A Review of Artificial Intelligence's Neural Networks (Deep Learning) Applications in Medical Diagnosis and Prediction

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This paper reviews deep learning applications in medical diagnosis and prediction, such as Convolutional Neural Networks, Fully Convolutional Networks, and Generative Adversarial Networks in medical image analysis. It further summarizes the strength and weaknesses of deep learning in medical imaging and suggests that deep learning's great potential in medical fields.

When doctors and researchers diagnose or analyze illnesses, they usually rely on detailed information about specific tissues and organs to make the optimal treatment plan. Therefore, medical imaging has become a necessary part of diagnosis, prediction, and treatment processes. Consequently, current medical imaging technologies such as magnetic resonance imaging (MRI), positron emission tomography (PET), and computer tomography (CT) are used widely for clinical examination and decision-making.

In its early form, medical imaging analysis mainly involves edge detection, textual features, morphological filtering, shape model building, and template matching. However, these methods require manual selection for specific tasks. In contrast, the more advanced technology of deep learning can learn medical image features directly from data samples and translate them into specified terms automatically.

Machine learning models are trained with a massive amount of data and ultimately result in more accurate classification or prediction. Deep learning is a subset of machine learning that learns hierarchical features from data, making it ideal for discovering complex structures in high-dimensional data like medical imaging. In recent years, deep learning has made significant progress owing to increased capacity of computing power, wider range of data, and better models and algorithms. The great success of deep learning in computer vision has inspired many researchers to apply it to medical image analysis, and many scholarly works have summarized and discussed the success and problems of deep learning in medical image analysis. Thus, the aim of this article is to review deep learning's application in medical diagnosis and prediction, followed by an evaluation of deep learning's strengths, weaknesses, and outlook.

DEEP LEARNING APPROACHES IN MEDICAL DIAGNOSIS

Deep Learning Overview

Deep Learning is a subset of machine learning methods based on artificial neural networks (ANN). ANN was inspired by information processing and distribution communication nodes in biological systems.[1]

Artificial neurons (Figure 1) are elementary units in an ANN. It is a mathematical function consisting of three parts: input, activation function, and output. Input represents the signal transmitted to the cell; activation function is a weighted sum representing the sensitivity of the cell toward input signals; output is the processed signal that serves as the input of the next layer.

An ANN (Figure 2) usually consists of multiple layers grouped by artificial neurons. The most common ANN structure consists of an input layer, one or more hidden layers, and an output layer. Each artificial neuron in the later layer takes the weighted sum of the former layer's output.

This imitation enables ANN to extract the hidden information from the original data and find the pattern of specific problems. Neural networks have been used on a variety of tasks, including computer vision, speech recognition, natural language processing, social network filtering, and medical diagnosis.

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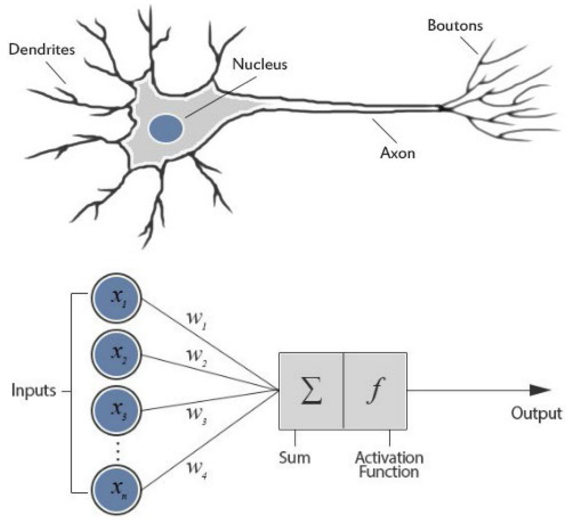

FIGURE 1. Example of artificial neuron.[2]

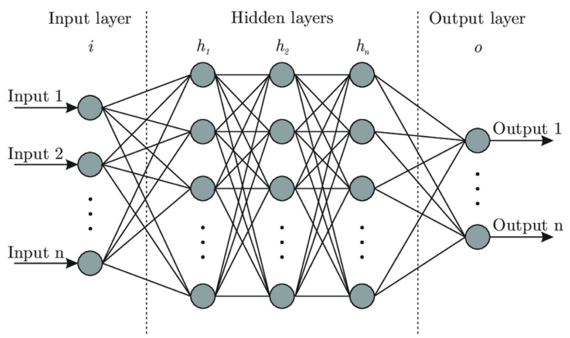

FIGURE 2. Architecture of ANN.[3]

Convolutional Neural Networks (CNNs)

CNN is a class of deep learning technique, most commonly applied to analyzing visual imagery.[4,5]

The structure of a CNN contains one input layer, one output layer, and multiple hidden layers (Figure 3). The hidden layers include convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract key information from images to a feature map; pooling layers reduce data dimension; fully connected layers connect every neuron in one layer to every neuron in another layer and output classifications.

