AI for Health Prediction and Health Care System: A Review

Nikita Thool[1], Prof. RoshaniTalmale[2]
[12]*Department of Computer Science and Engineering, TGPCET Nagpur India*

Abstract- Artificial intelligence (AI) expects to mirror human subjective capacities. It is conveying a change in outlook to healthcare, controlled by expanding accessibility of healthcare information and fast advancement of examination techniques. We review the present status of AI applications in healthcare and talk about its future. Man-made intelligence can be connected to different sorts of healthcare information (organized and unstructured). Famous AI techniques incorporate machine learning strategies for organized information, for example, the traditional help vector machine and neural system, and the cutting edge profound learning, just as normal language preparing for unstructured information. Significant ailment regions that utilization AI apparatuses incorporate malignant growth, nervous system science and cardiology. We at that point survey in more subtleties the AI applications in stroke, in the three noteworthy regions of early identification and conclusion, treatment, just as result expectation and forecast assessment.

Keywords- AI, Healthcare, Early Detection

I. INTRODUCTION

As of late AI techniques have sent tremendous waves crosswise over healthcare, notwithstanding fuelling a functioning dialog of whether AI specialists will inevitably supplant human doctors later on. We trust that human doctors won't be supplanted by machines soon, yet AI can help doctors to settle on better clinical choices or even supplant human judgment in certain practical zones of healthcare (eg, radiology). The expanding accessibility of healthcare information and quick advancement of huge information systematic strategies has made conceivable the ongoing effective utilizations of AI in healthcare. Guided by pertinent clinical inquiries, incredible AI techniques can open clinically applicable data covered up in the gigantic measure of information, which thusly can help clinical choice making.[1-3]

In this article, we study the present status of AI in healthcare, just as talk about its future. We first quickly survey four significant angles from medicinal specialists' points of view:

- motivations of applying AI in healthcare
- information types that have be broke down by AI frameworks
- instruments that empower AI frameworks to produce clinical important outcomes
- malady types that the AI people group are as of now handling.

A. Healthcare data

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.[12]

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 analysing 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.[14] Shin *et al* developed an electrodiagnosis support system for localising neural injury.

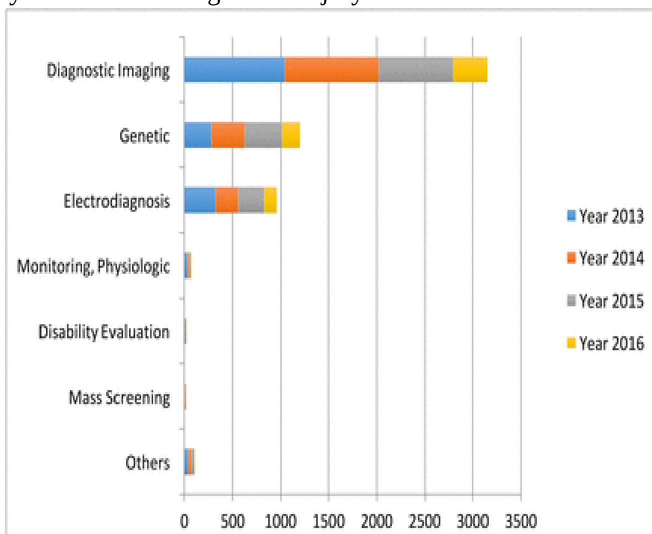

Fig.1: The data types considered in the artificial intelligence artificial (AI) literature. The comparison is obtained through searching the diagnosis techniques in the AI literature on the PubMed database.

