

Deep Learning in Healthcare

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Abstract. This article aims to discuss and demonstrate deep learning techniques used in healthcare. After introducing the feasibility of deep learning in the medical field, the article discussed the opportunities and challenges of deep learning in healthcare from different perspectives. Then, the article showed the current implementations and applications of deep learning in the medical healthcare system. Finally, the article summarizes deep learning techniques and applications in healthcare.

Keywords: deep learning; healthcare; neural network.

1. Introduction

"Big data" is a huge amount of information that can create miracles. It has become a topic of particular interest over the past two decades due to the statistical potential hidden in the data. Public and private organizations in various industries generate, collect, and analyze big data in order to improve their products and services (Dash, S., et al., 2019). In the healthcare and medical industry, healthcare systems are facing a great challenge: there is a trade-off between controlling costs and improving health outcomes. In this case, big data may help to achieve this goal in unprecedented ways (Pastorino, R., et al., 2019). The deeper insights provided by big data analysis for doctors translate into better care, shorter hospital stays, and fewer admissions and readmissions, it also provides clinical insights that are not might not be recognized by human beings, enabling doctors to more accurately prescribe treatments and make clinical decisions. The mining of medical big data will also help to gain a deeper understanding of the patient groups with the greatest risk of illness, so as to take proactive preventive methods. In short, the analysis of medical big data can help identify abnormal patients who consume medical services far beyond the normal range. It can be then used to inform and motivate patients to take care of their own health, and it can also be used to educate patients on how to improve physical fitness metrics. By combining financial and clinical data, it can also target treatments to highlight efficiency and effectiveness (Catalyst N., 2018).

Modern clinical experiments in biomedicine generate various types of data, which are often complex and unstructured, such as electronic health records, medical images, sensor data, etc. These data are heterogeneous, and a disease is often not explained by just a single piece of data, so using algorithms such as deep learning to derive insights and knowledge from such complex and high-dimensional medical data is a modern healthcare ideal. A key challenge to achieving change (Miotto, R., et al., 2018). Some statistical or data mining methods have been applied in medicine. These techniques usually require i) feature engineering (obtaining efficient and more powerful features from this data); ii) building a predictive or clustering model on top of this data. In scenarios with complex data and insufficient domain knowledge, unfortunately, there are many challenges in these two steps.

The fact is that biomedical data is plentiful and highly available presents, enormous opportunities for healthcare research. In particular, many features of deep learning can help healthcare, including its end-to-end learning solution with ensemble feature engineering, and its excellent performance on complex and multimodal data. In order to accelerate the pace of deep learning helping the medical field, the entire field of deep learning research must address the challenges related to the characteristics of healthcare data — which are sparse, noisy, heterogeneous, and time-series-based — requiring improvements on tools and methods to allow deep learning to interact with healthcare systems and support clinical decision making.

This article aims to demonstrate and discuss deep learning techniques used in healthcare. After introducing the feasibility of deep learning in healthcare, that is, linking the principles of deep learning with healthcare, it focused on deep learning in natural language processing (NLP), computer vision, integrated learning, and other general methods. Then, the article discussed the opportunities and challenges of deep learning in healthcare from different perspectives. Then, the article showed the current implementations and applications of deep learning in the medical healthcare system. Finally, the article summarizes deep learning technology and its application in healthcare.

2. Deep Learning Techniques

2.1. Mechanism

Before introducing deep learning, the first knowledge that need to be understood are machine learning and neural networks. Machine learning generally refers to a method that can learn data relationships without defining correlations between data a priori. A typical machine learning procedure consists of 4 steps: i). Data Reconciliation; ii). Representation Learning; iii). Model Fitting and iv). Performance Evaluation. Besides, building a machine learning system, namely artificial intelligence (AI) requires certain expertise, such as statistics and engineering, in order to transform raw data into proper representation from which the algorithm or architecture can detect patterns of the dataset. On the other hand, neural networks, considered a subset of machine learning, are computational models with hierarchically connected nodes. Its hierarchy is inspired by the structure of neuronal networks in the brain. Neural networks can learn representation from data, so they can be trained to recognize patterns, classify data and predict the future.

The difference between deep learning and machine learning lies in the process of learning representations from raw data. And the main difference is the number of hidden layers: deep learning refers to a computational model based on multiple hidden layers (deep) of a neural network. Such a model can learn data representations with multiple levels of abstraction, in other words, the connections of each hidden layer and the ability of the learned input to have meaningful abstractions.

