

Original Article

Machine Learning and Digital Health

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Abstract - The clinical use of machine learning algorithms is transforming the digital health care industry in a rapid phase. These algorithms will be implemented in the clinical setting of the health care professionals by embedding them in smart devices through the Internet of things and could be used by the patients to manage chronic conditions or diseases. The exponential growth of investment in machine learning signals that research is accelerating, and more products may soon be targeting market entry. The paper addresses the applications and challenges of machine learning in Digital health care services.

Keywords - Digital health care, Machine learning

I. INTRODUCTION

One of the most important and fastest-growing fields of our expertise in the medical applications of machine learning/deep learning⁶. Machine learning and AI technologies have been recently penetrating all areas of healthcare services, from improving digital healthcare management to new drug discovery. Even though it is unlikely that computers will completely replace doctors and nurses, modern technologies are already transforming the healthcare industry.

II. MACHINE LEARNING APPLICATIONS IN HEALTH CARE

A. Disease Identification / Diagnosis

An artificial intelligence-based system can be fed with relevant data and let the computer sift through the extensive database instead of relying on much more limited human knowledge. Therefore, disease identification was brought to the forefront of ML research in medicine, especially in Oncology. Boston-based biopharma company Bergl applies AI to research and develop diagnostics and treatments in multiple areas, including dosage trials for intravenous tumor treatment. Another important example is Google's

DeepMind Health¹ uses AI technology to address macular degeneration in aging eyes to find the early symptoms of visual problems caused by diabetes and age-related sight degeneration—the most important causes of sight loss. AI technologies will analyze more than one million eye scans and determine the first signs of visual degeneration, which most experienced doctors may miss.

B. Personalized treatments

Personalized medicine provides a more effective treatment based on individual health data paired with predictive analytics². The dominant research method in this domain is supervised learning, which allows physicians to select from more limited sets of diagnoses and estimate the given patient's risk based on the similarity of symptoms and genetic information.

C. Drug discovery and Manufacturing

Machine learning is a powerful tool in preliminary (early-stage) drug discovery that may be used in various activities, from initial screening of drug compounds to success rate prediction based on biological factors and to R&D discovery technologies like next-generation sequencing. Effective treatment for diseases like Type 2 diabetes can be developed by using powerful machine learning algorithms²

4 . Epidemic outbreak prediction:

Machine learning and AI technologies monitor and predict epidemic outbreaks worldwide by collecting data from satellites, historical information on the web, real-time social media updates, and more³. Support vector machines and artificial neural networks help predict malaria outbreaks based on temperature, average monthly rainfall, the total number of positive cases, and other data points. Predicting outbreak severity is particularly crucial for the countries which often lack medical infrastructure, educational opportunities, expertise, and access to treatments³.



III. CHALLENGES FACED IN DIGITAL HEALTH

A. Ethics, Privacy, and Trust

A key advantage of Big Data analytics is linking disparate data sources, which requires access to personally identifiable information (PII) or at least some proxy⁴. The use of PII presents privacy and ethical concerns. One way to protect privacy while sharing PII is to use privacy-preserving data linkage models, which share collections of one-way hashed identifiers to align diverse datasets. However, these systems require both datasets to access PII (or pre-hashed identifiers). Many current potential data providers may not have the ability to implement such a system due to technical and cost reasons. Data de-identification can help mitigate privacy concerns⁴. However, even de-identified data according to standards such as Safe Harbor are not necessarily anonymous – since unique de-identified data can be re-identifiable by triangulation across other data sources. Public data from Google or Twitter can point to an individual IP address, location, or other personal information and may require additional layers of oversight. Informed consent or assent for traditional clinical trials or studies may not be applicable for analyses of Big Data with potential personal information that imposes new challenges for Institutional Review Boards (IRB).

Developing Trust in the System

Loss of confidentiality or misuse of sensitive personal information can endanger the individual patient⁵. A particular issue in health disparities research is the lack of trust that has evolved in health care because of unethical treatment of disenfranchised minority populations. The Tuskegee Study of Untreated Syphilis, the Henrietta Lacks case, and the diabetes studies of the Pima Indians⁵ are examples that have created mistrust in US health care and scientific institutions. Mistrust of the health care system by entire population groups has led to an increased emphasis by researchers on community engagement and participation in health disparities research. This same philosophy is crucial to ensure that Big Data science serves minority populations respectfully and beneficially. Minority-serving institutions usually do not have the infrastructure that research-intensive universities have to capture, manage and analyze Big Data. Collaborations between minority-serving institutions and research-intensive institutions are needed to take advantage of the rapid growth of health informatics and technologies such that they will lead to the reduction of health disparities.

