NIPES

Journal of Science and Technology Research

Journal homepage: www.nipesjournals.org.ng

Artificial Intelligence a Paradigm Shift in Healthcare Sector Past, Present and Future Prospects

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Article Info

Keywords:
Artificial intelligence structured and unstructured data neurology and cardiology

Received 04 June 2023
Revised 02 July 2023
Accepted 09 July 2023
Available online 15 Sept. 2023
https://doi.org/10.5281/zenodo.8348838

Abstract

Artificial intelligence (AI) aims to mimic human cognitive functions. It is bringing a paradigm shift to healthcare, powered by increasing availability of healthcare data and rapid progress of analytics techniques. We survey the current status of AI applications in healthcare and discuss its future. AI can be applied to various types of healthcare data (structured and unstructured). Popular AI techniques include machine learning methods for structured data, such as the classical support vector machine and neural network, and the modern deep learning, as well as natural language processing for unstructured data. Major disease areas that use AI tools include cancer, neurology and cardiology. We then review in more details the AI applications in stroke, in the three major areas of early detection and diagnosis, treatment, as well as outcome prediction and prognosis evaluation. We conclude with discussion about pioneer AI systems, such as IBM Watson, and hurdles for real-life deployment of AI.

1. Introduction

Recently AI techniques have sent vast waves across healthcare, even fuelling an active discussion of whether AI doctors will eventually replace human physicians in the future. We believe that human physicians will not be replaced by machines in the foreseeable future, but AI can definitely assist physicians to make better clinical decisions or even replace human judgment in certain functional areas of healthcare (eg, radiology). The increasing availability of healthcare data and rapid development of big data analytic methods has made possible the recent successful applications of AI in healthcare. Guided by relevant clinical questions, powerful AI techniques can unlock clinically relevant information hidden in the massive amount of data, which in turn can assist clinical decision making.[1–3]. In this article, we survey the current status of AI in healthcare, as well as discuss its future. We first briefly review four relevant aspects from medical investigators' perspectives: 1.motivations of applying AI in healthcare, 2.data types that have be analyzed by AI systems, 3. mechanisms that enable AI systems to generate clinical meaningful results, 3. Disease types that the AI communities are currently tackling.

1.1 Motivation

The advantages of AI have been extensively discussed in the medical literature. AI can use sophisticated algorithms to 'learn' features from a large volume of healthcare data, and then use the obtained insights to assist clinical practice. It can also be equipped with learning and self-correcting abilities to improve its accuracy based on feedback. An AI system can assist physicians by providing up-to-date medical information from journals, textbooks and clinical practices to inform proper patient care.[6] In addition, an AI system can help to reduce diagnostic and therapeutic errors that are inevitable in the human clinical practice. Moreover, an AI system extracts useful information from a large patient population to assist making real-time inferences for health risk alert and health outcome prediction.

1.1. Literature Review

Before AI systems can be deployed in health-care applications, they need to be 'trained' through data that are generated from clinical activities, such as screening, diagnosis, treatment assignment and so on, so that they can learn similar groups of subjects, associations between subject features and outcomes of interest. These clinical data often exist in but not limited to the form of demographics, medical notes, and electronic recordings from medical devices, physical examinations and clinical laboratory and images [13].
Specifically, in the diagnosis stage, a substantial proportion of the AI literature analyses data from diagnosis imaging, genetic testing and electrodiagnosis (figure 1). For example, Jha and Topol urged radiologists to adopt AI technologies when analyzing diagnostic images that contain vast data information[13] Li *et al* studied the uses of abnormal genetic expression in long non-coding RNAs to diagnose gastric cancer. Shin *et al* developed an electrodiagnosis support system for localizing neural injury [15].

