Addressing the Healthcare Iron Triangle Through Artificial Intelligence and Machine Learning Applications

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Improving Healthcare Cost, Quality, and Access Through Artificial Intelligence and Machine Learning Applications

EXECUTIVE SUMMARY

Since the early 1970s, technology has increasingly become integrated into the healthcare field. With many unique complexities already present, Artificial Intelligence (AI) and Machine Learning (ML)-a set of learning techniques used by AI- have the capacity to revolutionize the delivery of patient care. This study lays the groundwork on the mechanics and processes of Machine Learning through discussion of Deep Learning (DL) and Natural Language Processing (NLP) and then discusses the application of these learning techniques in pattern recognition of malignant tumors in comparison to present methods of diagnostic imaging assessment. The discussion covers the implications of AI assistive technology more broadly in regards to ethical policy making, patient autonomy and the healthcare "Iron Triangle" of cost, quality and access. It concludes with the idea that failure to incorporate AI and ML techniques in healthcare may be malpractice.

INTRODUCTION

The term Artificial Intelligence (AI) was first coined by John McCarthy in 1956 at a conference over the topic in Dartmouth. McCarthy defines the term as the "science and engineering of making intelligent machines, especially intelligent computer programs" (Society for the Study of Artificial Intelligence and Simulation for Behavior, 2018). AI itself spans a vast field of computer science that has various different subsets such as Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP). In the age of big data, it can be tedious and time consuming to organize large amounts of unstructured data into useful information. AI techniques are designed to address this need. ML is a technique that AI uses to actively learn outside the bounds of normal programming. A typical computer program uses an if-then mechanism, which means that there is an explicit code that directs the software to produce "y" when given "x". However, ML is capable of processes that are not explicitly coded for and therefore able to dynamically "learn" from new information as it experiences it. DL is a subfield of ML and involves a system called an Artificial Neural Network. DL mimics the structure and function of how neurons fire in the human brain through enabling the machine to access large amounts of data through the neural network and then refine it into usable information. NLP is another subset of AI that allows for machines to identify and interpret meaning from human language. Examples of NLP include applications in speech recognition and text analysis.

Use of AI in the healthcare sector has a compound annual growth rate of 43.5% from 2018 and is expected to reach $27.6 billion by 2025 (Research and Markets, 2019). Currently, these AI learning techniques are positioned to play an increasingly prominent role in medicine due to the advances in computing power, learning algorithms, and availability of large datasets from medical records and electronic health monitors. Advances in computing power due to Graphic Processing Units (GPUs) have made high level processing more accessible and the mining of large swaths of available data more efficient. As learning algorithms have access to larger amounts of data, they can adapt and be trained to become even more accurate for clinical support in diagnostics, medical imaging assessment, and streamlining patient care for better quality outcomes. Increasing costs and the demand for higher quality care has prompted the adoption of AI applications in healthcare, but it is accompanied by several challenges in regards to policy-making, ethics, and level of integration.

Inside the Mind of a Machine

Automated neural networks (ANN) are essentially an interconnected group of nodes that are modeled to work just as neural firings work in the human brain. Some nodes are activated by external information, while other nodes are activated by the connections from the previously active neurons in a chain event

(Schmidhuber, 2015). The information exchanged in this chain of events leads to an external output response. Ethical considerations arise when accounting and assigning legal responsibility for an undesired outcome. Learning and credit assignment comes into action when programmers are trying to create a specific output response in a machine when given a certain input. Credit, or learning assignment, is the classification of weights put on certain information that trigger specific patterns that, in turn, lead to a desired output. This takes place in what is known as the hidden layer of the automated neural network where DL happens. The hidden layer of the ANN is the area between the input of information and the output where the algorithm accesses various pieces of information that, through credit assignment, enables it to output a specific desired function. This system is similar to the “black box” modality in which the process of a system is hidden from view and only the input and outputs are identifiable. Significant problems arise in this functioning system in regards to transparency when trying to diagnose the cause of an undesired outcome. When troubleshooting in a human driven system, typically there is a paper trail that can be used to trace back the problem to its source. In machine driven systems, there may be legal liability implications given the lack of a paper trail.

