fully labeled. To keep it simple, this figure shows a 2-dimensional feature space, with the value of one feature on the x-axis and the value of the other feature on the y-axis. However, these feature spaces can contain many more dimensions.

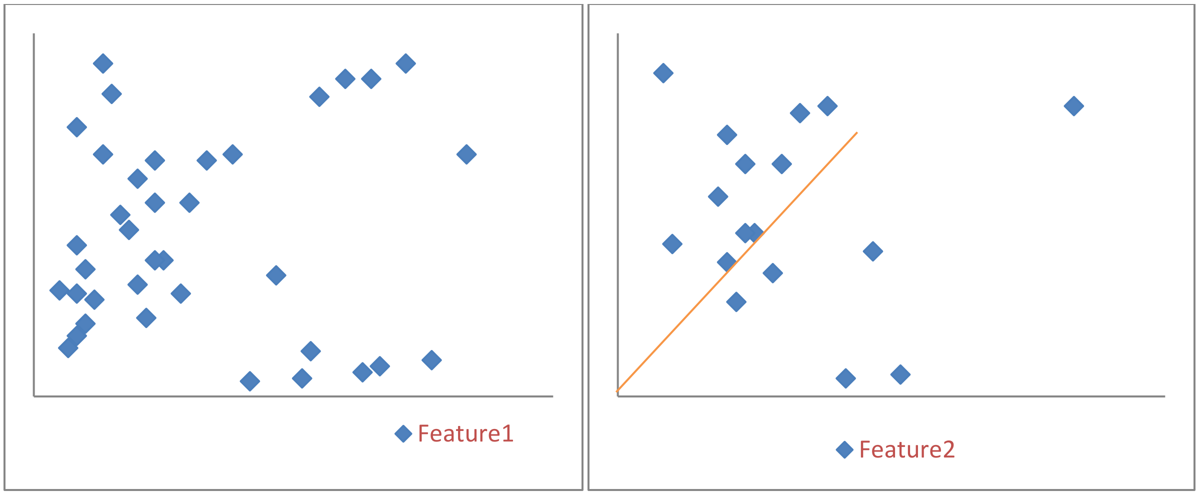

Figure 2: Regression line representing correlation between Feature1 and Feature2 using Support Vector Machine (SVM).

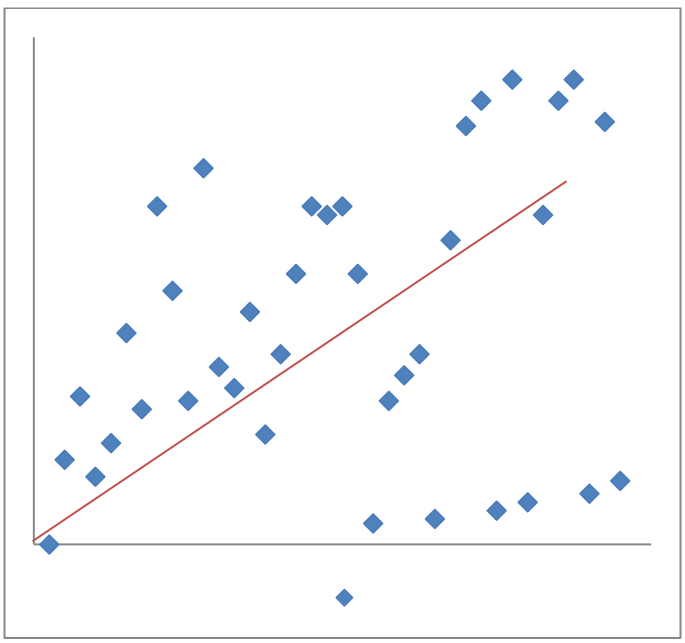

Figure 3: Value for Feature one of new data point

Predicted Y-value of new data point

The left inset shows an example of a "feature space" with two data features, resulting in two axes. All data points will be plotted in this space according to their value for feature 1 and feature 2. The middle inset presents how an SVM determines the line that best separates the two data classes. The method is called SVM because of the vectors, arrows (depicted in orange), that are used to calculate the line. The right inset shows that depending on how each new data point is plotted in feature space, it is determined to which class it belongs (i.e. on which side of the border it is).Thirdly, the algorithm randomly picks a line that separates the two classes in this space. The location of this border is optimized by choosing it to be as far away as possible from the data points of class A, as well as from the data points of class B. In other words, the algorithm aims to maximize the distance between the data points and the line. This is done by selecting the two points (one of each class) that are closest to this random line. The SVM will draw the “support vectors” between the data points and the line, as shown in the middle panel in Figure 5. The last step is to move the line around until the optimal location is found. This is when the length of the support vectors combined is the largest. After it is determined where this border should be, the algorithm is practically done. To classify a new image, it is plotted in feature space to determine on which side of the border it ends up. And there you have it: an algorithm that is able to classify new data points.

