Letter to Editor

Deep Learning in Sleep Medicine: Advantages and Drawbacks

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Considering the advancements in machine learning, neural networks (NNs), as models of the human brain with the ability of generalization, have gained a great deal of attention in numerous fields of science such as sleep medicine for years (1). NNs have been widely used in sleep apnea detection, sleep stage recognition, audio-based snore detection, insomnia identification, detecting sleep-related movement disorder (SRMD), etc. (2-4). The history of NNs can be divided into three main eras, including single-layer neurons, multi-layer networks (now are called conventional NNs), and deep learning (DL). Although conventional NNs are assumed a milestone in machine learning, they are fading to some extent with advent of DL. DL is a minor subset of artificial intelligence; however, it possesses a wide range of application due to its unique characteristics (5).

The main difference between conventional NNs and DL models is the training process. Figure 1 illustrates the training process in traditional NNs and DL. Conventional NNs apply features extracted by experts through a trial-and-error procedure. In other words, a limited number of features (in most cases with no prior knowledge) are extracted, which is time-consuming and not effective enough (6). In contrast to traditional NNs, DL just applies the original data, extracts features independently, and does not require experts to extract features (1, 5).

As conventional NNs apply backpropagation-related algorithms with slower convergence speed, there is a possibility to get stuck in local minimums while optimizing their cost function.

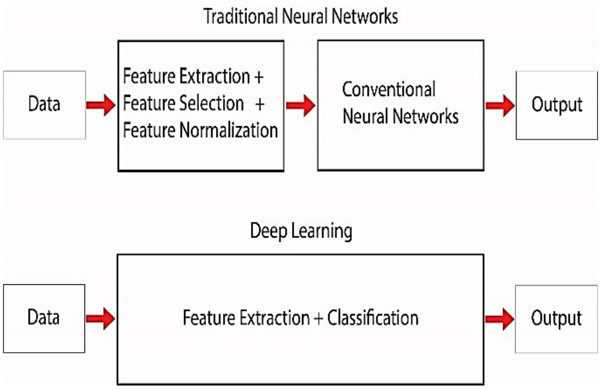

Figure 1. Traditional neural networks (NNs) in comparison with deep learning (DL)

This is considered the main drawback of traditional NNs (7). Several algorithms have been suggested to improve conventional NNs. However, their generalization performance is not competitive compared to other methods. This has motivated researchers to find a solution resulting in deep NNs. Although DL is part of NNs, there are some fundamental differences between traditional NNs and DL, which are presented in table 1.

Concerning differences between conventional NNs and DL, now, it is somehow clear when to apply DL in sleep medicine. With several tuning capabilities, DL outperforms conventional methods in complex problems when there is limited knowledge and a lack of domain understanding for feature introspection (8). DL needs a large amount of data and high-end infrastructure like graphics processing units (GPUs) to be trained appropriately and in a reasonable time.

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Table 1. Main differences between traditional neural networks (NNs) and deep learning (DL) models

Differences	Conventional NNs	DL
Requiring manual feature extraction	Yes	No
Computational complexity in the training process	Lower	Higher
Requiring a large number of sample data	No	Yes
Application in black box models	No	Yes
Easy to implement	Yes	No
Performance	Lower	Higher
Tuning ways	Limited tuning capabilities	Can be tuned in different ways
Required hardware	Can be trained using CPU	Needing GPU to train
Capabilities	Saturation happens in performance even with large amounts of training data	A larger amount of data means higher performance

NNs: Neural networks; DL: Deep learning; CPU: Central processing unit; GPU: Graphics processing unit

DL outshines when data size is large, and we have access to fast processors (9).

Considering recent studies in sleep medicine, it should be noted that in almost all applications, we have access to large data. In sleep stage detection, for instance, each 30-second window of recorded signals is labeled with one of the sleep stages which means there will be a considerable amount of data. This also applies to sleep apnea detection and other projects using polysomnography (PSG). Sleep stages and sleep-related disorders can be detected at a higher accuracy using DL. We can conclude that DL, as an effective tool with wide usage, has a lot to offer to researchers in the field of sleep medicine. It seems that scientists need to pay more attention to DL in their future projects.

Conflict of Interests

Authors have no conflict of interests.

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