Bridging the Gap Between Man and Machine: Natural Language Processing

Natural language processing is another branch of AI that is the process of computers understanding and manipulating the human language. AI machines are often compared and modeled after the human thinking and learning process. However, certain formal and concise properties that are involved in machine language are not always present in the ambiguity of human language, so the communication gap is often hard to bridge. NLP attempts to bridge this gap by using several techniques like syntactic and semantic analysis that dissect and extract understanding from the human natural language. Syntactical analysis involves assessing how exactly the natural language corresponds with grammatical rules, while the semantic analysis focuses on deriving meaning from the natural language. Semantic analysis is often harder to resolve, as the human language has a high capacity for abstract meaning. In the healthcare field, NLP has become increasingly present in extracting information from unstructured data made available from electronic health records (EHRs) for quality improvement and clinical research. Since the implementation of Meaningful Use programs in 2009, EHR use has become increasingly widespread. Despite the increase of use, though, there have been mixed reports on the overall quality of care that NLP seeks to remedy. For example, Wang et. al. (2016) published a study that analyzed the use of NLP in EHRs to identify complex patients with atrial fibrillation (AF) for targeted intervention. They found that, through the use of NLP analyzing unstructured data provided by EHRs, they were better able to identify and target individuals who were at higher risk of stroke. NLP offers a focused avenue for the EHR to boost quality of care by identifying at-risk patients in targeted populations and facilitating informed decision-making.

Algorithms versus Humans: How AI Measures Up

ML, a subset of AI, is defined as the application of AI that uses statistical techniques for fitting models to data and to "learn" by training models with data (Davenport T. & Kalakota R., 2019). Many ML algorithms currently in use, particularly in diagnostic radiology, have yielded more consistent and accurate results in identifying malignant tumor patterns than human radiologists. These results strongly suggest that usage of ML algorithms is an essential part of boosting quality and lowering associated costs through streamlining image processing and making more efficient use of time.

Several studies have surfaced in recent years about the success of algorithms outperforming humans in various specialized tasks. For example, the criteria traditionally used for assessments of glioblastoma MRI scans is known as the Response Assessment in Neuro-Oncology (RANO) that attempted to standardize evaluations in clinical practice. However, RANO relies on a manual two-dimensional measurement method that contrast-enhances target lesions and often leads to error and inconsistencies in diagnostics (Davenport, T., & Kalakota, R., 2019). The German Cancer Research Center (2019) developed a new pattern recognition software that uses ANN to create a three-plane analysis of MRI scans of gliomas. The new ML algorithm assessed more than 2,000 MRI scans of 534 gioblastoma patients and was found to be 36% more effective than traditional human driven methods of assessment and also produced a more precise prediction of overall survival (Kickingereder et. al., 2019). Assessment of whole slide pathology images is traditionally coined as a laborious and time-consuming task. As a result of these limitations on radiologists, backlog of assessments can occur and delay diagnosis. Over a period of time, it is reasonable to assume that these backlogs can compound, resulting in much longer wait periods. Taking into consideration the timeline on which these conditions may progress, this delay may have long term mortality rate implications. However, pattern recognition ML algorithms are not subject to fatigue or stress overload like human clinicians are at times and are able to shorten the duration of backlogs from an average of 11.2 to 2.7 days (Annarumma, et al., 2019). A study done by Rivera-Franco & Leon-Rodriguez (2018) suggested that early and reliable detection of tumor activity by a factor of three months or more had a 12% lower survival rate than those with shorter clinic visit-to-treatment time periods. Not only is the promptness of detection vital, but the accuracy of the results is crucial. In another example, The American Cancer Society reports that about half of the women getting annual mammograms over a 10-year period will have a false positive finding (2017). A false positive finding can, in turn, create unwarranted distress for the patient as well as wasted time and money on unnecessary tests, MRIs and invasive biopsies. ML algorithms have the capacity to revolutionize medical imaging diagnostics and to provide the essential clinical assistance needed to bolster quality outcomes and lower associated costs.

High Reliability in a Time of Deniability

Industries like the healthcare field and commercial airlines are both expected to produce results with high reliability (Polonsky, M., 2019). For example, in 2019, a Boeing Max 737 commercial jet crashed in Ethiopia, killing every person on board. This tragedy was attributed to the pilot's lack of training and knowledge in managing an AI software called the Maneuvering Characteristics Augmentation System (MACS). In this example, lack of appropriate training concerning new assistive software led to the tragic death of 157 passengers. Likewise, in healthcare, it is vital that clinicians are appropriately skilled and trained in how to use the assistive AI technology because lack of training may have grave consequences on long term survivability.

With any adoption of new technology comes the associated cost of usage training. Short term, this is a sunk cost. In the long term, however, training is an investment. A study published by IBM in 2019 estimated 120 million workers worldwide will need to be retrained as a result of AI integration and automation within the next 3 years (IBM, 2019). It is crucial for the workforce to adapt their skill sets accordingly in an era of evolving technology to enable growth and higher quality outcomes for their respective industries. This is an opportunity for growth in the healthcare field and should include a strategic plan for implementation and ongoing evaluation.