B. 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 analysed 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.

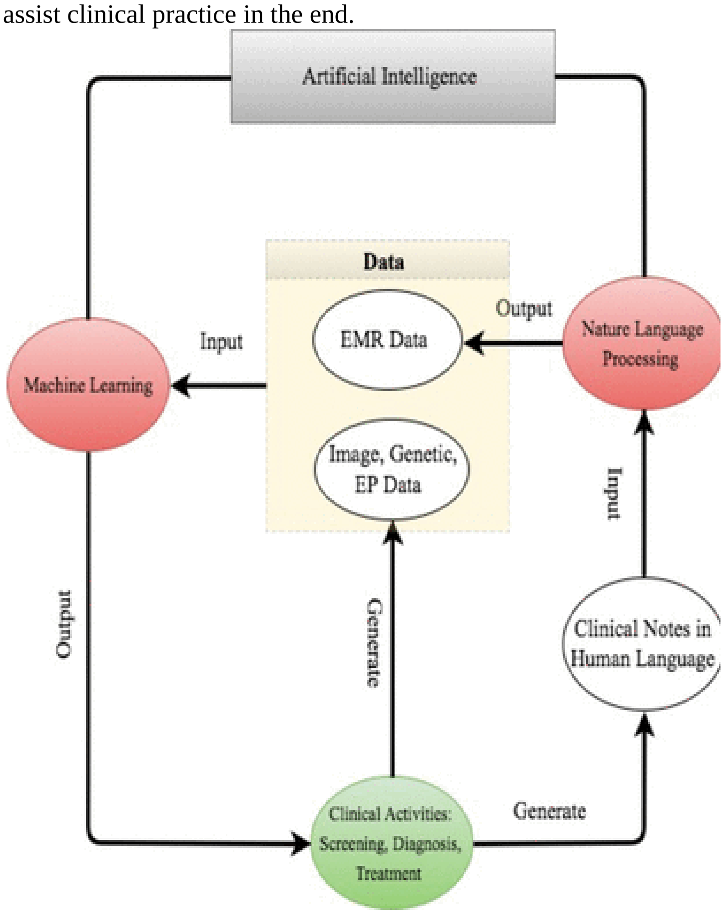

Fig.2: The road map from clinical data generation to natural language processing data enrichment, to machine learning data analysis, to clinical decision making. EMR, electronic medical record; EP, electrophysiological.

II. LITERATURE REVIEW

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

C. 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, and 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 *j*th trait of the *i*th 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 recently, semi supervised learning has been proposed as a hybrid between unsupervised learning and supervised learning, which is suitable for scenarios where the outcome is missing for certain subjects.

D. Support vector machine

SVM is mainly used for classifying the subjects into two groups, where the outcome Y_i is a classifier: $Y_i = -1$ or 1 represents whether the *i*th patient is in group 1 or 2, respectively. (The method can be extended for scenarios with more than two groups.) The basic assumption is that the subjects can be separated into two groups through a decision boundary defined on the traits X_{ij} , which can be written as:

$$a_i = \sum_{j=1}^{p} w_j X_{ij} + b,$$

where w_j is the weight putting on the *j*th trait to manifest its relative importance on affecting the outcome among the others. The decision rule then follows that if $a_i > 0$, the *i*th patient is classified to group 1, that is, labelling $Y_i = -1$; if $a_i < 0$, the patient is classified to group 2, that is, labelling $Y_i = 1$. The class memberships are indeterminate for the points with $a_i = 0$.

E. Neural network

One can think about neural network as an extension of linear regression to capture complex non-linear relationships between input variables and an outcome. In neural network, the associations between the outcome and the input variables are depicted through multiple hidden layer combinations of pre specified function. The goal is to estimate the weights through input and outcome data so that the average error between the outcome and their predictions is minimized. We describe the method in the following example.

Mirtskhulava *et al* used neural network in stroke diagnosis.[33] In their analysis, the input variables X_{i1}, . . . , X_{ip} are p=16 stroke-related symptoms, including paresthesia of the arm or leg, acute confusion, vision, problems with mobility and so on. The outcome Y_i is binary: Y_i =1/0 indicates the *i*th patient has/does not have stroke. The output parameter of interest is the probability of stroke, a_i , which carries the form of

$$a_i = h\left\{\sum_{k=1}^{D} w_{2l} f_k\left(\sum_{l=1}^{p} w_{1l} X_{il} + w_{10}\right) + w_{20}\right\}.$$

In the above equation, the w_{10} and $w_{20} \neq 0$ guarantee the above form to be valid even when all X_{ij} , f_k are 0; the w_{1l} and w_{2l}s are the weights to characterise the relative importance of the corresponding multiplicands on affecting the outcome; the f_k s and h are prespecifiedfunctionals to manifest how the weighted combinations influence the disease risk as a whole.

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.

III. 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.

IV. REFERENCES

[1]. Murdoch TB, Detsky AS. The inevitable application of big data to health care. JAMA 2013;309:1351–2.