In addition, physical examination notes and clinical laboratory results are the other two major data sources (Figure 1). We distinguish them with image, genetic and electrophysiological (EP) data because they contain large portions of unstructured narrative texts, such as clinical notes, that are not directly analyzable. As a consequence, the corresponding AI applications focus on first converting the unstructured text to machine-understand-able electronic medical record (EMR). For example, [13] used AI technologies to extract phenotypic features from case reports to enhance the diagnosis accuracy of the congenital anomalies [16]

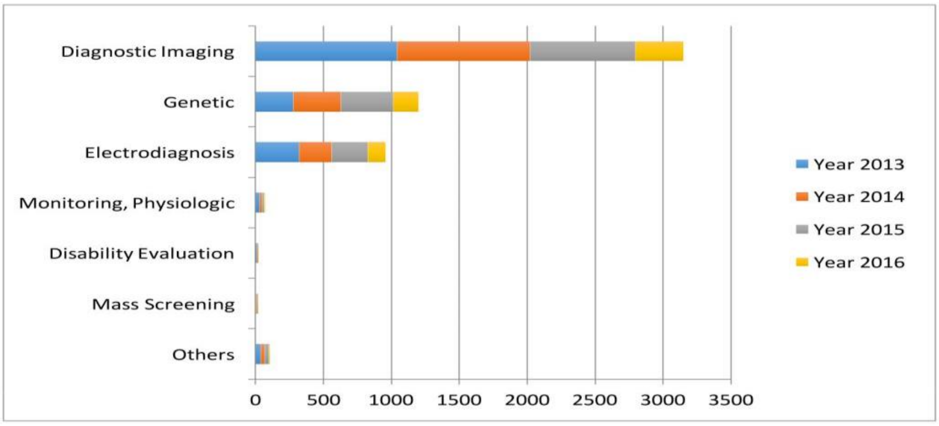

Figure 1 The data types considered in the artificial intelligence artificial (AI) literature. The comparison is obtained through searching the diagnosis techniques in the AI literature on the PubMed database.

1.2. AI devices

The above discussion suggests that AI devices mainly fall into two major categories. The first category includes machine learning (ML) techniques that analyse structured data such as imaging, genetic and EP data. In the medical applications, the ML procedures attempt to cluster patients' traits, or infer the probability of the disease outcomes.[17] The second category includes natural language processing (NLP) methods that extract information from unstructured data such as clinical notes/ medical journals to supplement and enrich structured medical data. The NLP procedures target at turning texts to machine-readable structured data, which can then be analyzed by ML techniques [18]

For better presentation, the flow chart in Figure 2 describes the road map from clinical data generation, through NLP data enrichment and ML data analysis, to clinical decision making. We comment that the road map starts and ends with clinical activities. As powerful as AI techniques can be, they have to be motivated by clinical problems and be applied to assist clinical practice in the end.

1.3. Disease focus

Despite the increasingly rich AI literature in healthcare, the research mainly concentrates around a few disease types: cancer, nervous system disease and cardiovascular disease (Figure 3). We discuss several examples as follows:

1. Cancer: Somashekhar demonstrated that the IBM Watson for oncology would be a reliable AI system for assisting the diagnosis of cancer through a double-blinded validation study [19] Esteva analysed clinical images to identify skin cancer subtypes.[20]

2. Neurology: Bouton developed an AI system to restore the control of movement in patients with quadriplegia [21]. Farina tested the power of an offline man/machine interface that uses the discharge timings of spinal motor neurons to control upper-limb prostheses [22].

3. Cardiology: Dilsizian and Siegel discussed the potential application of the AI system to diagnose the heart disease through cardiac image.[3] Arterys recently received clearance from the US Food and Drug Administration (FDA) to market its Arterys Cardio DL application, which uses AI to provide automated, editable ventricle segmentations based on conventional cardiac MRI images [23]

The concentration around these three diseases is not completely unexpected. All three diseases are leading causes of death; therefore, early diagnoses are crucial to prevent the deterioration of patients' health status. Furthermore, early diagnoses can be potentially achieved

Besides the three major diseases, AI has been applied in other diseases as well. Two very recent examples were Long *et al*, who analysed the ocular image data to diagnose congenital cataract disease[24] and Gulshan *et al*, who detected referable diabetic retinopathy through the retinal fundus photographs [25].