An essential facet of healthcare is the trust present in the patient/provider relationship. In order to maintain the integrity of that relationship, the provider must wield their tools in a way that reinforces consistent reliability. Therefore, to produce better quality outcomes, adoption as well as training is essential for clinicians to properly use AI technology and accurately interpret results in a time sensitive manner.

Liability in Policy Making

AI applications in healthcare offer consistent quality outcomes. Despite this, there are several barriers to long-term integration of AI. Two questions that go hand-in-hand with one another is level of integration and, in turn, legal liability. How much or how little will the clinician eventually rely on this clinical decision assistive technology; will it stay as an “expert second opinion”, or will it even replace the need for the practitioner? Fortunately, the implications of these questions have started to be addressed by recent proposed legislation.

The medical community has long and justifiably regarded their skill set as irreplaceable, but in recent years algorithms have statistically shown again and again to outperform clinicians in both surgery and radiology. These statistics leave us without a straightforward answer. However, AI clearly offers a pathway for better quality outcomes.

Another significant barrier that is closely related to usage is the question of liability. As technology becomes more integrated into healthcare, the capacity for error will also become increasingly apparent. When these errors are encountered, the question of liability resurfaces. The present-day legal liability theory that is most applicable to AI is the tort of negligence. However, this is a complex issue given the capability of AI to learn past what it is originally programmed for; as there is a “black box” between the input and output function that prevents the user from isolating the cause of harm. There are a number of ways that an AI manufacturing company can defend themselves in a products liability suit. Currently, AI is lightly regulated and is more so thought of as an “expert second opinion” than an entity that is entrusted to make its own decisions. However, after a few years of consistent AI use in healthcare, it is a very real possibility that it will cultivate a high level of trust because of the consistency and quality of results it delivers. The amount of responsibility AI will undertake in the next decade is crucial to determining regulation policies and procedures for when algorithms do make a mistake. Luckily, the several underlying issues with AI have already been recognized and legislation is being drafted to create a framework for regulation regarding algorithms. This legislation, the 2019 Algorithm Accountability Act, was introduced in the 116th Congress. It is currently undecided whether or not this Act will pass through, but it includes sanctions requiring auditing of any AI systems as well as any automated decision making system that makes or facilitates a human decision that impacts consumers.

Leaps and Bounds in the Scientific Community

AI is just one of the new technologies that is the changing the way we approach healthcare. In 1987, the discovery of clustered DNA repeats that would eventually turn into the technology known today as CRISPR-Cas9, made large ripples in both the scientific and medical community. Essentially what this biotechnology does is allow for germline editing of the human genome in attempts to produce a desired genetic makeup. With CRISPR-Cas9, scientists are able to identify and have the ability to eradicate many genetic diseases and predispositions like sickle cell anemia, cystic fibrosis, HIV, and Huntington's disease. In fact, in China, the first HIV resistant twins were born in 2018 as a result of such biotechnology (Raposo, V. L., 2019). However, many have raised concerns relating to the morality of embryonic genetic editing.

The answers to how to proceed with this technology and others such as AI may not be simple. AI has not made so bold a claim as to alter the intrinsic genetic makeup of the human person; but it shoulders the same weight of responsibility all the same. Misapplications of AI have the ability to both directly and indirectly harm an individual's autonomy, health, and preferences. Therefore, informed dialogue and decision-making within the medical and scientific community is vital in determining the bounds in which AI is to be used while adhering to necessary ethical standards. With these standards in place, use of AI and ML in the medical field can maximize overall benefits while minimizing negative consequences.

Establishing an Ethical Framework of Use

Given what AI is capable of, whether that is great harm or great good, both ethical guidelines and regulations are necessary to ensure a practical framework of use. The first step in establishing these regulations, however, is engaging the medical community in an informed dialogue of the complexities that can arise with AI interface in the system. A study done at University of California-Berkeley suggests that these new advances in artificial intelligence have created new threats to the privacy of patient health information. Many companies that have smart devices using AI in the tracking of physical activities and vital rate monitoring offer the means to identify individuals by matching activity patterns to an identity (Hickey, J., 2018). Many are alarmed at the ease in which AI allows companies to gain access to health information without proper protections in place, as this new method of data exchange may not be covered in the protections that the Health Insurance Portability and Accountability Act of 1996 (HIPAA) Privacy Rule offers. HIPAA sanctions protect patient information regarding traditional health care, but does not account for tech companies like Facebook, 23andMe, and Ancestry distributing such information. For example, 23andMe recently sold a stake of their company for $300 million under a 4-year contract with a drug-making company called GlaxoKlineSmith. As a part of this deal, GlaxoKlineSmith has been given genetic information from thousands of