[2]. Kolker E, Özdemir V, Kolker E. How Healthcare can refocus on its Super-Customers (Patients, n=1) and Customers (Doctors and Nurses) by Leveraging Lessons from Amazon, Uber, and Watson. OMICS 2016;20:329–33.

[3]. Dilsizian SE, Siegel EL. Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. CurrCardiol Rep 2014;16:441.

[4]. Patel VL, Shortliffe EH, Stefanelli M, et al. The coming of age of artificial intelligence in medicine. ArtifIntell Med 2009;46:5–17.

[5]. Jha S, Topol EJ. Adapting to Artificial Intelligence: radiologists and pathologists as information specialists. JAMA 2016;316:2353–4.

[6]. Pearson T. How to replicate Watson hardware and systems design for your own use in your basement. 2011 https://www.ibm.com/ developerworks/community/blogs/InsideSystemStorage/entry/ibm_ watson_how_to_build_your_own_watson_jr_in_your_basement7? lang=en (accessed 1 Jun 2017).

[7]. Weingart SN, Wilson RM, Gibberd RW, et al. Epidemiology of medical error. BMJ 2000;320:774–7.

[8]. Graber ML, Franklin N, Gordon R. Diagnostic error in internal medicine. Arch Intern Med 2005;165:1493–9.

[9]. Winters B, Custer J, Galvagno SM, et al. Diagnostic errors in the intensive care unit: a systematic review of autopsy studies. BMJ QualSaf 2012;21:894–902.

[10]. Lee CS, Nagy PG, Weaver SJ, et al. Cognitive and system factors contributing to diagnostic errors in radiology. AJR Am J Roentgenol 2013;201:611–7.

[11]. Neill DB. Using artificial intelligence to improve hospital inpatient care. IEEE IntellSyst 2013;28:92–5.

[12]. Administration UFaD. Guidance for industry: electronic source data in clinical investigations. 2013 https://www.fda.gov/downloads/ drugs/guidances/ucm328691.pdf (accessed 1 Jun 2017).

[13]. Gillies RJ, Kinahan PE, Hricak H. Radiomics: images are more than pictures, they are data. Radiology 2016;278:563–77.

[14]. Li CY, Liang GY, Yao WZ, et al. Integrated analysis of long noncoding RNA competing interactions reveals the potential role in progression of human gastric Cancer. Int J Oncol 2016;48:1965–76.

[15]. Shin H, Kim KH, Song C, et al. Electrodiagnosis support system for localizing neural injury in an upper limb. J Am Med Inform Assoc 2010;17:345–7.

[16]. Karakülah G, Dicle O, Koşaner O, et al. Computer based extraction of phenoptypic features of human congenital anomalies from the digital literature with natural language processing techniques. Stud Health Technol Inform 2014;205:570–4.

[17]. Darcy AM, Louie AK, Roberts LW. Machine Learning and the Profession of Medicine. JAMA 2016;315:551–2.

[18]. Murff HJ, FitzHenry F, Matheny ME, et al. Automated identification of postoperative complications within an electronic medical record using natural language processing. JAMA 2011;306:848–55.

[19]. Somashekhar SP, Kumarc R, Rauthan A, et al. Abstract S6-07: double blinded validation study to assess performance of IBM artificial intelligence platform, Watson for oncology in comparison with manipal multidisciplinary tumourboard ?first

study of 638 breast Cancer cases. Cancer Res 2017;77(4 Suppl):S6-07.

[20]. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin Cancer with deep neural networks. Nature 2017;542:115–8.

[21]. Bouton CE, Shaikhouni A, Annetta NV, et al. Restoring cortical control of functional movement in a human with quadriplegia. Nature 2016;533:247–50.

[22]. Farina D, Vujaklija I, Sartori M, et al. Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation. Nat Biomed Eng 2017;1:0025.

[23]. Marr B. First FDA approval for clinical Cloud-Based Deep Learning in Healthcare. 2017. https://www.forbes.com/sites/bernardmarr/2017/ 01/20/first-fda-approval-for-clinical-cloud-based-deep-learning-inhealthcare/#7a0ed8dc161c (accessed 1 Jun 2017).