Another difference is that traditional neural networks are usually limited to 3 layers, and are trained to obtain supervised representations that are only optimized for specific tasks and are generally cannot be generalized. Whereas each layer of a deep learning system optimizes local unsupervised criteria and generates representations of observed patterns from the data it receives as input from lower layers. It is worth noting that the feature layers of deep learning are not designed by humans but are derived from data through a learning process.

2.2. Deep Neural Networks

A recurrent neural network (RNN) is an application of deep learning whose architecture is capable of learning from streams of information. RNN is suitable in various scenarios, including analysis of speech, text, and time-series data. Generally, RNN is fed with training data that has a meaningful representation to preserve data and strong interdependencies about previous occurred time steps. Therefore, each intermediate layer of the RNN can serve as the current input and the past input, thus providing the input of new information for the next layer. Due to such characteristics, RNNs are also known as memory networks. The RNN model is simple, therefore its tolerance of exploding and vanishing gradients is poor (Pandey, S.K. and Janghel, R.R., 2019.). There are two variations of RNN, namely, Long Short-term memory (LSTM) and Gated Recurrent Unit (GRU). They are introduced to resolve the vanishing gradient problem, which is a general problem of deep learning, generated by long input sequences.

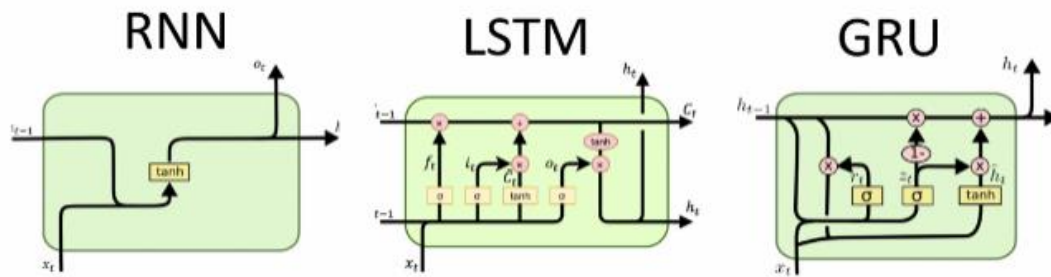


Figure 1 - RNN, LSTM & GRU

Convolutional Neural Networks (CNN) is one of the most widely used deep learning techniques that are inspired by natural visual perception techniques (Pandey, S.K. and Janghel, R.R., 2019.). Generally speaking, CNN is a neural network based on convolution calculation. Because the principle of convolution calculation is simple, it can be combined into neural networks of different depths and forms, and many architectures have appeared in its development history, such as LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, etc.

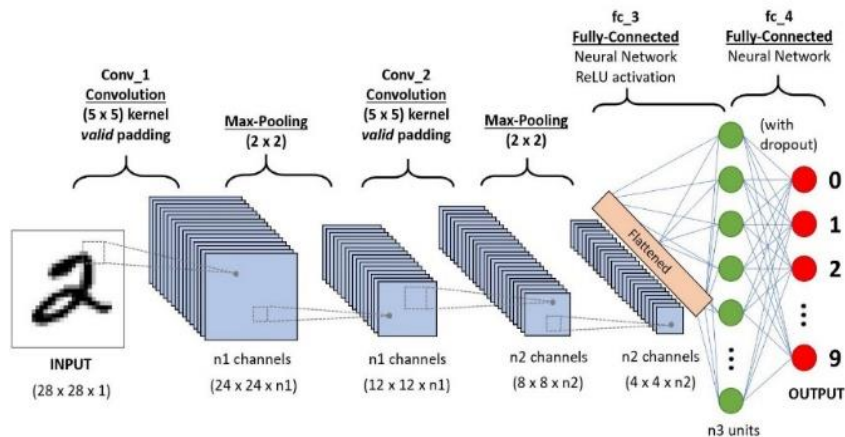


Figure 2 – A typical CNN sequence to classify handwritten digits

Generative adversarial network (GAN) is another deep learning technique made up of 2 models: generative model G and distribution model D. G encapsulates D and the data distribution, which as a whole is used to evaluate the probability that a sample comes from the training data. In simple terms, the core of the training procedure of generative models is to maximize the probability of discriminative matching failures. GANs can learn to mimic any data distribution and can be used in any domain, such as text, images, audio, and video. (Pandey, S.K. and Janghel, R.R., 2019.).