Another classification example: K-Nearest-Neighbors

Another example of a classification method is the K-Nearest-Neighbors (KNN) technique. As is the case with SVMs, the training data is plotted in feature space . However, appointing classes happens based on a specific number (K) of nearest data points, for K equals 1, we check which single data point is closest to our test example (the orange point) by drawing a circle (orange circle) that is just large enough such that one extra data point falls within this circle. In this example, we will assign these points to class A. In the middle panel K equals 3, which means the size of the circle in increased such that 3 data points are enclosed. The algorithm then counts how many of these points belong to class A or to class B and assigns the new point to a specific class based on which class the majority of points in the circle belong to. In the middle and right panels this is class B, so the new data point is classified as class B. For the more detail-oriented readers: it is up to the algorithm designer to specify if a simple majority is used for classification or some other cutoff.

Test Examples : K-Nearest-Neighbors

K=1, K=3,K=20

The K-nearest-neighbor method uses the K-nearest data points to classify a new data point. If the majority of these K data points are of a certain class, the new data point will be classified as this particular class.

Clustering Techniques

Clustering is quite similar to classification in the sense that these methods group input data into different classes based on predefined features. However, clustering techniques are typically used when no ground-truth labels are available for the different classes. Thus, clustering algorithms define their own grouping system (or “labeling”, if you will) to classify the input data. Hence it should be considered an unsupervised learning method. Let’s find out how clustering techniques work using an example.

A CLUSTERING EXAMPLE: K-MEANS CLUSTERING

K-means clustering is a basic example of a clustering technique. It is an iterative method, meaning that the process is repeated until an optimal distribution of classes is found. First, all data points are plotted in feature space. Second, all data points are randomly assigned to one of the K clusters and the location of the centroid or geometric center is determined for each cluster. In the second iteration each data point is reassigned to a new cluster based on its nearest centroid. New centroid locations are established based on these new cluster assignments. This process is repeated (or ‘iterated’) until the cluster assignment of the data points does not change anymore.[8] At that time, the optimal division of data points into clusters is determined and therefore the optimal location of the centroids is set

Neural networks (artificial)

Neural networks are also part of the machine learning realm. It is a specific group of methods which solve classification problems, but they are also suited to function as a regression or clustering technique or they can perform segmentation tasks. Neural networks can be used in both supervised and unsupervised algorithms; hence they are a very versatile set of techniques. In the following sections we will explain how simple neural networks work their magic and we will dive into deep neural networks in the next section.

3. RESULTS AND DISCUSSION

NEURAL NETWORKS WORKS

A simple neural network, also called a perceptron, consists of two layers both made up of "nodes". Neural networks contain an input layer and an output layer. The input layer receives the image features that are manually derived from the image and performs specific calculations using these features. The output layer receives the outcomes of the calculations from the nodes in the input layer and will give you the outcome to the question the neural network is supposed to answer. When we come to the section on deep learning, we will see that in deep neural networks the input layer actually is the image. With a perceptron, this is not the case though. Before data enters the perceptron, we need to design and derive the image features during pre-processing. The input layer then receives these image features and performs calculations based on these features. The output layer tells you what type of tumor it the network expects to be shown in the input image.

