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Artificial Intelligence in neurosciences: A clinician's perspective

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Abstract:

Even after making allowance for an unprecedented hype, it is an undeniable fact that, in the coming decade, deployment of Artificial Intelligence (AI) will cause a paradigm shift in the delivery of healthcare. This paper will review the practical utility of AI in neurosciences from a clinician's perspective. Steering clear of the complex, technical, computational jargon, the authors will critically review the exponential development in this area from a clinical standpoint. The reader will be exposed to the fundamentals of AI in healthcare and its applications in different areas of neurosciences. Powerful AI techniques can unlock clinically relevant information, hidden in massive amounts of data. Translating technical computational success to meaningful clinical impact is, however, a challenge. AI requires a thorough and systematic evaluation, prior to integration in the clinical care. Like other disruptive technologies in the past, its potential for causing a great impact should not be underestimated. A scenario in which medical information, gathered at the point of care, is analyzed using sophisticated machine algorithms to provide real-time actionable analytics seems to be within touching distance.

Key Words:

Artificial Intelligence and neurosciences, Artificial Intelligence in neurology, Artificial Intelligence in neurosurgery

Key Message:

Deployment of Artificial Intelligence (AI) in healthcare and in neurosciences is slowly becoming a reality. A century ago, electricity transformed industry after industry. Today it is AI. The compound annual growth rate of AI in the healthcare industry is 40% and is projected to reach an investment of US $6.6 billion in 2021. Neurosurgeons and neurologists need to be future ready, to use AI in their practice. Using AI to reach a patient is no longer a question of if – it is a question of 'how' and it is a matter of 'now'!

The term 'Artificial Intelligence' or AI was first introduced by McCarthy in 1956.[1] As a clinician, the primary author is of the opinion that the A in AI should stand for augmenting, amplifying, accelerating and assisting in an ambient milieu. What is 'artificial' in AI? AI is after all an extension, a by-product of the natural intelligence which Homo Sapiens are endowed with. Augmented Intelligence helps to expand the role of a domain expert. Accelerated engineering and analysis can help in expediting the processing of data-rich workflows. AI is today enabling a constellation of mainstream technologies that are having a substantial impact on our everyday lives. AI is an example of pole vaulting, not just leap frogging.

AI can be viewed as the use of computer systems to enable the performance of tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making and translation between languages. Tomorrow's 5P (predictive, personalised, precision, participatory and preventive) medicine, when fully functional, will have AI as a major component. As 80% of the 41 zetabytes (410 trillion GB) of digital information currently available is unstructured, AI will be required to detect patterns and trends, which our grey matter at present is unable to decipher.

Components of AI

Machine learning (ML), the basis of AI, is a field of computer science that gives computers the ability to learn without being explicitly programmed. Evolving from the study of pattern recognition and computational learning theory, these algorithms can learn from and make predictions on data. These analytical models allow researchers, data scientists, engineers, and analysts to produce reliable, repeatable decisions and results and uncover hidden insights, through learning from historical relationships and trends in the data. ML models have been shown to augment the decision

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making capacity of clinicians in neurosurgical applications. However, creating, validating, and deploying ML models in the clinical setting is accompanied by several concerns. Viewing ML in a *human-and-machine* context rather than a *human-vs-machine* setting is essential.[2] Deep learning is a subset of machine learning that has networks capable of learning in an unsupervised manner, from data that is unstructured or unlabelled.

Natural Language Processing (NLP) is the ability of a computer program to understand human language *as it is spoken*. Computers traditionally require humans to interact with them *in a programming language that is precise, unambiguous and highly structured*. Human speech, however, is ambiguous and the linguistic structure depends on many complex variables, including the slang used, the regional dialects and the social context. NLP takes this into account, interprets free text and makes it analysable.