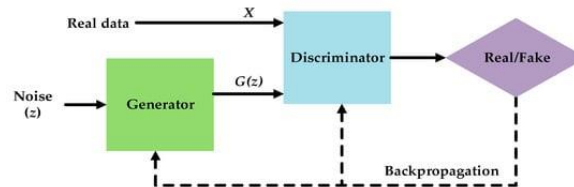


Figure 3 – Generative Adversarial Networks

In addition to the above-mentioned basic deep neural network structures, there are many novel architectures, such as encoder-decoder, transformer, ELMO, BERT, etc. In addition, neural networks can also be combined with pre-trained embedding or pre-trained models for better performance.

2.3.Ensemble Methods

The ensemble method is a technique that ensemble multiple basic models to generate one optimal predictive model. The concept of the ensemble method is originally described in machine learning.

BAGGing (or Bootstrap, AGGgregating) and Random Forest are typical ensemble methods. Where in the context of deep learning, there are the following methods that can be seen as ensemble methods.

Multi-view learning is considered improving the generalization of a model by learning data ensemble of multiple feature sets, so multi-view learning is also called data fusion (Xu, C., et al, 2018). Among them, datasets with multiple feature sets, also known as multi-views, are common in many practical scenarios. For example, the same book was translated in different languages; the same status was seen from different angles; the same disease was indicated by different physiological indicators. These views usually represent diverse and complementary information of the same data (Zhao, J., et al., 2017).

Federated learning is another emerging fundamental AI technique. First proposed by Google in 2016, it is a method for localizing models on the terminal for users with Android phones (Yang, Q., et al., 2019). Its core is to maximize the efficiency of machine learning while ensuring information security, that is, under the initial goal of protecting the privacy of personal data, ensuring legal compliance, and simultaneously distributing or using multiple computing nodes for efficient machine learning. Machine learning architectures that can be used for federated learning are not only neural networks but also include traditional machine learning: random forests, SVMs, etc.

3. Challenges and Opportunities

3.1. Data Volume and Quality

Deep learning is a set of highly intensive calculation models that require a large number of parameters. Therefore, the basis for achieving the goal of deep learning is the availability of massive amounts of data. In practice, while there is no enforced minimum number of training samples, the general rule is to have at least about 10 times the number of parameters in the hidden layers (Miotto, R., et al., 2018). Also, this is one reason that deep learning is very successful in the fields that can easily collect large amounts of data, such as computer vision. Refer to medical data, for example, ECG data in clinical trials, each recording approximately 0.5h - 24h. Considering recordings of a patient making the data duration of 100 – 200 hours in total, it is an enormous amount of data, which might increase the training performance and generalization. Similarly, other types of medical data like EEG and CT scans are occupied a large volume. However, the medical data described above is the features rather than data samples (Pandey, S.K. and Janghel, R.R., 2019). When medical treatment and deep learning cooperate, it is often because they cannot get enough patients to train a robust model. In addition, understanding diseases and their variability is very complicated for non-medical fields experts. Therefore, from the perspective of big data, compared with other industries, the amount of data required to effectively train a robust deep learning model is more strict and challenging.

Unlike other domains where data is clean and well-structured, healthcare data is incomplete, noisy, and ambiguous in addition to being heterogeneous. For example, considering EEG data, we can observe this phenomenon, which is contaminated by various artifacts caused by blinking (eyes), lateral eye movements (electromyography), and muscle activity. Some forms of healthcare data are recorded in the domain where voltage fluctuations are recorded. While other forms of data, such as MRI and CT scans, are recorded in electromagnetic images, resulting in data heterogeneity. These data may also be incomplete, which may be due to missing values caused by improper operation of the recording equipment or instrument failure. Therefore, training a robust model with such a diverse dataset remains challenging. Several more issues to consider are data redundancy, sparsity, and missing values. (Miotto, R., et al., 2018; Pandey, S.K. and Janghel, R.R., 2019.).

3.2. Domain Complexity and Model Interpretability

Unlike other application domains, the issues in biomedicine and healthcare are complex: the diseases are highly heterogeneous, and for most of them, the causes and progression methods are still not fully understood. In addition, in actual clinical scenarios, the number of patients is usually small, and it is hard to require as many patients as possible (Pandey, S.K. and Janghel, R.R., 2019.).

Incorporating expert knowledge in the medical field into the deep learning procedures to guide the efficient development of the model is an important future research direction (Miotto, R., et al., 2018).

