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SUBJECT: Artificial Intelligence (AI) Application in Public Health and Recommendations

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Executive Summary

Upon most occasions, big data is seen by hospitals as one of the least critical capabilities, in sharp contrast to other industries. However, big data in healthcare has enormous potential to improve patient care and ultimately achieve reasonable costs. Healthcare spending is being cut, and the focus is on how to cut costs without compromising the quality of healthcare. This change is forcing health care organizations to open the door to AI-based solutions. In addition, we can see a growing market demand for precision medicine, clinical decision processes, and patient personalized demands. Especially in COVID-19, public health services must use AI technologies in Georgia. I raised two policy options for the Georgia government to develop AI technologies in the public health sector.

Introduction

Big Data, Machine Learning (ML) & Artificial Intelligence (AI)

AI implies the use of a computer to model intelligent behavior without human intervention and is also a field of computer science that aims to mimic human intelligence with computer systems. This mimicry is accomplished through iterative, complex pattern matching, generally at a speed and scale that exceed human capability (Maddox, Rumsfeld, & Payne, 2019).

Machine Learning (ML) can be viewed as a popular subdiscipline of Artificial Intelligence (AI). ML uses large data sets and identifies interaction patterns among variables. ML can be applied in various fields, such as automatic driving, smart homes, clinical decision systems, etc. ML learns from experience and improves its performance to optimize processes and resource allocation. Take clinical decisions for example. 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, disease history, and disease-specific data. (Jiang, Jiang, Zhi, Dong, Li, Ma, Wang, Dong, Shen, & Wang, 2017).

The ML approaches can be divided into two categories: supervised and unsupervised. Unsupervised learning allows computers to explore large amounts of unclassified data and to discover novel disease or treatment patterns (Chen & See, 2020). Also, 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) (Jiang et al., 2017). Supervised methods aim to develop predictive algorithm using regression (linear or multiple) or classification methods (decision trees or neural networks) (Chen & See, 2020). Furthermore, supervised learning considers the subjects' outcomes together with their traits, and goes through a certain training process to determine the best outputs associated with the inputs that are closest to the outcomes on average. For example, the outcome can be the probability of getting a particular clinical event, the expected value of a disease level, or the expected survival time.

Clearly, compared with unsupervised learning, supervised learning provides more clinically relevant results. Hence, AI applications in healthcare most often use supervised learning. Relevant techniques include linear regression, logistic regression, naïve Bayes, decision tree, nearest neighbour, random forest, discriminant analysis, support vector machine (SVM) and neural network (Jiang et al., 2017).

Deep learning is a subset of machine learning that mimics the operation of the human brain using multiple layers of artificial neuronal networks to generate automated predictions from training data sets. There are applications for deep learning algorithms in health care that are quite interesting. For example, the Food and Drug Administration now allows pharmaceutical companies to model drug interactions using AI algorithms that accurately identify drug toxicity without the usual decade of animal testing (Bini, 2018).

Natural language processing (NLP) is another subdiscipline of AI that aims to bridge the divide between the languages that humans and computers use to operate (Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018). NLP uses algorithms that allow machines to identify key words and phrases in natural language corpora (ie, unstructured written text). AI applications are able to determine the meaning of text. The field of NLP has quickly evolved to focus on managing and processing information from large datasets.

All these technological advances have led to an explosion of high volume, high velocity, and high variety health data. These so-called 3 Vs are what define datasets as Big Data. Big Data can help researchers make sense of the plethora of rich and diverse health data currently being generated (Velmovitsky, Bevilacqua, Alencar, Cowan, & Morita, 2021).

Importance of AI in Public Health

AI technologies are now adopted in areas of the public sector and have proven to be valuable tools in public health efforts. A key area of adoption of AI in the public sector is healthcare. AI can do lots of works, such as mining medical records, assisting repetitive jobs, and designing treatment plans. It changes the manual health system into automatic, in which humans conduct the routine works/tasks in medical practice to the management of patients and medical resources. AI also offers the potential for a huge improvement in patient care and a reduction in health care costs. The increasing population is expected to be able to encourage the demand for health services. The health service sector needs innovative solutions to find out how to be more effective and efficient without excessive expenditure (BDVA Task Force 7- Sub-group Healthcare, 2020). In addition, the healthcare sector links to various stakeholders, which includes government policy makers, public hospitals, and private firms' Information Technology (IT) managers (Sun, & Medaglia, 2019).