Fuzzy Logic (FL) is a multi-valued logic, which is similar to human thinking and interpretation. It has the potential of combining human heuristics (a problem solving technique that finds a rapid but an approximate solution, and is employed when the classic methods are too slow or fail to find any exact solution) into computer assisted decision making. Fuzzy logic could become the basis of all clinical decision making and the understanding of neurosciences. Clinical scenarios present in shades of gray. Instead of "present or absent", the patients' symptoms are described using terms like "never, rarely, sometimes, often, most of the times, always, etc". Each specific symptom could also be "mild, moderate or severe". *FL can quantify all these multiple variables*. The National Aeronautics and Space Administration (NASA) smart probe project used fuzzy logic in developing probes for real time identification of gray and white matter and in the differentiation between normal tissue and tumor cells.[3]

Data Mining (DM)

DM can be defined as the methods and processes used to perform knowledge discovery. DM intersects database technology, modelling techniques, statistical analysis, pattern recognition, and machine learning. It makes the use of advanced tools for large database management and automatic/semiautomatic analyses in order to identify significant trends and associations deemed informative. DM helps in the identification of relations, patterns and models supporting prediction and the clinician's decision making processes, e.g., for the diagnosis, prognosis, and treatment planning.[4] DM has been applied to identify significant changes in heart rate variability, in response to complex auditory stimuli. It is concerned with the analysis of large databases to find significant and previously unsuspected relationships among data.[5]

AI and Healthcare

AI's dependence on data has major consequences for healthcare. This industry is highly regulated, as is the access and the use of medical data. System compliance is easier with AI. In a world where algorithms can make diagnoses, wearable devices can track vital signs and robots can be remotely controlled to perform surgical procedures, will clinicians of tomorrow eventually become an endangered species? AI may be the province of the world's biggest technology companies, but endorsement and recommendation from clinicians is still required, if AI tools designed to drive patient engagement, are to be accepted. With supporting AI tools, the future role of specialists will not be to extract information from images and histology, but *manage the information extracted by AI*, in the clinical context. AI will hopefully place back the aspect of 'humanity' in healthcare by allowing clinicians to focus on the patient, instead of getting drowned in voluminous data.[6] Vosburgh in a thought provoking article, "Surgery, Virtual Reality, and the Future", has emphasised that AI should ideally address the problems surgeons really have, not what engineers think they have.[7] Technology that adapts to and faithfully represents the patient's anatomic, functional and physiologic status needs to be implemented. Only information that is needed should be supplied, and that too, only when needed. Workflows should be augmented, not redefined.

It is a paradox that the application of AI in neurosciences presupposes a better understanding of the intelligent functioning of the biological brain.[8] AI aims to mimic human cognitive functions. Increasing availability of healthcare data and rapid progress of analytical techniques are leading to a paradigm shift in healthcare. AI augments decision making by clinicians by uncovering clinically relevant information hidden in a massive amount of data. AI can be equipped with learning and self-correcting abilities to improve its accuracy based on the feedback it receives. An AI system can assist clinicians by providing up-to-date medical information from journals, textbooks and clinical practices to improve patient care. An AI system extracts useful information from a large patient population. This helps in making real-time inferences. ML techniques analyse structured imaging, genetic data, cluster patients' traits and infer probability of disease outcomes. NLP methods extract information from unstructured data such as clinical notes/medical journals supplementing and enriching structured medical data. NLP procedures target at turning texts to machine-readable structured data, which can then be analysed by ML.[9]

A scenario in which medical information, gathered at the point of care, is analysed using sophisticated machine algorithms to provide real-time actionable analytics seems to be within touching distance. The creation of data-driven predictions underpins personalised medicine and precision public health. Translating technical success to meaningful clinical impact is the next great challenge [Figure 1]. Partnerships between clinicians and data scientists, supported by the growing strength of clinical informatics, is beginning to yield positive results AI requires a thorough and systematic evaluation prior to integration in the routine clinical care; however, like other disruptive technologies in the past, its potential for causing a huge impact should not be underestimated.[10]

AI is the basis of precision medicine (PM), which will eventually be a part of the neurological management. PM is an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment and lifestyle. PM presupposes the availability of massive computing power and algorithms that can learn by themselves at an unprecedented rate.[11]

DeepMind Technologies Ltd, a wholly-owned subsidiary of the Google conglomerate, is using AI with data-driven tools and techniques and machine learning methods to improve healthcare. Microsoft, International Business Machines (IBM) Corporation and Apple are investing heavily in health related AI.[12] AI will be the most disruptive technology due to the requirement of radical computational power, endless amounts of data and unprecedented advances in deep neural networks. Stephen Hawking had opined that the development of full AI could spell the end of the human race. Elon Musk concurred adding, "a fleet of AI enhanced robots is capable of destroying mankind".