The key element of a convolutional layer is the convolution kernels, which are several matrices containing certain target patterns within the input image. In the example provided (Figure 4), the input picture is a black and white picture with an X in the middle. While the specific patterns we are looking for are two

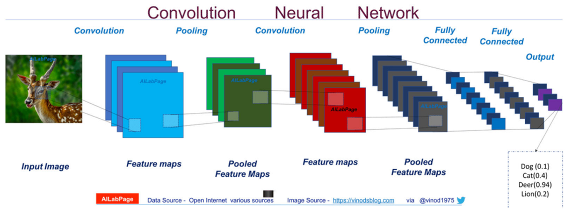

FIGURE 3. Example of a CNN.[6]

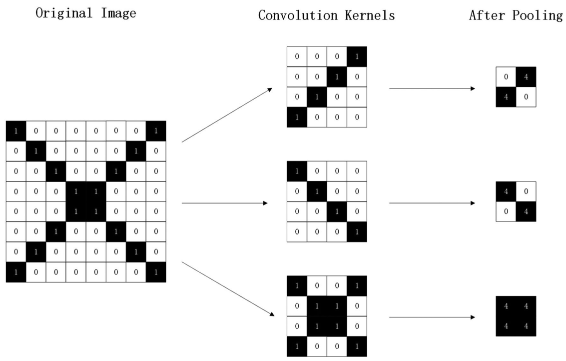

FIGURE 4. Example of convolution kernels.

slashes and one cross, these features are broken down into convolution kernels. After multiplying the original image by the convolution kernels and pooling, we can get three outputs indicating information in different parts of the original picture, respectively.

By doing so, CNN targets the key features within the input picture and makes decisions according to these extracted features. CNN has been applied to image classification in many areas and usually has a much higher classification accuracy than humans and other algorithms.

When applying CNN to medical diagnosis, medical images will be the input of the network, and CNN will generate models that result in the diagnosis of specific diseases. In this way, doctors can double-check their diagnosis result with the help of CNN.

Fully Convolutional Networks (FCNs)

FCN (Figure 5) is an end-to-end, pixel-to-pixel network mainly used for image semantic segmentation[7] The FCN has been applied in multiple domains due to its outstanding accuracy in image segmentation.

Unlike CNN, FCN replaces the fully connected layers with convolutional layers. Convolutional layers extract features from the original image and compress the information in multiple convolution outputs. Several rounds of convolution and pooling create a

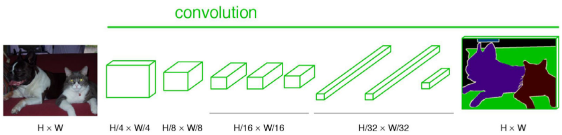

FIGURE 5. Example of an FCN.[7]

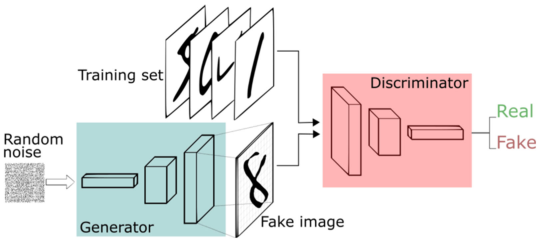

FIGURE. 6. Example of GANs.[9]

heatmap with abstracted features. The last step in FCN is to unsample the heatmap through deconvolution layers. Deconvolution is a reverse process of convolution that decompresses the information and fills the image with additional pixels. After convolution and deconvolution, the item's border within the original image will be presented clearly in the output image.

Medical diagnosis reached through FCN provides a clear view of the border between sick and healthy tissues. For example, a well-trained brain tumor detection FCN model can provide high-quality thermal maps to help doctors identify tumors more accurately.