B. Missing Data and Statistical Uncertainty

Well-analyzed Big Data can bring novel insights but poorly analyzed Big Data can be misinterpreted, especially in minority health and health disparities research⁶, where results lacking social or cultural context can be misleading. Progress in health disparities research and science will require improvements in the completeness, standardization, and validity of demographic measures and social determinants reported from multiple sources, including electronic medical records, clinical trials, genomic research, and various forms of administrative records such as Medicare and Medicaid. Other types of data sources such as surveys, extrapolations, and imputations may suffice for national reports and overall trending but are insufficient for analyzing places that are critical for health disparities research. Further, health disparities populations must be fully incorporated in the precision medicine cohort and research questions and similar cutting edge personalized biomedical initiatives.

Statistical uncertainty may still be a problem when data are big; small differences in Big Data may be statistically significant because of the large number of observations. Still, the findings may not be useful for clinicians or patients. Moreover, conclusions drawn from Big Data cannot automatically be generalized to minority populations. Uncertainty around these issues related to Big Data may be resolved in the future with newly developed methods, algorithms, technologies, and sound statistical training; however, this will not happen unless health disparities research is a consistent focus in the development of Big Data. Another concern is that Big Data may not collect race/ethnicity or may overlook certain small sample populations (e.g., American Indians, Alaska Natives, Pacific Islanders, and sexual and gender minorities) with unique characteristics that may be critical for understanding the etiology of specific conditions and health care delivery in such populations.

C. Data Access and Sharing

The power of Big Data cannot be achieved unless challenges such as secure storage, integration, harmonization, access, and sharing are addressed⁶. Data sharing is essential for translating research findings to improve human health. The NIH policy requires that research data be made as widely and freely available as possible while safeguarding participants' privacy and protecting confidential and proprietary data. To address the lack of data interoperability standards, Bahga and Madiseti propose a cloud-based approach to design interoperable EHR systems for clinicians, patients, and third-party payers. Systems like MedCloud and Home-Diagnosis were proposed to manage large patient data and conduct analysis. Acceptance of strategies to address these problems is

gaining ground, but conversions to common data models are not trivial.

D. Data Science Training and Workforce Diversity

Big Data science brings together clinicians, health researchers, government agencies, commercial enterprises, and patients in one place for information exchange. Data scientists will need to partner with physicians, nurses, researchers, and patients to understand the data better and transform unstructured or structured numbers into systemic information and knowledge⁶. Patient consumers of Big Data may demand specific clinical trials, individualized treatment plans, and precision or personalized medication.

IV. CONCLUSION

In the era of information explosion, Big Data approaches are likely to be able to contribute to understanding the causes of health disparities and to identifying useful opportunities for their reduction, but only if Big Data collection includes health disparities populations and if researchers who focus on these populations are trained to use Big Data. Big Data could lead to discoveries and new experiments in health disparities research that were never before possible. To realize this potential, a focus on health disparities is

needed to plan and implement Big Data resources. Otherwise, these promising new approaches will likely worsen disparities. To merit the trust of patients and adoption by providers, machine learning algorithms must fully align with data protection requirements, minimize the effects of bias, be effectively regulated, and achieve transparency.

REFERENCES

- [1] Atzori L, Iera A, Morabito G. The Internet of Things: a survey. *Comput Networks*. 2010; 54(15):2787–2805. <http://dx.doi.org/10.1016/j.comnet.2010.05.010>.
- [2] Patrick K, Hekler EB, Estrin D, Mohr DC, Riper H, Crane D, et al. The pace of technologic change: implications for digital health behavior intervention research. *Am J Prev Med* 2016 Nov;51(5):816-824.
- [3] Murray E, Hekler EB, Andersson G, Collins LM, Doherty A, Hollis C, et al. Evaluating digital health interventions: key questions and approaches. *Am J Prev Med* 2016 Nov;51(5):843-851.
- [4] <https://medium.com/sciforce/machine-learning-and-ai-technologies-in-the-healthcare-industry-ad824211be19>
- [5] <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5398183/>
- [6] <https://www.nature.com/articles/npp2016>
- [7] <https://jamanetwork.com/journals/jamapsychiatry/article-abstract/2616170>
- [8] <https://ieeaccess.ieee.org/special-sections/data-enabled-intelligence-for-digital-health/>