The Gartner Hype cycle for emerging technologies describes the different phases of innovation as a trigger, a peak of inflated expectations, a trough of disillusionment and finally a scope of enlightenment and plateau of productivity.[13] Obviously, we are nearer the beginning of the Hype cycle.

Prediction Models Using AI

Newer evolutionary computation-based approaches are being used to develop highly robust models capable of classifying >99% of cases with data mining in clinical research. After training, *EpiCS,* a type of learning classifier system, specially adapted to model clinical data, achieved an accuracy (P value < 0.001) comparable to the logistic regression analysis and decision tree induction, the two traditional methods of data analysis.[14] In a study of 1271 head trauma records, artificial neural networks (ANN) and multivariable logistic regression models were compared in their ability to predict outcomes in head trauma. Reproducibility of the findings were studied. ANNs significantly outperformed logistic models in both fields of discrimination and calibration, but under performed in accuracy.[15] Prediction of intracranial pressure trends with ANN has been reported.[16] In a prospective trial of 150 patients scheduled for low back surgery, AI outperformed clinicians in predicting the likely operative findings. However, probability systems often require an impractical number of patients to establish a data base.[17] ANN proved superior to logistic regression models in predicting recurrence of chronic subdural hematoma[18] and craniocervical injuries.[19] Brain death prediction, based on ensembled ANN networks, in a neurosurgical intensive care unit has been reported.[20] Middleton, in a review of clinical decision support systems (a 25-year retrospective analysis and a 25-year future vision), has emphasised that predictive analytics and cognitive aids across the translational spectrum and continuum of care will be critical in improving health care.[21]

Illustrations of Neuroscience-related Clinical Applications Deploying AI

707 patients with mental health issues were studied. Using 345 variables, an analysis was carried out with AI tools. The authors reported that eventually AI tools could help to reduce the risk of suicide.[22] A study from Taiwan reported that Bayesian statistics (learning from evidence as it accumulates) helped clinicians explore other potential risk factors for dementia.[23] Supervised machine learning and ontology-based approaches (a set of concepts, that show the properties of the variables and the relationship between them) have been employed to obtain useful information from plain text clinical data. This has resulted in automatic classification of International Classification of Diseases version 10 (ICD-10) related cause of death from autopsy reports.[24] Objective grading of facial paralysis using AI analysis of video data has been reported.[25] Clinical decision support systems (CDSS) based on machine learning algorithms could assist in combined stimulation and medication therapies for Parkinson's Disease. Accurate prediction occurred in 86% (12/14) of motor improvement scores, 100% in tremor outcome and 93% in speech outcome, one year after surgery. The authors emphasise that prediction accuracy is dependent on the quality of the clinical measurements, used to populate the database.[26]

AI in upskilling neurosurgical procedures

Brain tumor ablation has been identified as an ideal procedure for autonomous robotic surgery. It involves perception of the environment by the robotic system and a corresponding adaption of its behaviour to the changing environmental parameters. Knot tying in suturing is also a challenge for deployment of AI.[27] The shape and exact location of motor cortical areas varies among individuals. The exact knowledge of these locations is crucial for planning of neurosurgical procedures. Robot-assisted image guided transcranial magnetic stimulation (Ri-TMS) to elicit motor evoked potential responses recorded for individual muscles, have been used to reconstruct functional motor maps of the primary motor cortex.[28] It is becoming increasingly difficult for a neurosurgical resident to "learn" on a patient in the OT. Realistic neurosurgical simulations is the need of the hour. A computer-based, virtual reality platform offers simulated resistance and relaxation, with passage of a virtual three-dimensional (3D) ventriculostomy catheter through the brain parenchyma into the ventricle.Advances in AI and science and technology of haptics (recognizing objects through touch) is improving the learning of clinical skills and procedures.[29]