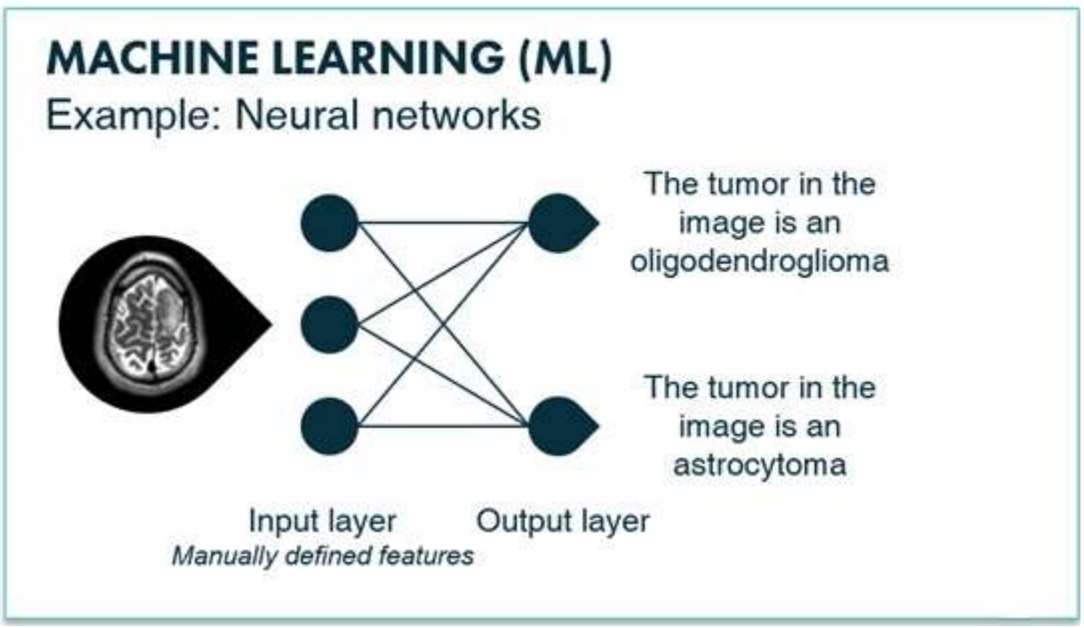

Figure 4: A simple neural network, a perceptron, consists of two layers: an input layer and an output layer.

AI in radiology industry

There are multiple ways of looking at the industry of artificial intelligence (AI) in radiology. One option is to look at all possible use cases AI can handle. To make sure we cover all possibilities it makes sense to group them according to modality and body site. Another option is to sketch the complete radiology workflow and draw all possible ways an algorithm can work its magic. This may sound a little vague, but we will explore different ways of grasping the current concepts of AI in radiology.

Steps in the integrated diagnostic workflow

In this section we will discuss the radiology workflow and look at the steps within the diagnostic chain that algorithms can support.

Radiology Image To Radiology Report

This is where most companies showcasing, for example, at RSNA are operating. These companies usually develop software as a direct support tool for the radiologist: images go in, reports come out often with quantified results.

Raw Scanner Data To Radiology Image

Applying smart algorithms to raw data directly from the scanner, like MRI k-space, can be done for three reasons. Firstly, it can increase image quality. Secondly, it can enable down sampling of the acquired data, hence decreasing scanner time. Thirdly, it may enable lower dose X-rays or CT scans. This is also referred to as deep imaging.

Raw Scanner Data To Radiology Report

It starts to become really interesting when we start skipping steps in the diagnostic chain. For example, it can be done by omitting the image as we know it and letting an algorithm compose radiology reports based on the raw scanner data directly. This, of course, gets tricky when performing a quick check on the algorithm results: human brains do not do well with k-space representations. But if solid performance is proven, it can support radiologists by taking over mundane and laborious tasks which are currently hindering radiologist's work list.

Radiology Image to Pathology Report

Another approach pushing healthcare forward would be to derive pathological or genetic information based on images alone. An algorithm should be able to figure out image features characterizing different types of tumors which are not (yet) discernible by radiologists. In the future, this technique may help to prevent invasive biopsies.

Data to Health Outcome

This is as close as we get to a holy grail in medical imaging: connect raw scanner data directly to the expected health outcome. Imagine scanning a patient and right after the scan being able to postulate what this patient can expect in the future. Of course, besides images, you need to include other information in the training dataset that is needed to develop the algorithm. For example, the possible treatments connected to the outcome as different treatments will most likely cause different outcomes.

Many other steps in the diagnostic chain can be supported by AI algorithms. In the future we will expand this section with examples of research illustrating other steps.

AI radiology use case by use case

Let's assume we want to cover all possible radiology challenges that can be solved by extracting information from medical images. The "space" we end up with, is what we will call "the industry of AI in radiology". This is quite a reasonable approach. Different imaging modalities have very different characteristics. The result of this being that you cannot simply expect an algorithm that has been developed for brain volume measurements on MRI images to do the exact same analysis using a CT scan. To develop an algorithm that can do both your training dataset needs to comprise of both MRI and CT scans. And you need a lot of those. More than double the amount of data needed for a simple "one modality based" algorithm. The algorithm not only needs to recognize what is brain tissue and what is not, but it also has to figure out whether it is dealing with an MRI or a CT scan.