AI and robotics in health care have developed quickly, especially for early detection and diagnostic application. AI is needed for early detection and diagnosis. It is used in various ways to detect diseases more accurately, reliably, and quickly. For instance, Google's DeepMind Health Technology integrates machine learning with a neuroscience system to model the human brain using AI and provides diagnostic and decision-making support to healthcare professionals (Sunarti, Fadzlul Rahman, Naufal, Risky, Febriyanto, & Masnina, 2021).

Applications in Public Health System

Epidemic Outbreak Prediction

COVID-19, caused by SARS-CoV-2, was first discovered in December 2019 and has since become a global pandemic. Chen and See (2020) introduce examples of how AI has been applied to COVID-19. First, BlueDot, a Canadian company specializing in infectious disease forecasting, uses an AI engine that continuously gathers data for a multitude of diseases from a range of different sources globally. BlueDot was able to predict the COVID-19 outbreak and alert its users even before the World Health Organization did. Second example is an AI-powered chatbot named SGDormBot, which has been used for symptom-based mass screening of migrant workers for COVID-19 in Singapore. Third, Yang et al (2020) developed an AI-based model that used a form of recurrent neural network (RNN) for epidemiological modelling. The model was trained using the 2003 severe acute respiratory syndrome (SARS) epidemic data from China, while incorporating the epidemiological parameters of COVID-19 and public health interventions like the lockdown of Hubei province. Using the model, it was predicted that the number of cases in Hubei would peak in early February. When the number of predicted infections was plotted against real-time epidemiologic trends, there was considerable similarity between the actual numbers and predictions made by the AI, supporting the accuracy of such models for forecasting disease development. Similar work is in progress using a wide range of data sources. Lastly, South Korea developed an artificial neural network that has also been used to build a classifier prediction model for patient outcomes. The Korea Centers for Disease Control and Prevention collected patient characteristics like age and gender, extracted the independent predictors, and classified patients with COVID-19 into 2 groups: deceased and recovered. This helped policy makers target the most vulnerable patients, directing attention and resources toward their care.

AI could also benefit surveillance task of government in pandemic outbreak. Infrared thermal cameras used to screen the public for fever have been paired with AI-powered facial recognition systems to determine if individuals are wearing surgical masks. A US-based computer vision startup has started offering a software that uses camera images to observe for compliance with social distancing rules. With the proliferation of such technologies, it is increasingly evident that AI-based surveillance can greatly help with public health interventions that slow the spread of infection (Chen & See, 2020).

Health Informatics and Electronic Health Records (EHRs)

Health informatics describes the acquisition, storage, retrieval and use of healthcare information to improve patient care across interactions with the health system (Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018). Health informatics can help shape public health programs by ensuring that critical information is available for making sound policies and program decisions. EHRs, which are digital versions of patient and population health information, are an important source of data for health informatics. Their use has become much more prevalent in low-resource settings, which in an era of networked computers, has expanded potential applications of AI to improve public health informatics and decision making. OpenMRS is one example of an EMR platform that is currently being used in more than 15 African countries. OpenMRS was used in Kenya to build and implement an EMR system called Bora to improve maternal and child health and improve HIV treatment in rural areas. Researchers found that this system helped to increase the completeness of data collected and close critical gaps in care. DHIS2 is another open source EMR platform used for collecting, validating, analysing and presenting aggregate and patient-based statistical data. It is now used in more than 40 countries of Asia, Africa and Latin America (Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018).

Clinical Decision Support (CDS)

AI can contribute to the reduction of health inequalities. Clinical decision making has three integrated phases: (1) diagnosis, (2) assessment of severity, and (3) management. CDS systems is an ever-growing application of AI in healthcare, and it leverages the big data collected through EHRs and other information at public hospital and clinics to help clinicians make informed decisions regarding the diagnosis, treatment, and prognosis of various conditions. Thus, the CDS systems help clinicians to alleviate the common problem in their daily practice[1].

