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Artificial Intelligence and Neurology

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Abstract

Computers and information technology has played a pivotal role in the advancement of healthcare. Artificial Intelligence (AI) in medicine has significantly evolved over the last few decades, now making it possible to initiate its involvement in real world clinical practice. AI can also be incorporated in a personalized, integrated, adaptive and context aware environment creating the so called Ambient Intelligence (AmI). Neurology is a discipline of medicine that deals with the disorders of nervous system. Large amount of literature exist in regards to utilization of AI and AmI in several aspects of neurology. Using AmI, individual's neurological function can be monitored around the clock for early recognition of neurological disorders. Electroencephalography and electromyography data can be interpreted by AI with high accuracy. Treatment responses can be monitored objectively by AmI in many conditions like movement disorders and epilepsy. Large quantity of data produced in the neurocritical care units can be processed by AI for better monitoring, treatment and outcome prediction. AI can reduce the cost of care and may potentially benefit remote parts of the world by playing role of an expert adviser. In this brief article, author has discussed the application and potential of AI and AmI in neurology. Some obstacles in their development are briefly discussed and several speculations about their future are made.

Keywords: Neurology; Artificial Intelligence (AI); Ambient Intelligence (AmI); Pervasive healthcare

Introduction

Medical knowledge has significantly expanded in the era of information technology making it impossible for a single human to keep track of all the knowledge. This has led to heavy utilization of computer and information technology in medicine. While artificial intelligence (AI) in medicine has been around since 1970s, the initial systems (e.g. INTERNIST-1 [1], MYCIN [2], ONCOCIN [3]) had major limitations requiring extensive programming by humans and exhibited little or no self-learning behavior. Since then, the field of artificial intelligence has significantly evolved with introduction of a number of sophisticated algorithms, some of which are capable of self-learning. Rule based fuzzy expert systems [4] and supervised learning algorithms like artificial neural networks [5] and support vector machines [6,7] are the examples of most widely utilized AI techniques in healthcare; but the list is by no means limited to them. Despite of many advances in the AI, some experts believe that its application in healthcare is still far from its true potential and that our efforts are limited [8].

The concept of pervasive health monitoring involves deploying electronic sensors and wireless networks in the individual's surroundings that are ubiquitous and allows real time personalized health monitoring of every individual in the population, irrespective of location and time [9,10]. It includes smart monitoring devices embedded in the living environment (including cell phones, homes, hospitals, work places, automobiles, etc.), wearable intelligent textiles that continuously records a number of physiological parameters, wearable motion sensors, brain computer interface and many more [11-18]. Ambient Intelligence (AmI) incorporates AI and pervasive health monitoring to create a personalized, integrated, intelligent and context aware environment for the individuals [19].

Neurology is a discipline of medicine that deals with the disorders of nervous system. Clinical examination of the nervous system is an integral part of the diagnosis and treatment of neurological disorders. Some aspects of clinical examination, like cognitive and motor function assessment, may readily be performed by AmI with reasonable accuracy over a prolonged period of time. AI may be able to assist humans even in many non-clinical aspects of neurology. In this article, author has discussed the application, impact and potential of AI and AmI in neurology. Some obstacles in their development are briefly discussed and several speculations about their future are made.

Applications in Neurology

Stroke is one of the most common neurological disorders and AmI can potentially have heavy impact on its epidemiological and clinical course. Stroke occurs when there is either an interruption of blood supply to part of brain (known as ischemic stroke) or the rupture of a blood vessel in the brain causing hemorrhage (known as hemorrhagic stroke). Treatments for ischemic as well as hemorrhagic strokes are time sensitive and are most effective when administered within first few hours of onset [20-22]. However, the patients commonly don't recognize the symptoms or they may be rendered disabled to activate emergency medical services. Therefore, these treatments are largely underutilized [23,24] due to delayed hospital presentation [25,26] or unclear time of symptom onset (as in patients waking up with strokes) [27]. Using AmI, individual's neurological function can be monitored around the clock [28-30] and presence of any alarming neurological signs can activate emergency medical services, even without patient's knowledge [19]. AmI in conjunction with tele-stroke networks [31], automated imaging interpretation [32-34] and prehospital thrombolysis [35] can exclude significant sources of delay in the management of acute stroke. Prognosis of stroke can also be predicted, even prior to treatment using the AI [36,37]. AmI can detect cardiac arrhythmias (especially atrial fibrillation) in cryptogenic strokes and can even potentially prevent the first cerebrovascular event by monitoring every individual in the population [38-40]. Stroke recovery can be improved as well using AmI in the neurorehabilitation [18,41,42].