The rest of the paper is organised as follows. In section 2, we describe popular AI devices in ML and NLP; the ML techniques are further grouped into classical techniques and the more recent deep learning. Section 3 focuses on discussing AI applications in neurology, from the three aspects of early disease prediction and diagnosis, treatment, outcome prediction and prognosis evaluation.
We then conclude in section 4 with some discussion about the future of AI in healthcare.

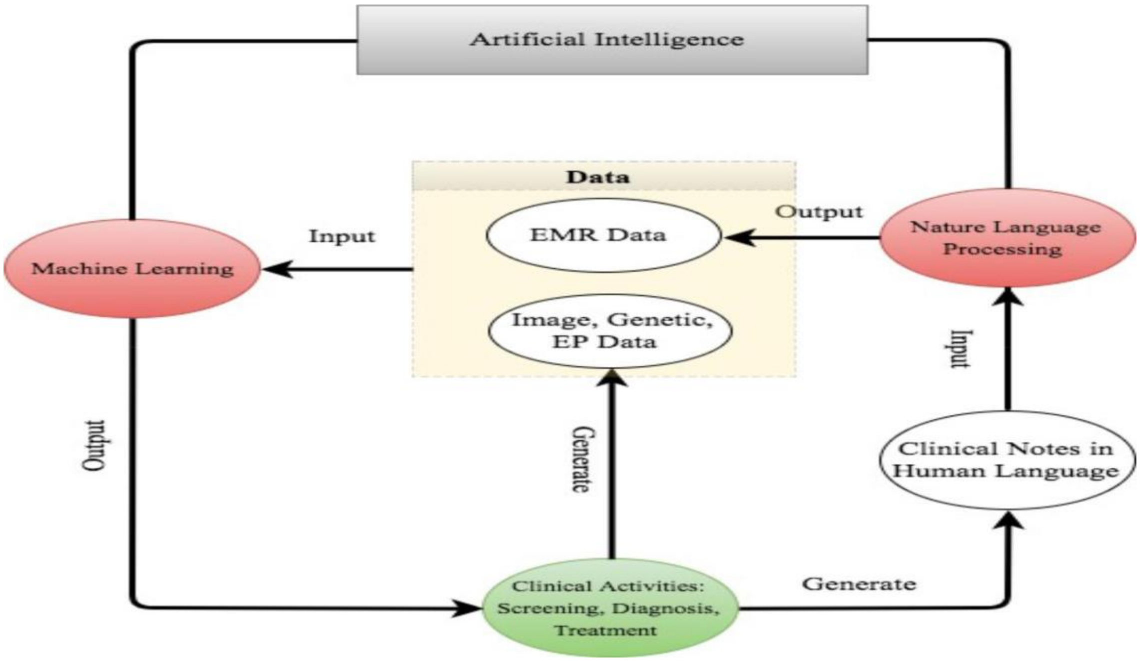

Figure 2 The road map from clinical data generation to natural language processing data enrichment, to machine learning data analysis, to clinical decision making. EMR, electronic medical record; EP, electrophysiological.through improving the analysis procedures on imaging, genetic, EP or EMR, which is the strength of the AI system.

1.4 The AI devices: ML and NLP

In this section, we review the AI devices (or techniques) that have been found useful in the medial applications. We categorise them into three groups: the classical machine learning techniques,[26] the more recent deep learning techniques[27] and the NLP methods.[28]

1.4.1 Classical ML

ML constructs data analytical algorithms to extract features from data. Inputs to ML algorithms include patient 'traits' and sometimes medical outcomes of interest. A patient's traits commonly include baseline data, such as age, gender, disease history and so on, and disease-specific data, such as diagnostic imaging, gene expressions, EP test, physical examination results, clinical symptoms, medication and so on. Besides the traits, patients' medical outcomes are often collected in clinical research. These include disease indicators, patient's survival times and quantitative disease levels, for example, tumour sizes. To fix ideas, we denote the jth trait of the ith patient by X_{ij}, and the outcome of interest by Y_i.

