APPLICATION OF ARTIFICIAL INTELLIGENCE FOR HEALTH AND HEALTH CARE

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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. Major disease areas that use AI tools include cancer, neurology and cardiology.

Data mining has been used intensively and extensively by many organizations. In healthcare, data mining is becoming increasingly popular, if not increasingly essential. Data mining applications can greatly benefit all parties involved in the healthcare industry. For example, data mining can help healthcare insurers detect fraud and abuse, healthcare organizations make customer relationship management decisions, physicians identify effective treatments and best practices, and patients receive better and more affordable healthcare services. The huge amounts of data generated by healthcare transactions are too complex and voluminous to be processed and analysed by traditional methods. Data mining provides the methodology and technology to transform these mounds of data into useful information for decision making. This article explores data mining applications in healthcare. In particular, it discusses data mining and its applications within healthcare in major areas such as the evaluation of treatment effectiveness, management of healthcare, customer relationship management, and the detection of fraud and abuse. It also gives an illustrative example of a healthcare data mining application involving the identification of risk factors associated with the onset of diabetes. Finally, the article highlights the limitations of data mining and discusses some future direction.

The healthcare environment is generally perceived as being ‘information rich’ yet ‘knowledge poor’. There is a wealth of data available within the healthcare systems. However, there is a

lack of effective analysis tools to discover hidden relationships and trends in data. Knowledge discovery and data mining have found numerous applications in business and scientific domain. Valuable knowledge can be discovered from application of data mining techniques in healthcare system.

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.

INTRODUCTION

Knowledge discovery in databases is well-defined process consisting of several distinct steps. Data mining is the core step, which results in the discovery of hidden but useful knowledge from massive databases. A formal definition of Knowledge discovery in databases is given as follows: "Data mining is the non-trivial extraction of implicit previously unknown and potentially useful information about data" **[1]**. Data mining technology provides a user-oriented approach to novel and hidden patterns in the data. The discovered knowledge can be used by the healthcare administrators to improve the quality of service. The discovered knowledge can also be used by the medical practitioners to reduce the number of adverse drug effect, to suggest less expensive therapeutically equivalent alternatives. Anticipating patient's future behaviour on the given history is one of the important applications of data mining techniques that can be used in health care management.

DATA MINING

Data mining can be considered a relatively recently developed methodology and technology, coming into prominence only in 1994.[**2**]It aims to identify valid, novel, potentially useful, and understandable correlations and patterns in data[**3]** by combing through copious data sets to sniff out patterns that are too subtle or complex for humans to detect.**[4]** Data mining techniques can be broadly classified based on what they can do, namely description and visualization; association and clustering; and classification and estimation, which is predictive modelling. Description and visualization can contribute greatly towards understanding a data set, especially a large one, and detecting hidden patterns in data, especially complicated data containing complex and non-linear interactions.

HEALTHCARE DATA MINING APPLICATIONS

There is vast potential for data mining applications in healthcare. Generally, these can be grouped as the evaluation of treatment effectiveness; management of healthcare; customer relationship management; and detection of fraud and abuse. More specialized medical data mining, such as predictive medicine and analysis of DNA micro-arrays, lies outside the scope of this paper.

Treatment effectiveness. Data mining applications can be developed to evaluate the effectiveness of medical treatments. By comparing and contrasting causes, symptoms, and courses of treatments, data mining can deliver an analysis of which courses of action prove effective. For example, the outcomes of patient groups treated with different drug regimens for the same disease or condition can be compared to determine which treatments work best and are most cost-effective**.**

Before AI systems can be deployed in healthcare 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, electronic recordings from medical devices, physical examinations and clinical laboratory and images.