AI in seizure disorders

A machine learning approach, to predict the outcome of epilepsy surgery, based on supervised classification and data mining, taking into account not only the common clinical variables, but also the pathological and neuropsychological evaluations, is now available. Outcome could be predicted with an accuracy of almost 90% using some clinical and neuropsychological features. Importantly, not all the features were needed to perform the prediction.[30,31] Automatic seizure detection using scalp electroencephalogram (EEG) and advanced artificial intelligence techniques have been reported following preprocessing with filtering and artefact removal.[32]

AI in the Neurosurgical OT

It is now accepted that brain tumors cause substantial reorganization of functional systems. AI assisted functional registration exhibits higher predictive power than anatomical registration. Functional localization of activated but displaced regions is necessary, particularly in cases where tumor-induced changes of the hemodynamics make direct localization difficult. Matching functional brain regions across individuals is challenging, largely due to variability in their location and extent. Addition of pathology can cause substantial reorganization of functional systems. Advances in neural information processing systems using AI addresses these issues.[33]

AI in Neuro-oncology

Current machine learning techniques provide opportunity to develop noninvasive and automated glioma grading tools, utilizing quantitative parameters derived from multi-modal MRI data. Zhang *et al*., reported a classification accuracy of over 90%, which is more than that of an experienced neuro-radiologist.[34] Prediction models based on data-mining and machine-learning algorithms have provided a much more accurate prediction of prognosis in malignant gliomas than is possible using histopathologic classification alone.[35] Fully automated enhanced tumor compartmentalization was compared with semi-automatic segmentation done by four experts. Though feasible, the results were similar and took a longer time.[36] The use of machine learning algorithms along with extraction of relevant features from MRI images and MR spectroscopy holds the promise of replacing conventional invasive methods of tumor classification.[37]

Artificial Intelligence in Neuro-traumatology

Machine-learning models have been developed for predicting mortality following trauma in motorcycle riders.[38] Artificial neural networks (ANN) have been used to predict outcome following head injury. ANN significantly outperformed regression models and clinicians on multiple performance measures. The authors opine that this form of modeling could ultimately serve as a useful clinical decision support tool.[39] Fuzzy logic and machine learning algorithms have been used in the study of traumatic brain injuries.[40,41]

AI in Imaging Services

Filtering incoming images based on priority using deep learning is now well accepted. The algorithm looks at the images to identify brain hemorrhage or stroke. If the computer detects one of the flagged factors, the patient will move up on the priority list to have their images analyzed first. If the algorithm does not detect any critical factors, the record falls towards the bottom of the priority list. AI can help image quality control, imaging triage, efficient image creation, computer-aided detection, computer aided-classification, and automatic report drafting. Deep learning algorithms can improve MRI image quality, even notifying the technologist that images are too fuzzy to be read accurately. MRI image quality will improve in reducing the patient's time in the machine. Along with neuroimaging technology, network analysis is improving, leading to a better preoperative evaluation. Presurgical localization of the eloquent cortex, glioma grading measured by resting state fMRI and localization of epileptic focus are a few examples of the use of AI. Big data analysis of healthy controls has led to the quantification and visualization of individual variations for functional localization. A functional cortical atlas has been developed using datasets from 1,000 healthy controls.[42]

AI in Stroke

AI has been used in the management of stroke, in the areas of early detection and diagnosis, treatment, outcome prediction and prognosis evaluation. The US Food and Drug Administration (FDA) has approved an mHealth app that uses AI software to analyze CT scans for signs of a stroke, and then sends a text message to a neurologist. The clinical decision support tool could help in speeding up time-to-treatment for stroke victims. VizAI's Contact app[43] is seen as a clinical decision support tool, helping doctors to more quickly identify a stroke and pull in the necessary specialist resources to commence treatment. The FDA has stressed that the application should be limited to analysis of imaging data and not serve as a replacement of a full patient evaluation.