Depending on whether to incorporate the outcomes, ML algorithms can be divided into two major categories: unsupervised learning and supervised learning. Unsupervised learning is well known for feature extraction, while supervised learning is suitable for predictive modelling via building some relationships between the patient traits (as input) and the outcome of interest (as output) more interest. A patient's traits commonly include baseline data, such as age, gender, disease history and so on, and disease-specific data, such as diagnostic imaging, gene expressions, EP test, physical examination results, clinical symptoms, medication and so on.

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Clustering and principal component analysis (PCA) is two major unsupervised learning methods. Clustering groups subjects with similar traits together into clusters, without using the outcome information. Clustering algorithms output the cluster labels for the patients through maximising and minimising the similarity of the patients within and between the clusters. Popular clustering algorithms include k-means clustering, hierarchical clustering and Gaussian mixture clustering. PCA is mainly for dimension reduction, especially when the trait is recorded in a large number of dimensions, such as the number of genes in a genome-wide association study. PCA projects the data

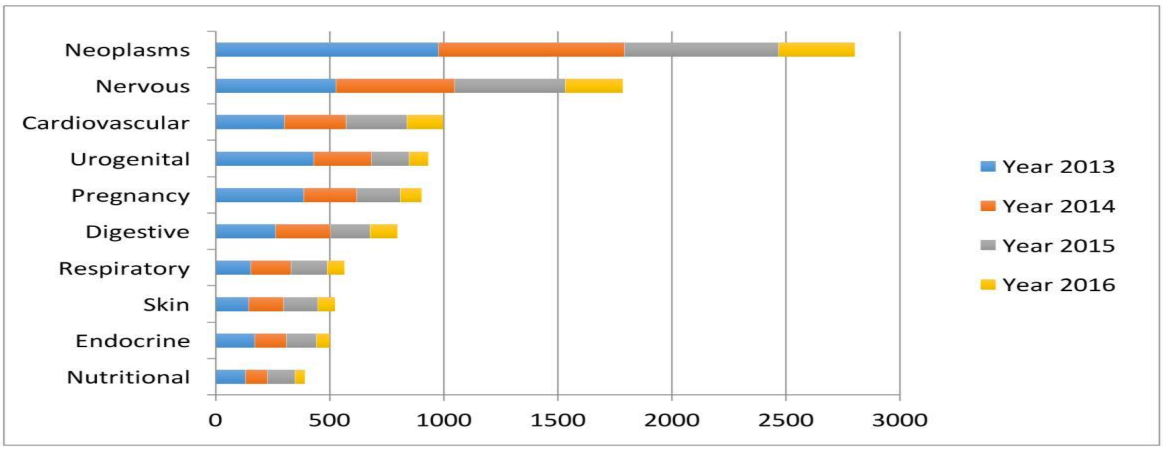

Figure 3 The leading 10 disease types considered in the artificial intelligence (AI) literature. The first vocabularies in the disease names are displayed. The comparison is obtained through searching the disease types in the AI literature on PubMed.

1.4.2 Deep learning: a new era of ML

Deep learning is a modern extension of the classical neural network technique. One can view deep learning as a neural network with many layers (as in Figure 9). Rapid development of modern computing enables deep learning to build up neural networks with a large number of layers, which is infeasible for classical neural networks. As such, deep learning can explore more complex non-linear patterns in the data. Another reason for the recent popularity of deep learning is due to the increase of the volume and complexity of data [37]. Figure 10 shows that the application of deep learning in the field of medical research nearly doubled in 2016. In addition, Figure 3 shows that a clear majority of deep learning is used in imaging analysis, which makes sense given that images are naturally complex and high volume.
Different from the classical neural network, deep learning uses more hidden layers so that the algorithms can handle complex data with various structures. In the medical applications, the commonly used deep learning algorithms include convolution neural network (CNN), recurrent neural network, deep belief network and deep neural network. Figure 12 depicts their trends and relative popularities from 2013 to 2016. One can see that the CNN is the most popular one in 2016.