Seizures are defined as transient, synchronous activation of a large number of neurons that results in focal or generalized dysfunction in brain activity and consciousness. Such disturbance in the electrical activity of the brain can sometimes be recorded using a number of recording electrodes on the scalp in form of an electroencephalogram (EEG). Due to transient duration of the event, the abnormality may not be recorded on the EEG and therefore, continuous EEG monitoring with automatic seizure detection could dramatically change the management of these patients. AI algorithm based seizure detection techniques for scalp EEG [43-48] and intracranial EEG [49-53] have evolved significantly and even surpassed human ability in certain aspects [44]. Responsive cortical stimulation involves implantation of seizure detection device that not only detects seizures, but can also suppress the seizure from spreading [54]. Ambulatory/home EEG and accelerometers as parts of AmI can yield critical information on seizure frequency and semiology in certain patients [55-58]. Algorithms have been developed that can predict risk of recurrent seizures in the future based on several patient risk factors [59]. AmI can ensure better compliance in taking seizure medications [19], as forgetting a single dose may result in a breakthrough seizure. Self-driving cars will be able to provide more mobility and independence to the millions of patients across the world living with seizures or other neurological disabilities [60,61]. Similar to the EEG recordings, electrical potential recordings of the muscle and nerves (electromyography) can also be interpreted by AI [62,63] and then integrated with clinical [64] and imaging [65] data to help with the diagnosis of a number of neuromuscular disorders.

Neurodegenerative disorders (e.g. Alzheimer's disease, Parkinson's disease, Lou Gehrig's disease etc.) result in a very gradual decline in individual's cognitive and/or functional status, and such conditions may be diagnosed earlier with help of AmI that monitors individual's neurological function over a prolonged period of time. AmI can assist with activities of daily living in the cognitively impaired [66,67]. A brain computer interface device has been successfully implanted in a patient of Lou Gehrig's disease, enabling her to communicate better [68]. AI has been extensively studied in the field of movement disorders, especially in Parkinson's disease that often leads to disabling tremors and muscle rigidity. It can differentiate different types and subtypes of movement disorders [69-73] and can even interpret the neuroimaging [74]. Quantification of movement abnormalities can be utilized in the medical and surgical management [75]. Electrical stimulation of certain deep structures in the brain (also known as deep brain stimulation) significantly improves the symptoms of Parkinson's disease. Various stimulation parameters require frequent adjustments to obtain optimal clinical response and certain closed loop systems have been developed that can optimize these parameters automatically for individual patient by feedback information received from the body motion sensors [76,77].

Several catastrophic neurological emergencies like neurotrauma, large strokes, status epilepticus and brain infections require more frequent monitoring of neurological and other bodily functions, which is usually done by nurses and physicians. Neurocritical care units are equipped with a number of patient monitoring systems that generate large quantity of data pertaining to ventilation, hemodynamics, intracranial pressure, body temperature, fluid intake-output, serial neurological examinations and neurophysiologic parameters (e.g. electromyography, continuous EEG). Many of these parameters may require expert supervision around the clock that can potentially be provided by a single intelligent computer system to a large number of patients simultaneously. Closed-loop AI systems can potentially perform real time adjustment of ventilator settings [78-81], antiepileptic drugs, anesthetics/analgesics [82-84], neuromuscular blockade [85,86], glucose management [87], and blood pressure, fluids and electrolytes management [88,89] etc. with little or no human input [90,91]. Intelligent algorithms have been developed that can predict mortality in hemorrhagic stroke [92] and outcome after traumatic brain injury [93,94]. Prediction of intracranial pressure has also been achieved by AI [95,96]. More complex predictive algorithms in the future may take thousands of variables into account in order to predict complications and outcome with fair degree of certainty, well ahead of time. Wealth of data produced in the neurocritical care units makes them an ideal environment to incorporate AI techniques that can efficiently handle such data.

Future Direction and Limitations

AI systems have been developed which can learn from the electronic medical records and develop their own optimal treatment plan [97]. Such selection of optimum path can be individualized for each patient and can dynamically change over time to adapt the changes in clinical scenario. Nowadays, large scale projects are under progress to develop cloud based intelligent computer systems to integrate and analyze enormous amount of patient data and medical literature [98]. These platforms may thrive on the exponentially increasing healthcare data and learn from it. The expected final product might be a capable expert computer system that is always up to date with medical knowledge, contain medical records of every individual, may guide physicians and surgeons around the world and may even learn from its own experience to become better over time. Initial goal would be to incorporate these systems effectively in physician's workflow and then eventually to replace the physician in performing many tasks. Complex medical conditions might be managed with the guidance of these systems at a very little or no cost, even in the remote parts of the world.

Very small number of professionals with both clinical and programming proficiency, lack of international biomedical information sharing network platforms and lack of credible international standards for communication and data exchange has been few of the major obstacles resulting in slow development and underutilization of AI [8]. Furthermore, new ethical, legal and privacy issues may arise [99,100] and dramatic shifts in the role and demand of medical personnel as well as in their reimbursement may occur. Major changes in the education curriculum of medical professionals may have to take place. Thus, the path towards utilizing AI in real world medicine may not always be straightforward. But the rising cost of healthcare [101-104] may prove to be an independent driving force to develop these technologies. We know that the health information technology not only improves the quality of care, but also reduces its cost significantly [105,106]. Many of these observations led to formation of funding programs (e.g. HITECH) by the US federal government to stimulate investment in the electronic health records [107]. Similarly, AI may also potentially reduce the cost of care markedly [97] and in future, this may translate into creation of promotional policies to accelerate investment in AI by rewarding the hospitals and the physicians who incorporates it into their workflow. Initial monetary investments can eventually be paid off by the numerous advantages of AI. Despite of certain limitations, the advantages of these systems are numerous. With the aid of advanced AI and AmI, acute neurological emergencies may be timely managed, chronic neurological diseases may be recognized early, treatments may be individualized and the quality of life with neurological disability may be improved.

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