23andMe users in order to develop drug targets as well as to be used in clinical trial selection (Ducharme, 2018). It is important to note that although 23andMe users sign a consent form, it is unlikely that they are fully aware their information is being used in this way and are not compensated from the profit that their genetic information generates. Currently, HIPAA does not offer any protections on how an individual's genetic information is used outside of a clinical or insurance setting. Given this new age of information exchange, the efforts to preserve the autonomy of the individual's health information is needed more now than ever and suggests that the current legislation in place may not have the capacity to do so.

AI Impact on the Healthcare Iron Triangle

There is an immense opportunity present in the healthcare environment for the potential benefits AI can offer in regards to addressing the "Iron Triangle" of healthcare; cost, quality and access. Traditionally, the triangle required a trade-off consequence when trying to increase either of the three elements. However, AI has the potential to create an entirely different pathway that can simultaneously short-cut costs, bolster quality and increase access.

Rising healthcare costs for the individual have become a major concern for the American public. AI has been estimated to offer almost $45 billion in annual savings by 2025, breaking down the cost savings in several AI applications that include robot-assisted surgeries, automated imaging diagnosis, fraud detection and providing virtual assistance to patients (TM Capital, 2017). With AI reducing functional costs for the provider and streamlining care, the healthcare consumer will experience savings as well.

Cutting costs with AI, however, does not mean outcome quality suffers. In fact, AI through ML techniques may offer even better quality outcomes than before. AI used with ML algorithms have already made great strides in improving accuracy of diagnosis with medical imaging and diagnostic procedures. Literature in minimally invasive surgeries performed with robotic assistive technologies like the da Vinci Surgical System have suggested the enhancement of the maneuverings of surgical procedures followed by reports of less blood loss and lower rate of complications (Sayari et al., 2019).

As the US experiences a shift towards an aging population, there will be a considerable strain on the current healthcare system. To match the population statistics, the healthcare workforce has anticipated to grow by 14% from 2018 to 2028, considerably faster than the average for other occupational groups (Bureau of Labor Statistics, 2020). With this trend in growth comes the question of accessibility. With a projected physician shortage nearly doubling within the next nine years, AI is projected to address 20% of unmet clinical demand by automating certain tasks, reducing wait time, and streamlining patient care (Forbes, 2019). By short circuiting typically laborious and time-consuming tasks, it allows for clinicians to practice at the top of their respective license. For example, AI can remotely assess a patient’s symptoms and only alert the physician when their direct intercession is necessary. By doing this, AI both decreases the cost of such work -as wasted time is wasted money- and allows for healthcare professionals to devote their valuable time with patients in order to ultimately deliver higher quality care (Collier, 2017).

The Bottom Line

High quality health outcomes should be on the forefront of any healthcare organizational goals. In 2015, it was estimated that the US healthcare expenditures comprised 17.7% of total GDP annually (Centers for Medicaid and Medicare Services, 2019). It is wholly ineffective, wasteful, and unethical for systems to fail to provide a minimum guaranteed quality of care. As a provider, the healthcare industry has a duty of care to patients. Since the birth of organized healthcare, there has been a focus on the patient/provider relationship as the foundation of care. With this relationship comes a level of trust endowed by the patient to the provider to guide and facilitate quality outcomes with the active participation and compliance of the patient. As data is gathered and organized from AI technology outcomes, it is becoming increasingly apparent that this technology has capability to revolutionize the current healthcare system. With this foreseeability, failure to act in such an area of opportunity for growth would be negligent. It conceivably breaches the duty of care owed from the provider to the patient and, therefore, could be arguably construed as malpractice.

CONCLUSION

This study discussed several subsets of Artificial Intelligence that create new pathways to improve patient care outcomes. Several published studies that put AI algorithms to the test indicate great benefit in the support they can offer to clinicians in terms of accuracy and efficiency. These results call for a high level of integration of AI technology in order to bolster quality outcomes for the end users of the healthcare system; the patients. While many challenges arise in the adoption of AI, with the properly established ethical framework of use and informed policy making, it is capable of addressing and improving cost, quality and access.

The world is on the edge of another technological revolution and the change that accompanies it is inevitable. The adoptions of these technologies have major implications on the future of patient care, current health data legislation, and the administrative process. There are many challenges that arise when faced with any concept of change, but the benefits AI and its learning techniques present to the current healthcare system to better serve its users is too great to surpass.

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