Issues

Issue 1: Lacking large amounts of high-quality data

Experts frequently emphasized that most AI approaches are predicated on access to clean, high-quality data, which can be difficult to find for health applications (Morgenstern, Rosella, Daley, Goel, Schünemann, & Piggott, 2021). Many factors make it difficult for developers to access high-quality data. “Artificial Intelligence in Health Care: Benefits and Challenges of Technologies to Augment Patient Care Data” report stated that data are often siloed in different systems, such as medical imaging archival systems, diagnostic systems, EHRs, electronic prescribing tools, and insurance databases. The various siloes store data in varying formats that cannot easily be reconciled and aggregated, even if the data could be shared.

Issue 2: Lacking appropriate governance models to guide the use of AI healthcare technologies

The collection, use, storage, and sharing of individual and population-based data raise important questions regarding consent, ownership, and access. If not properly governed and managed, there is a risk this data could be used to persecute or marginalize particular individuals, groups, or communities with, for instance, gender, ethnicity, socio-economic group, pathology, or sexual orientation. While some AI technologies can induce ethnicity, which is relevant in

[1] Clinical Decision Support (CDS) Systems. https://artificialintelligence.health/clinical-decision-support.html

certain clinical cases, this function could also be used for racial profiling or discrimination. The datasets used for AI may have selection bias, meaning participants that are not representative of the population as a whole. For example, the algorithm was biased towards predicting lower health needs for Black patients because it used healthcare costs as a proxy for demand. Less money had been spent on Black patients with the same level of need in its training data.

Privacy concerns were acknowledged as another concern when obtaining data for public health purposes. As more AI systems are developed and deployed in clinical settings, large quantities of patient data will be in the hands of more people and organizations, which can contribute to patient privacy risks. Health records are rich in valuable and sensitive information, such as social security numbers, addresses, mental health information, communicable disease diagnoses, and credit card information (National Academy of Medicine, 2020).

Policy Options

Policy Option 1: Policymakers could develop or expand a high-quality data access mechanism.

A major lesson from the experience of those working on AI in resource-poor settings is that "AI should build intelligence into existing systems and institutions rather than starting from scratch or hoping to replace existing systems, however broken" (Wahl, Cossy-Gantner, Germann, & Schwalbe, 2018). The success of AI applications requires knowledge of local markets, clear usability requirements and access to adequate training data via field testing.

Increasing the availability of high-quality data could facilitate the development and testing of AI tools. One expert told us that increased data access could expand the number of developers and researchers who create and test tools. Policymakers could consider increasing data access by creating a type of mechanism known as a cloud-based platform where users can store, share, access, and interact with data and other digital objects. For example, the Stanford Institute for Human-Centered Artificial Intelligence proposed a National Research Cloud, a partnership between academia, government, and industry to provide access to resources. This platform includes a large-scale, government-held data set in a secure cloud environment to develop and train AI (National Academy of Medicine, 2020). Public health emergencies are unpredictable. If there is no systematic and complete public health emergency command platform, it will be effortless to cause delays in response, delays in rescue, and failure to take care of them. For example, Zhu, Chen, Dong, and Wang (2021) introduced an Emergency Command Platform used in China and reviewed the emergency workflow for public health.

AI investments should focus on areas likely to reduce inequities, including improved access to public health services and health information. Using data from the web, for example, NLP has been applied to a wide range of public health challenges, from improving treatment protocols to tracking health disparities. NLP and machine learning are also being used to guide cancer treatments in low-resource settings, including Thailand, China, and India (Morgenstern, Rosella, Daley, Goel, Schünemann, & Piggott, 2021).

Policy Option 2: Rigorous regulations are required.

Regular, predictable oversight of AI tools could help ensure that AI tools remain safe and effective after deployment in private IT companies, government agencies, and clinical agencies. In addition, a forum consisting of relevant stakeholders could help recommend additional mechanisms to ensure appropriate oversight of AI tools. Therefore, the Georgia government could set a new commission and hold AI Business Meetings among stakeholders so that the state government could gain a range of comprehensive views of regulatory frameworks for data governance in healthcare. The Business Meetings should focus on two elements in the early stages: 1) data collection and management for ensuring quality, interoperable, and machine-readable data; and 2) data sharing for preserving privacy. The foremost requirement is that each county's jurisdiction has a minimum viable set of principles and standards for data governance (Verma, Rao, Eluri, & Sharma, 2020).

Recommendation

All these two policy options are my recommendations. I hope that AI is a promising technology to address concerns surrounding the quality and cost of Georgia public healthcare is emerging from the massive volume of health data.

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