Generative Adversarial Networks (GANs)

GAN (Figure 6) is another method of deep learning, which comprises two neural networks, i.e., generative network and discriminative network, competing with each other.[8] Typically, generative network learns from the latent space and tries to imitate the real sample as output. On the other hand, discriminative network distinguishes candidates produced by the generator from the true data distribution. These two networks continually modify each other and adjust the parameters accordingly.

When applying GANs to medical diagnosis, the discriminative network can assist doctors to distinguish abnormal images, acting as a regulator and a detector, while the generative network can generate large volumes of diverse data by learning from millions of CT or MRI images. The data used by the generative network are usually gathered with limited consent from patients and at a low cost.[10]

CHALLENGES AND STRENGTHS

One of the most challenging tasks in medical image analysis is to deliver critical information about the shapes and volumes of the organs. There is no deep learning method that can achieve this task perfectly.

Although CNN has a promising capability in image classification and pattern recognition,[11] it has limited capability in segmentations. For example, CNN can only identify the existence of tumor in a medical image, but it cannot specify the contour of the tumor or further segment the tumor from healthy tissues.

FCN provides a solution in semantic segmentation. By restoring the output to the same size as the input image, FCN can make predictions and classify images at the pixel level, which provides clear indications of locations. However, FCN has limitations in fixed receptive size. If the object size changes, it will be harder for FCN to detect the object.[11] Furthermore, FCN can have inaccurate segmentation in small organs if the foreground and background of the image are imbalanced.[12] The solutions could be resizing the image to feed the network[13] and applying two-step segmentations in a hierarchical manner.[14]

Besides these shortcomings, deep learning has other challenges. Overfitting happens when data are limited and a model captures the patterns and regularities.[15] GAN offers a solution, where simulated images can provide supplement dataset in training deep learning models.

Moreover, deep learning is computationally expensive. As neural networks usually need to deal with large datasets with complex layer designs, it can take several weeks to train the model from scratch, while traditional algorithm generally takes only a few minutes, hours, or days. Furthermore, this level of data processing is highly dependent on hardware because it requires parallel processing power. One of the solutions provided by CNN is the pooling layers that reduce the dimensionality of the parameters[16] and decrease the amount of data significantly.

Despite the challenges illustrated above, the performance of deep learning significantly surpasses other learning algorithms after the amount of data reaches a certain level. By analyzing data sets, the algorithms are trained to make decisions by commenting on similar events. This feature allows the machine to work on much more complex tasks and further assist in reducing repetitive work. Furthermore, the neural networks generally have high fault tolerance. Missing data or data corruption does not affect the results. This is valuable because in traditional algorithms, inappropriate handling of missing data or corrupted data can significantly affect the result.

FUTURE OUTLOOK

The growing interest in deep learning and its applications have attracted more researchers to investigate its potential and overcome the challenges in medical imaging. For instance, data digitization and standardization provide a solution to inconsistent size and image positions.[17] In 2017, Nvidia announced its collaboration with GE Healthcare, which will bring AI computing to GE's 500,000 imaging devices around the world, with priorities in machine intelligence, smart hospitals, and patient information monitoring to empower radiologists. Beyond implementing AI within hospitals, the entire healthcare industry is transforming into a digitized and connected industry through the Internet of Things, digital health management, and the development of patient-centric value chains.

The development of hardware is the foundation of deep learning. From the 1990s, the development of graphics processing unit (GPUs) has significantly increased the computing power, and according to Moore's Law, the number of transistors in a dense integrated circuit doubles around every two years. Future technology advancements in computer performance are underway and will enable researchers to build more complex ANNs. As for now, methods such as field-programmable gate array (FPGA)-based accelerators and general-purpose GPUs can shorten the training time significantly.

Cloud computing has also incited many discussions within the healthcare industry. Providers are embracing the cloud that provides affordable and flexible pricing, which in turn accelerates the progress of health data digitization and process management. The cloud computing services will also enable global data sharing and allow researchers to test their deep learning models on larger scales. Nonetheless, moving on to the cloud also raises concerns for data privacy and security. If patients' data are stored on the cloud, the data face risks of theft and misuse. While data deidentification can help reduce the risk of data breaches, current deidentification approaches are not enough to completely ensure data safety and the industry needs time to get accustomed to new technological developments as well.

Overall, deep learning application in medical diagnosis and prediction shows promising results. Future development on digitization, computer performance, and cloud computing opens many doors for deep learning applications by enabling global data sharing and generating higher quality data.

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