The CNN is developed in viewing of the incompetence of the classical ML algorithms when handling high dimensional data, that is, data with a large number of traits. Traditionally, the ML algorithms are designed to analyse data when the number of traits is small. However, the image data are naturally high-dimensional because each image normally contains thousands of pixels as traits. One solution is to perform dimension reduction: first preselect a subset of pixels as features, and then perform the ML algorithms on the resulting lower dimensional features. However, heuristic feature selection procedures may lose information in the images. Unsupervised learning techniques such as PCA or clustering can be used for data-driven dimension reduction.

The CNN was first proposed and advocated for the high-dimensional image analysis [38]. The inputs for CNN are the properly normalized pixel values on the images. The CNN then transfers the pixel values in the image through weighting in the convolution layers and sampling in the subsampling layers alternatively. The final output is a recursive function of the weighted input values. The weights are trained to minimise the average error between the outcomes and the predictions. The implementation of CNN has been included in popular software packages such as Caffe from Berkeley AI Research, CNTK from Microsoft and TensorFlow from Google[40].

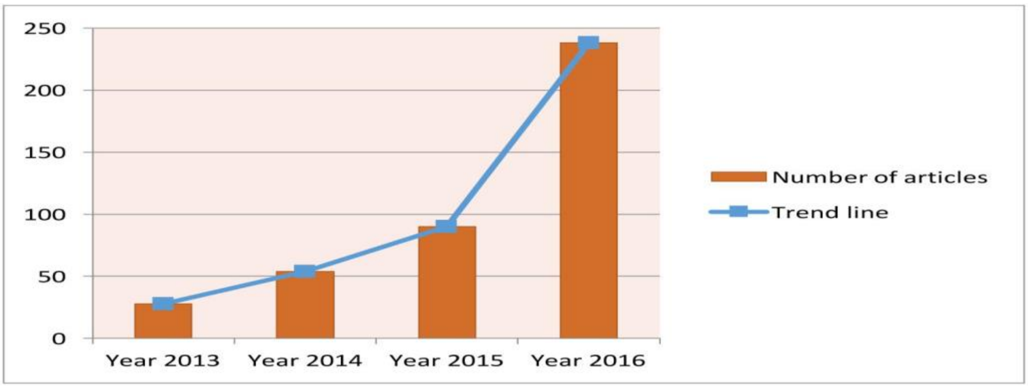

Figure 10 Current trend for deep learning. The data are generated through searching the deep learning in healthcare and disease category on PubMed

Recently, the CNN has been successfully implemented in the medical area to assist disease diagnosis. Long *et al* used it to diagnose congenital cataract disease through learning the ocular images.The CNN yields over 90% accuracy on diagnosis and treatment suggestion. Esteva *et al* performed the CNN to identify skin cancer from clinical images.The proportions of correctly predicted malignant lesions (ie, sensitivity) and benign lesions (ie, specificity) are both over 90%, which indicates the superior performance of the CNN. Gulshan *et al* applied the CNN to detect referable diabetic retinopathy through the retinal fundus photographs.The sensitivity and specificity of the algorithm are both over 90%, which demonstrates the effectiveness of using the technique on the diagnosis of diabetes. It is worth mentioning that in all these applications, the performance of the CNN is competitive against experienced physicians in the accuracy for classifying both normal and disease cases

