REVIEW ARTICLE

From Admission to Discharge, How Artificial Intelligence Could Optimize Patient Care: A Brief Review

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Abstract: The applications of artificial intelligence (AI) in healthcare have been steadily growing over the past few years. This is largely due to the availability of large amounts of healthcare data, coupled with a dramatic increase in computational power. Today AI-based algorithms have been developed for numerous applications, from predicting patient outcomes to optimizing the clinical workflow. Given the current pace of innovation, AI is bound to play a significant role in healthcare in the years to come.

Keywords: Artifical intelligence, admission, discharge, patient care.

Over the past decade almost every major industry has seen significant advances aided by artificial intelligence (AI), and the healthcare industry has been no exception. The most recent examples of AI in medicine have shown promise in several areas, ranging from radio-diagnostics to cancer therapy (1). With interest and investment flooding in, AI is poised to disrupt conventional healthcare in ways that were not thought possible just a few years ago.

In this article, we have explored a few examples of how AI has been used to improve patient care with special emphasis on the inpatient setting. We have also reviewed basic concepts and terminology in the field of AI to better understand the examples cited.

AI is an umbrella term for the general intelligent computing capable of mimicking human intellect; it encompasses machine learning (ML) and deep learning. At a high level, ML entails processing data to infer patterns which are then applied to approximate decisions using predictive models. In essence, it is a way for computers to learn from example and make inferences, much like how humans learn from their surroundings. Deep learning involves applying artificial neural networks (ANNs) – i.e., multi-layered abstract computational functions loosely modeled after neuronal connections in the brain. Deep learning allows for incredibly complex and abstract patterns to be discovered, enabling breakthrough performance and accuracy in speech recognition, natural language processing (NLP), computer vision and beyond (2).

AI is by no means a new concept; however, the reason for its recent widespread adoption is the availability of large amounts of data coupled with a dramatic increase in computational power. We accumulate exabytes (a billion gigabytes) of healthcare data every year, and that number is expected to increase 10-fold by 2020 (3). There are several reasons for this significant increase in data volume, but it is primarily fueled by the widespread implementation of electronic health records (EHR). Incentivized by the HITECH portion of the 2009 Recovery Act, EHR adoption in the US has now surpassed ninety percent (4).

Rather than being empowered by ever increasing patient data, we frequently find ourselves overwhelmed. AI could help decipher much of this information, by finding patterns that elude human intellect. To help understand its potential applications we have broken down a hospital admission to see how AI could help care for the patient at every step, from admission to the time of discharge.

AT THE TIME OF ADMISSION

Admitting to the inpatient service can be a time-consuming process, depending on the complexity of the case. One of the most cumbersome steps is obtaining relevant and up-to-date medical information on the patient. This often involves sifting through volumes of electronic records and includes review of clinical notes, most of which are in the free-text or unstructured format.

AI could offer an elegant solution to this aided by the development of natural language processing (NLP) tools. These systems work by analyzing the sequences of text within the EHR to derive meaningful contextual relationships between them. In essence they “read” the EHR looking for clinically relevant data points. These tools have been used to analyze clinical notes and extract risk factors, disease characteristics, and relevant drug therapies for several chronic diseases (5).

NLP based tools could potentially comb through numerous electronic records in minutes and organize data most valuable to the current admission. Everything from documented comorbidities and relevant outpatient work-up to the most recent medication lists can be easily compiled and made available to the admitting team (5-6). NLP helps us unlock the full potential of EHR data by transforming clinical text into structured data, that can then be used to guide clinical decisions.

ON THE MEDICAL FLOOR

The true value of an AI based system would come from real-time analysis of patient data resulting in actionable insights. After being trained on numerous patient data sets, these systems have shown promise in reliably predicting adverse outcomes before they are clinically evident.

A clear example of this comes from a septic shock prediction tool developed by Saria and colleagues at the Johns Hopkins University (7). TREWS, or Targeted Real-time Early Warning Score, was developed to identify patients at the highest risk of developing septic shock and subsequent organ failure. Using a form of machine learning called “supervised learning,” they trained models using data from over thirteen-thousand critical care patients. The training dataset included routinely collected measurements like age, vital signs, laboratory test results, and clinical history. The validated score was able to identify patients who would go on to develop septic shock with an area under the receiver operating characteristic curve (AUROC) of 0.83. Moreover, it was able to identify said patients on an average of 28 hours before the onset of shock and before any evidence of sepsis-related organ dysfunction in two-thirds of those cases. In a condition where every hour of delay in antibiotics can result in increased mortality, such tools could significantly affect outcomes.

Even in less acute settings, it is important to identify patients who are less likely to respond to therapy and necessitate greater resource utilization. Rajkomar *et al* used deep learning neural networks to reliably predict acute medical events by analyzing raw EHR data (8). The data sets included: patient demographics, provider orders, diagnoses, procedures, medications, laboratory values, vital signs, flow sheet data, and even free text clinical notes. Using data from over two-hundred-thousand hospitalized patients, they developed a model that was able to predict the likelihood of an in-hospital mortality (AUROC 0.93), prolonged length of stay (AUROC 0.75), and even patients final discharge diagnosis (frequency weighted AUROC 0.90) surpassing traditionally used models in all cases. Moreover, with regards to outcomes like in-hospital mortality, deep learning models were able to make reliable predictions 24-48 hours earlier than traditional methods.

FOLLOWING DISCHARGE

Identifying patients at the greatest risk of readmission has been a priority area in our efforts to cut down on healthcare spending. However, most of our current readmission risk prediction models perform quite poorly and are thus limited in their utility. This is likely because of the limited number of data points that were considered while developing these models. As an extension of the study mentioned above, Rajkomar and colleagues were also able to reliably predict unplanned readmissions with an AUROC of 0.75–0.76, yet again surpassing traditional models (8).

Similar success has also been seen with chronic conditions like heart failure. Using a form of deep learning called unified deep networks (UDN), Golas *et al*, developed a heart failure readmission prediction model that was able to reliably predict 30-day unplanned readmissions with an AUROC of 0.70 (9). Such prediction tools would allow healthcare providers to identify high-risk groups and target them for early intervention.

DISCUSSION

Although there is no denying that AI will play a big role in shaping the future of healthcare, there is also reason for caution in these early stages. A recent study looking into the quality and safety of AI applications in healthcare noted a few potential areas of concern with the current models (10). It is important to remember that a generated algorithm is only as good as the data it was trained on. Poor quality of training data would invariably result in erroneous predictions. Moreover, when real world and training data differ, it could lead the algorithm to draw wrong inferences, a phenomenon known as “over-fitting” (11).

Another concern is an increased reliance on machine-generated suggestions. As AI gains increasing acceptance, there might be a tendency for healthcare professionals to become complacent and “blindly trust” the computer-generated assessments, and in doing so, confound clinical judgment.

The true promise of AI is to assist physicians, not replace them. By automating redundant activities and supporting clinical decision making, the hope is to make healthcare professionals more efficient and improve patient outcomes. The first step towards acceptance of these new technologies comes from having a better understanding of them and recognizing their benefits while keeping in mind their limitations.

Notes

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