Additionally, we need to take different organs into account. Different organs have different shapes, structures and differ in multiple other features, making it very difficult for one algorithm to deal with multiple organs simultaneously. The same problem arises as with the different modalities: combining multiple organs in one algorithm, requires a vast amount of data.There is yet one level deeper we need to go: different use cases within an organ. Detecting a liver tumor is a very different task for an algorithm than that determining the amount of fat present in the liver. Therefore, most companies out there develop very specific solutions for detecting or calculating a certain value or characteristic in a certain organ on a certain modality.

DEEP LEARNING (DL)

Deep learning is a subset of machine learning with the main differentiating factor being that deep learning uses "deep neural networks", whereas machine learning comprises a much broader set of techniques. Deep neural networks are similar to the simple network described previously. However, deep networks have hidden layers between the input and the output layer to refine the calculations and hence the predictions. Simple neural networks require pre-processing to derive the image features which will be the input data for the network, whereas deep neural networks can use the image directly as input. Deep neural networks is an extension of "regular" neural networks. In contrast to simple or shallow neural networks they use hidden layers before passing the results to the output layer.

THE NODES OF A NEURAL NETWORK

In the context of radiology, the input layer would be the medical image (or all the pixels of a medical image). In an ideal world every pixel would be assigned to an individual node. However, due to memory limitations we usually work with sets of pixels that are assigned to an individual node. These nodes then pass the value of the pixel sets on to the first hidden layer. One node in the input layer connects to all the nodes in the hidden layer. This simply means that the value from this first input node is passed on to all nodes in the hidden layer and used there in calculations. This is called a fully connected layer. The hidden layers are where the magic happens. They receive input from nodes in the previous layer (this can be the input layer or another hidden layer) and perform calculations using this input combined with a set of weights. End result is an output which is passed on from this hidden layer node to the next hidden layer or the output layer. The goal of training your neural network is to determine the optimal value for the weights of every node. The higher the accuracy of your algorithm, the better you have determined your weights.

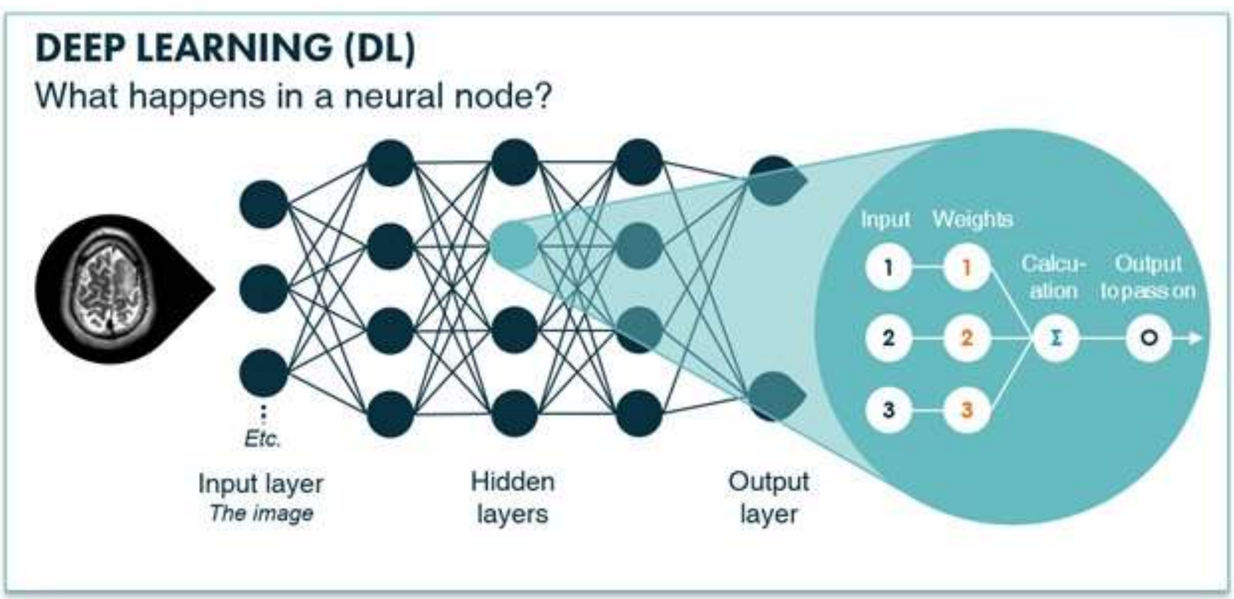

Figure 5: A node in a hidden layer receives input from nodes in the input layer, performs calculations using certain weights and then passes on new values to the next (output) layer.