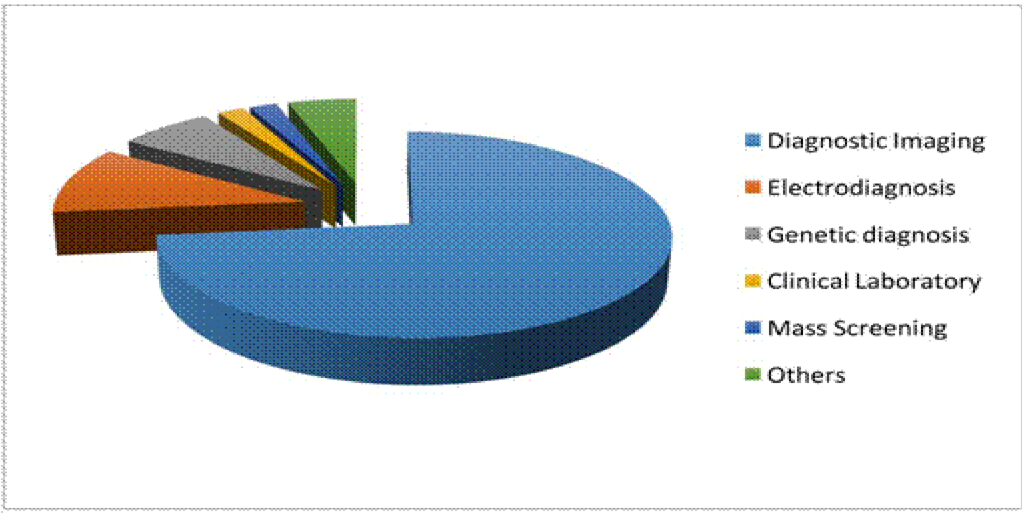

Figure 11 The data sources for deep learning. The data are generated through searching deep learning in combination with the diagnosis techniques on PubMed

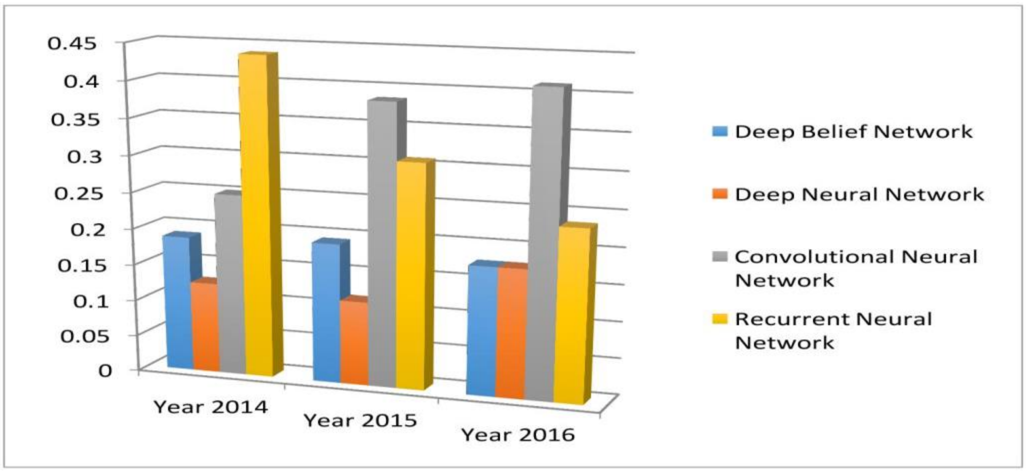

Figure 12 The four main deep learning algorithm and their popularities. The data are generated through searching algorithm names in healthcare and disease category on PubMed.

2.0. Natural language processing

The image, EP and genetic data are machine-understand-able so that the ML algorithms can be directly performed after proper preprocessing or quality control processes. However, large proportions of clinical information are in the form of narrative text, such as physical examination, clinical laboratory reports, operative notes and discharge summaries, which are unstructured and incomprehensible for the computer program. Under this context, NLP targets at extracting useful information from the narrative text to assist clinical decision making.

An NLP pipeline comprises two main components: text processing and classification. Through text processing, the NLP identifies a series of disease-relevant keywords in the clinical notes based on the historical databases. Then a subset of the keywords are selected through examining their effects on the classification of the normal and abnormal cases. The validated keywords then enter and enrich the structured data to support clinical decision making.