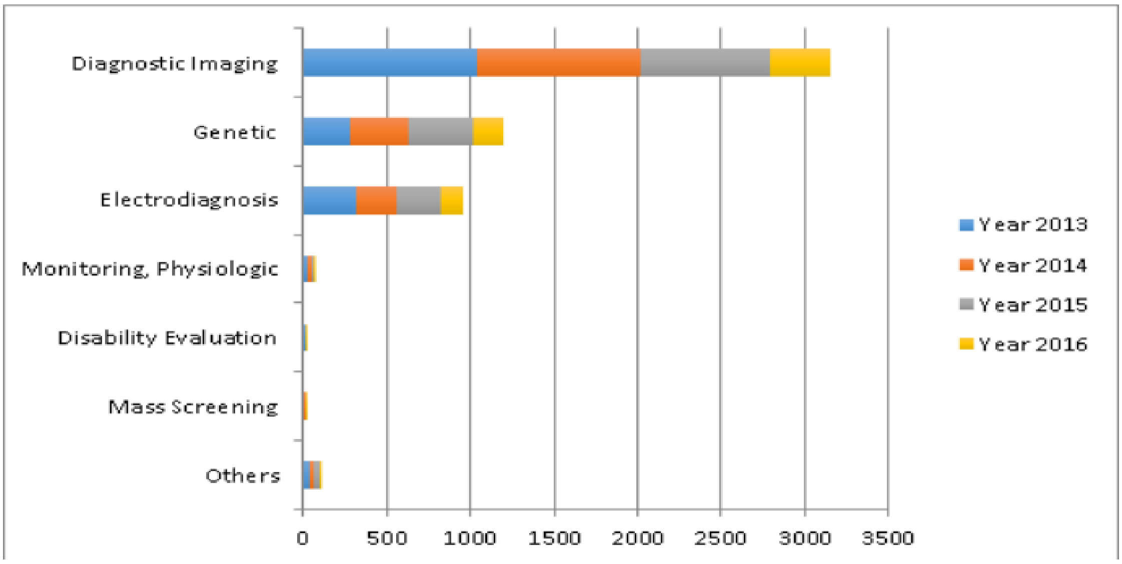

Figure 1 The data types considered in the artificial intelligence artificial (AI) literature. The comparison is obtained through searching the diagnosis techniques in the AI literature on the PubMed database.

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.**[7]**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 analysed by ML techniques.**[8]**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.

AI APPLICATIONS IN CLINICAL PRACTICE:

The process of developing a new technique as an established standard of care uses the robust practice of peer-reviewed R&D, and can provide safeguards against the deceptive or poorly-validated use of AI algorithms.

The use of AI diagnostics as replacements for established steps in medical standards of care will require far more validation than the use of such diagnostics to provide supporting information that aids in decisions.

CONFLUENCE OF AI AND SMART DEVICES FOR MONITORING HEALTH AND DISEASE :

Revolutionary changes in health and health care are already beginning in the use of smart devices to monitor individual health. Many of these developments are taking place outside of traditional diagnostic and clinical settings.

In the future, AI and smart devices will become increasingly interdependent, including in health-related fields. On one hand, AI will be used to power many health-related mobile monitoring devices and apps. On the other hand, mobile devices will create massive datasets that, in theory, could open new possibilities in the development of AI-based health and health care tools.