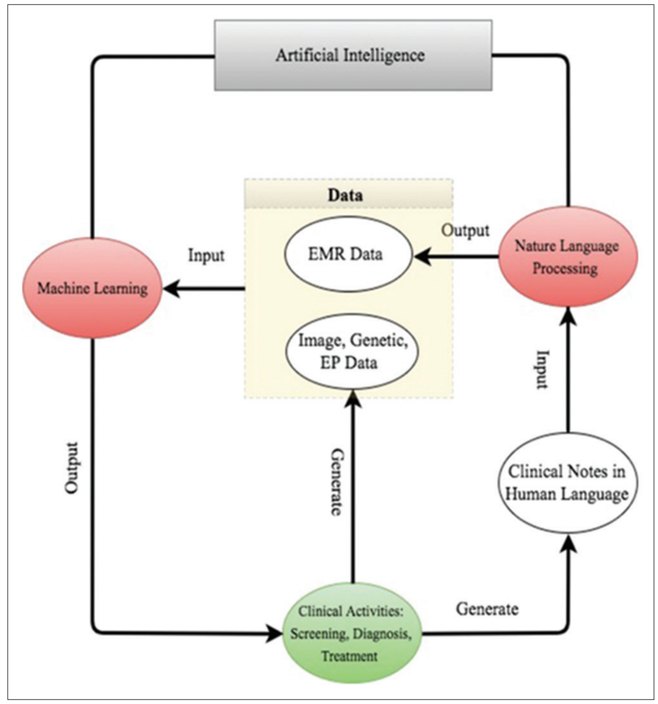

Figure 1: Road map from clinical data generation to natural language processing data enrichment, to machine learning data analysis, to clinical decision making (Reprinted with permission from Fei Jiang *et al*.[9])

AI in Neurorehabilitation

A new wave of AI facilitated brain–machine interfaces helps disabled people connect with the outside world. With AI facilitated sensory substitution, eyes to see and hands to feel will not be required. One will see and feel with one's brain, making it possible for people with severe motor disabilities to use brain signals to operate a robotic arm or a neural prosthesis.[44,45]

AI Facilitated Smart Devices

Swallowscope is an example of an AI facilitated smart device. It is a smartphone-based device with a real-time swallowing sound processing algorithm, for the automatic screening, quantitative evaluation, and visualisation of swallowing ability. It includes a cloud-based system for the server side, analysing and automatically sharing the swallowing sound. This wearable device can continuously monitor swallowing activities and assess the swallowing ability without causing discomfort to the wearer.[46]

AI in Neurosciences in India

Khurana *et al*.,[47] have described the analysis of a large volume of data from a multiethnic population in the proposed Indo-US collaborative stroke registry. It is in studies like these that deployment of AI would be of considerable help . Advances in computer technology and imaging, development of sophisticated VR simulators with haptic feedack and the recent addition of 3-D printing technology, have opened a wide arena for the development of high fidelity patient-specific models to complement current neurosurgical training. It is a matter of justifiable pride that state-of-the-art simulation in neurosurgical training is being introduced at AIIMS, New Delhi.[48] AI could be an integral part of this application.[47,48]

Conclusion

"The good physician treats the disease; the great physician treats the patient who has the disease - Medicine is a science of uncertainty and an art of probability - Listen, listen, listen the patient is telling you the diagnosis". One wonders how Sir William Osler, author of the above statements[49] would have reacted to the introduction of AI in health care. For centuries, the essence of practicing medicine, has been a physician obtaining as much data about the patient's health or disease as possible and taking decisions. Wisdom presupposed experience, judgement, and problem-solving skills using rudimentary tools and limited resources. Though a neurosurgeon trained in the Before Computer (BC) era, the primary author now has to be familiar with "deep learning" and "Bayesian Networks".

Charles Dickens began his immortal "Tale of Two Cities" with the statement: "It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us".[50] He could very well have been referring to AI. Good and evil are two sides of the same coin. Time alone will tell if AI in neurosciences will be a bane or a boon. To the clinician, AI will be adopted as an integral part of a neuroscientist's armamentarium only when there is evidence that AI leads to better outcomes, and reduces costs. We are in a stage of transition. All transitions offer great opportunities. AI will never ever replace a commiserating clinician. Hopefully, the AI enabled clinician will now spend more time empathising with his patient rather than getting drowned in voluminous data.

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