The output layer receives its inputs from the last hidden layer and combines these inputs into the final answer. The output layer of our example deep neural network in Figure 10 consists of two nodes: the first will return "positive" if the algorithm classifies the tumor as an oligodendroglioma, and the second will return a positive if the algorithm classifies the tumor as an astrocytoma.

Proposed Method

The sky seems to be the limit when it comes to applying AI in radiology. But for now there are still quite some challenges to overcome before AI will be widely applied and fully adopted in the radiology workflow of which we will discuss a few below.

A sufficient amount of quality labeled data

Within the medical field, access to large high-quality labeled datasets for training is not straight forward. Other general databases are extremely powerful because they include a vast amount of images which are accurately labeled. Comparing the typical medical imaging dataset of approximately 1000 images to a non-medical database which can contain up to 100 000 000 pictures, it can only be concluded that the volume available is clearly still several orders of magnitude behind. A way to overcome this problem is using augmentation. Radiologists are extremely busy healthcare professionals. They cannot afford to make any mistakes. They need to interact with a wide range of referring physicians; neurologists, urologists, orthopedic practitioners, the list goes on. They need to be sharp, always.

Benefits of AI in radiology

There are several ways AI can advance the performance of radiologists even further. In this section we will discuss a few of these approaches. This list is not exhaustive. There are many more ways for AI to benefit the radiologist. We will expand this section in the future.

Provide a more differentiated diagnosis

Many AI solutions are focused on providing extra information. This can be by quantifying information enclosed in an image, where it is currently only reported in a qualitative way. Or the software can add normative values, allowing physicians to compare patient results to an average based on a cross-section of the population. The difficulty with this benefit is that we do not always know yet how to handle this extra information.

Offer a second opinion

Having an AI algorithm run in the background offers an easy way for obtaining a second opinion. The algorithm results can serve as a simple backup check on the diagnosis of the physician. An additional benefit of having AI software running as a second opinion is that it allows the radiologist to gradually get used to working with AI and build trust as they see that it adds value. To serve this purpose well it is very important the software performs strongly and does not return a lot of false positives or negatives.

Eliminate inter- and intra-observer variability

Even the best trained, most experienced radiologists might differ in their diagnosis sometimes. Well rested in the morning, something different might catch the attention than after a long working day. Additionally, different radiologists might emphasize different aspects in their reports. This can be tricky for referring physicians, as they need to take into account these variations when synthesizing all the information they have, before coming to a final diagnosis. AI software has the ability to decrease or even eliminate this variability between radiologist reports.

Artificial intelligence radiology benefits

There are many tasks AI can perform in the context of radiology. Some tasks will require just a medical image as input and will base the analysis purely on the pixels (or voxels). Others will go one step further and will combine radiological images with information obtained from other sources.

Using only the image as input

AI that uses only a medical image as input, will deliver results that are mostly similar to what radiologists otherwise would do manually. For example, automatic segmentations of specific organs can be done manually (e.g. liver and HCC segmentation to determine whether a resection can and should be performed). However, these type of analyses are very time consuming and therefore very suited to "outsource" to an algorithm. Another example is the quantification of specific distances (e.g. automatic measurement of RECIST scores). Again this can be done manually, but many radiologists experience this as monotonous task, making it a suitable candidate to get some AI help.

CONCLUSIONS

AI techniques have been steadily developed since 1965 but recently have undergone resurgence due to breakthrough performance arising from a combination of factors: wide availability of labeled data, advances in neural network architectures, and availability of parallel computing hardware. In radiology, AI applications currently focus on anomaly detection, segmentation, and classification of images. Familiarity with the terminology and key concepts in this field will allow the radiology community to critically analyze the opportunities, pitfalls, and challenges associated with the introduction of these new tools. Radiologists should become actively involved in research and development in collaboration with key stakeholders, scientists, and industrial partners to ensure radiologist oversight in the definition of use cases and validation process, and in the clinical application for patient care

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