Deep learning models are usually regarded as black boxes because it allows neurons to learn data representations without supervision. Although this may not be a problem in other fields, in healthcare, not only is algorithm performance important, but also the motivation behind the computational work. In other words, the interpretability of the deep learning model, that is, which phenotype-driven predictions are provided, is essential to persuade medical professionals to accept the actions recommended by the predictive medical system, for example, the prescription of a drug, the risk of onset of a certain disease (Miotto, R., et al., 2018).

Therefore, it is not only important to involve experts in the medical field and to guide the deep learning process to a certain extent, but it is also necessary for researchers in the field of deep learning to make a certain effort on model interpretability.

3.3.Temporal, IoT and Electronic Health Records

Diseases always develop and change in uncertain ways over time. Especially cancer, a cancer patient sentenced to death is very likely to be cured because of a good attitude. However, many current models, even those that have been proposed in the medical field for commercial, expect the presence of static vector-based information sources as input data. Designing deep learning methods that can process temporary medical data is an important research direction.

After the concept of IoT (Internet of Things) was put forward, the medical field took the lead in applying IoT to medical equipment to systematically collect various indicators of patients. These data are stored as electronic health records and used in some data analysis and mining methods.

3.4.Privacy and Ethical Issue

Medical privacy is a core ethical issue involving the use of big data in healthcare. A large amount of personal information can be widely accessed electronically. The main consideration for the public concerned about the privacy of medical data is that the data may be misused by employers, insurance companies, and governments (White, G. and Ariyachandra, T., 2016).

Ethicists said that regulations need to be formulated to protect personal privacy as much as possible. In most clinical trials, after looking for potential subjects, they will be asked to sign an informed consent form.

4. Implementations and Applications

4.1.Medical Imaging

With the success of deep learning in computer vision, its earliest application in clinical data is in medical image processing, especially for analyzing brain magnetic resonance imaging (MRI) scans to predict Alzheimer's disease and its variants. Specifically, CNNs were used to infer hierarchical representations of low-field knee MRI scans, in order to automatically segment cartilage structures from which osteoarthritis risk could be predicted. Although the input data used by this method are 2D images, it achieves better results than methods that use multi-scale features in 3D that are manually selected by doctors. In addition, a similar approach has been applied to the segmentation of multiple sclerosis lesions in multi-channel 3D MRI and the differential diagnosis of benign and malignant breast nodules on ultrasound images (Miotto, R., et al., 2018).

To summarize, there are four main ways to apply deep learning technology in medical imaging. Among them, deep learning has made great contributions to image analysis in medical imaging, especially the development of classification, segmentation, and detection.

4.2.Diagnosis

Using big data and deep learning techniques, especially multi-view learning for diagnosis or support, is another common application of deep learning in the medical field.

The direct reason that multi-view learning can help diagnosis is that medical data is multi-view data, in other words, completely different types of data, such as basic patient information (gender, age, blood type, etc.), image information (ECG, CT scan, etc.), electrical Signals and biological signals (blood pressure, blood sugar, etc.) are both describing the state of the same individual, which is the most suitable multi-view learning data.

At present, the diseases that have been successfully applied to automatic or semi-automatic diagnosis are sleep attack, stroke, and so on.

4.3.Health Monitoring

Federated learning and wearable IoT sensing devices are changing various mobile applications, such as health monitoring. As the gap between small wearable devices (i.e., Apple Watch) and medical devices begins to close, a single wearable device can now monitor various medical indicators. This helps wearable device users monitor their own health, promote preventive health care, and help manage the persistent disease.

Federated learning might be the key element for enabling this new kind of application. Especially recently, only a few studies using the deep model have been used for commercial purposes, and most of the collaborations are in the clinical stage, which is mainly due to the limitations of the hardware. Running reliable and deep learning models efficiently on mobile devices to process heterogeneous, complex, and noisy sensor data can drain the device's battery and computing resources. Therefore, it is still a challenging task while federated learning is a solution currently trying to face such a challenge (Miotto, R., et al., 2018; Zhao, R., et al., 2019).

5. Conclusion

The basic neural networks in deep learning can be applied to the healthcare field in a single form, combined form, or in combination with other technologies, such as IoT. Although the current healthcare field and deep learning cooperation applications have appeared, such as medical image analysis, disease diagnosis as well as prediction, and daily health monitoring, some of them are still in clinical trials. And when the medical field cooperates with deep learning, it will inevitably face data volume, data quality, interdisciplinary, interpretability, and some information security as well as ethical issues. Deep learning in the medical field needs to continue to develop.

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