The NLP pipelines have been developed to assist clinical decision making on alerting treatment arrangements, monitoring adverse effects and so on. For example, Fiszman *et al* showed that introducing NLP for reading the chest X-ray reports would assist the antibiotic assistant system to alert physicians for the possible need for anti-infective therapy. Miller *et al* used NLP to automatically monitor the laboratory-based adverse effects.Further-more, the NLP pipelines can help with disease diagnosis. For instance, Castro *et al* identified 14 cerebral aneurysms disease-associated variables through implementing NLP on the clinical notes.[45] The resulting variables are success-fully used for classifying the normal patients and the patients with cerebral, with 95% and 86% accuracy rates on the training and validation samples, respectively. Afzal *et al* implemented the NLP to extract the peripheral arterial disease-related keywords from narrative clinical notes. The keywords are then used to classify the normal and the patients with peripheral arterial disease, which achieves over 90% accuracy.

3.0. Discussion

Although the AI technologies are attracting substantial attentions in medical research, the real-life implementation is still facing obstacles. The first hurdle comes from the regulations. Current regulations lack of standards to assess the safety and efficacy of AI systems. To over-come the difficulty, the US FDA made the first attempt to provide guidance for assessing AI systems [68]. The first guidance classifies AI systems to be the ‘general wellness prod-ucts’, which are loosely regulated as long as the devices intend for only general wellness and present low risk to users. The second guidance justifies the use of real-world evidence to access the performance of AI systems. Lastly, the guidance clarifies the rules for the adaptive design in clinical trials, which would be widely used in assessing the operating characteristics of AI systems. Not long after the disclosure of these guidance, Arterys’ medical imaging platform became the first FDA-approved deep learning clinical platform that can help cardiologists to diagnose cardiac diseases [23-68].

The second hurdle is data exchange. In order to work well, AI systems need to be trained (continuously) by data from clinical studies. However, once an AI system gets deployed after initial training with historical data, continuation of the data supply becomes a crucial issue for further development and improvement of the system. Current healthcare environment does not provide incentives for sharing data on the system. Nevertheless, a health-care revolution is under way to stimulate data sharing in the USA [69]. The reform starts with changing the health service payment scheme. Many payers, mostly insurance companies, have shifted from rewarding the physicians by shifting the treatment volume to the treatment outcome. Furthermore, the payers also reimburse for a medication or a treatment procedure by its efficiency. Under this new environment, all the parties in the healthcare system, the physicians, the pharmaceutical companies and the patients, have greater incentives to compile and exchange information. Similar approaches are being explored in China.

4.0. Conclusion

We reviewed the motivation of using AI in healthcare, presented the various healthcare data that AI has analysed and surveyed the major disease types that AI has been deployed. We then discussed in details the two major categories of AI devices: ML and NLP. For ML, we focused on the two most popular classical techniques: SVM and neural network, as well as the modern deep learning technique. We then surveyed the three major categories of AI applications in stroke care. A successful AI system must possess the ML component for handling structured data (images, EP data, genetic data) and the NLP component for mining unstructured texts. The sophisticated algorithms then need to be trained through healthcare data before the system can assist physicians with disease diagnosis and treatment suggestions.
The IBM Watson system is a pioneer in this field. The system includes both ML and NLP modules, and has made promising progress in oncology. For example, in a cancer research, 99% of the treatment recommendations from Watson are coherent with the physician decisions.Furthermore, Watson collaborated with Quest Diagnostics to offer the AI Genetic Diagnostic Analysis.In addition, the system started to make impact on actual clinical practices. For example, through analysing genetic data, Watson successfully identified the rare secondary leukaemia caused by myelodysplastic syndromes in Japan.

The cloud-based CC-Cruiser in [24] can be one prototype to connect an AI system with the front-end data input and the back-end clinical actions. More specifically, when patients come, with their permission, their demographic information and clinical data (images, EP results, genetic results, blood pressure, medical notes and so on) are collected into the AI system. The AI system then uses the patients' data to come up with clinical suggestions. These suggestions are sent to physicians to assist with their clinical decision making. Feedback about the suggestions (correct or wrong) will also be collected and fed back into the AI system so that it can keep improving accuracy.

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