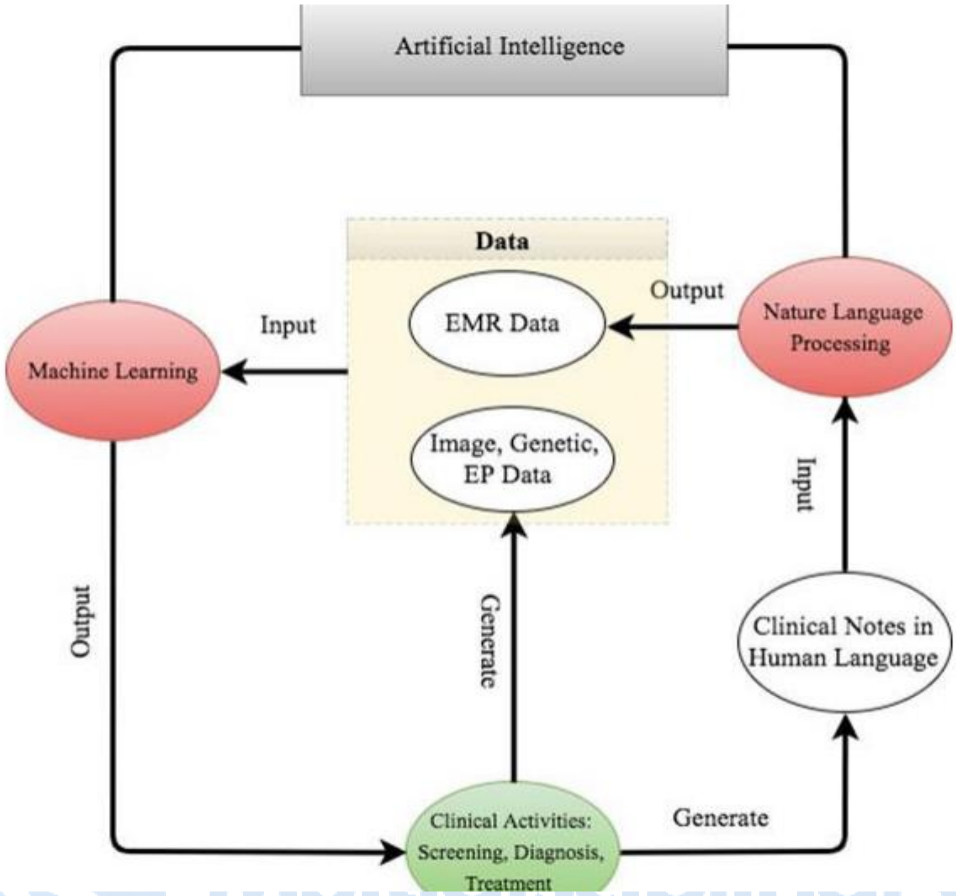

Figure 2 The road map from clinical data generation to natural language processing data enrichment, to machine learning data analysis, to clinical decision making. EMR, electronic medical record; EP, electrophysiological.

AI APPLICATIONS IN STROKE

Stroke is a common and frequently occurring disease that affects more than 500million people worldwide. It is the leading cause of death in China and the fifth in North America. Stroke had cost about US$689billion in medical expenses across the world, causing heavy burden to countries and families.Therefore, research on prevention and treatment for stroke has great significance. In recent years, AI techniques have been used in more and more stroke-related studies. Below we summarise some of the relevant AI techniques in the three main areas of stroke care: early disease prediction and diagnosis, treatment, as well as outcome prediction and prognosis evaluation.

EARLY DETECTION AND DIAGNOSIS

Stroke, for 85% of the time, is caused by thrombus in the vessel called cerebral infarction. However, for lack of judgement of early stroke symptom, only a few patients could receive timely treatment. Villar et al developed a movement-detecting device for early stroke prediction. Two ML algorithms — genetic fuzzy finite state machine and PCA — were implemented into the device for the model building solution. The detection process included a human activity recognition stage and a stroke-onset detection stage. Once the movement of the patient is significantly different from the normal pattern, an alert of stroke would be activated and evaluated for treatment as soon as possible. Similarly, Maninini et al proposed a wearable device for collecting data about normal/pathological gaits for stroke prediction .For diagnosis of stroke, neuroimaging techniques, including MRI and CT, are important for disease evaluation. Some studies have tried to apply ML methods to neuroimaging data to assist with stroke diagnosis.

Comprehensive Training Databases of Health Data for AI Tool Development.

The availability of and access to high quality data are critical in the development and ultimate implementation of AI applications in health care.

AI algorithms based on high quality training sets have already demonstrated performance for medical image analysis at the level of the medical capability that is captured in their training data.

AI algorithms cannot be expected to perform at a higher level than their training data, but should deliver the same standard of performance consistently for data within the training space.

Laudable goals for AI tools include accelerating the discovery of novel disease correlations and helping match people to the best treatments based on their specific health, life-experiences, and genetic profile. Definition and integration of the data sets required to develop such AI tools is a major challenge.

Extreme care is needed in using electronic health records (EHRs) as training sets for AI, where outputs may be useless or misleading if the training sets contain incorrect information or information with unexpected internal correlations.

Techniques for learning from un labelled data could be helpful in addressing the issues with using data from a diverse set of sources.

LIMITATIONS OF DATA MINING DATA MINING

Applications can greatly benefit the healthcare industry. However, they are not without limitations. Healthcare data mining can be limited by the accessibility of data, because the raw inputs for data mining often exist in different settings and systems, such as administration, clinics, laboratories and more. Hence, the data have to be collected and integrated before data mining can be done.

LIMITATIONS OF AI METHODS IN HEALTH AND HEALTH CARE APPLICATIONS

There is potential for the proliferation of misinformation that could cause harm or impede the adoption of AI applications for health. Websites, Apps, and companies have already emerged that appear questionable based on information available.

CONCLUSION AND DISCUSSION

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.

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