The Impact of Computer Science in Medicine

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Introduction

Over the past century we have seen drastic improvements in healthcare through medical advancement. This has been achieved through the improvement of medical techniques and research conducted into diseases and infections. However, this rapid advancement has led to an increasingly complex medical field. As a result, machine learning in healthcare is not just a useful tool, it is a necessity moving forward in improving patient outcomes. How machine learning has already been used to improve one’s health is the focus of our paper. Though not widespread, it has been shown to be effective in a few key areas. It is currently being used in improving the prescription of medications to patients and to model the risk of patients developing diseases. Another use is in the identification of where patients are receiving substandard healthcare. Finally it’s being used to ensure that doctors are receiving information on highly-specialized diseases that due to their rarity would not otherwise be identified. Our paper will argue that machine learning is currently having a considerable beneficial impact on medical care, and has the potential to become even more useful in the future.

Predicting Patient Risk of Developing Diseases

Prevention is often better than treatments or cures, particularly when it comes to one’s health. This assumption is affirmed by the renewed focus of the UK’s National Health Service, in increasing its investment in preventative medicine (Stephens, 2014). The most important aspect of preventing a problem from developing is effective risk modelling, a field in which machine learning can excel.

Through machine learning analysis of medical data, it is possible to more accurately model the risk of disorders with complex genetic markers such as anorexia nervosa (Guo et al., 2016). There has also been success in predicting cases of sudden cardiac arrest, which is impacted less by genetics and far more by lifestyle choices (Manis et al., 2013). It is important to bear in mind that risk modelling is reliant upon the analysis of multiple complex variables that, without the aid of machine learning, would be impossible to analyze effectively on a large scale. From risk analysis, we can more effectively target resources to improve the health of the general populous, while reducing the overall strain applied to healthcare infrastructure. As medical records are more frequently digitized and machine learning develops, future risk modelling with improve (Mains et al., 2013). However, this is predicated upon the widespread collection of relevant medical data through blood tests, genetic testing and blood pressure checks.
Further one must assume that the data collected is accurate and one is able to reproduce consistent, accurate predictions. The final assumption is that patients will heed the advice given to them by experts, which is not always the case.

**Identifying Exceptionally Rare Disease**

There are many rare diseases and illnesses today that can be incredibly hard for doctors to diagnose and treat, due to a lack of available information to assist them. Computer science is able to help improve these diagnosis rates and positively impact the medical field. Researchers at Indiana University have developed a machine learning algorithm that can help medical professionals better identify and differentiate rare diseases from more common chronic illnesses (Macleod et al., 2016).

Approximately 10% of the world suffers from rare diseases, and while the diseases themselves are poorly understood, there are many distinct experiences people with rare diseases share that can be used to help diagnose their illness (Macleod et al., 2016). By collecting behavioral data through many self reported surveys, a machine learning algorithm has been developed that can classify people with rare diseases based off unique challenges shared among those afflicted. The algorithm progressively determines correlations between self reported survey data taken from individuals with already diagnosed illnesses, so that it can effectively recognize these patterns in future cases. By using a behavioural identification process, accurate diagnoses can still be made for poorly scientifically understood diseases that would have otherwise been misdiagnosed due to lack of information.

The process is not perfect since self reported surveys require a number of assumptions to be made. For the machine learning to properly classify diseases, all survey responses must be considered accurate and there are no mistakes in previous diagnoses. The algorithm itself must also be assumed to always produce the optimal answer when doctors are unsure, and since that will not always be the case, there will invariably be misdiagnoses. These misdiagnoses would be inevitable as with a human doctor, however probably less frequent. This could still lead to a loss of trust of patients toward computer involvement in their healthcare and harm the further integration of technology in medicine.

**Improving Prescription of Medication**

Improving the prescription of medication is of paramount importance as it directly influences a vast proportion of patient outcomes. In recent times there has been an increase in the number of available options for medication, which creates the opportunity for significantly better patient outcomes. However, this has been mired in
difficulty due to the sheer number of medications that can be prescribed. By implementing machine learning, these overwhelming options can be effectively managed and patient outcomes will see an improvement.

An example of the opportunity for machine learning in the prescription of medication, is when an overweight patient presents with three associated common conditions: high cholesterol, high blood pressure and diabetes. To treat these conditions they need 6 medications, but due to the number of remedies being produced there are over 1.3 trillion treatment options to choose from (Prescription Intelligence, 2016). This number of combinations is impossible for a doctor to compute for each patient. To make those numbers manageable it is necessary to implement machine learning into the prescription of medication. This has been done with great success in trials, in two ways that improve patient outcomes. The first is through the analysis of potential side effects due to interactions with other available drugs. This is a problem which accounts for 100,000 deaths per year in the US, numbers that machine learning can greatly reduce (Cai et al., 2017). Predicting adverse interactions can be conducted before drugs even go on the market, preventing side effects before they affect any patients. Secondly, machine learning can weigh the benefits of a drug against its side effects, and determine the optimal patient medication. The University of Indiana, concluded that they were able to improve patient outcomes using this approach by 30-35%, equating to an average saving of $308 per treatment (Bennet and Hauser, 2013).

As impressive as these improvements are they are likely to become greater in the future as we develop more personalized drugs based upon the patient, and as machine learning improves. This will create even more complexity in prescription, but better opportunities for improving our health, necessitating the use of machine learning in the prescription of medication.

**Identifying Substandard Care**

Patient safety is a major concern for every hospital, yet many adverse events still occur regularly. In this case adverse events consist of nosocomial (hospital originating) infections, harmful drug doses, and falls. Currently, most adverse events “rely on spontaneous reporting” of the situation, so only small fraction of these incidents are actually detected (Bates et al., 2003). Although manually reviewing patient charts can detect possible adverse events, it is financially impractical (Bates et al., 2003). To counteract this, technology has been developed to analyze large quantities of hospital data to detect and resolve adverse events much more efficiency.
Hospitals already maintain large administrative databases of patient hospitalization. These can be screened by algorithms to detect any anomalies suggesting possible adverse events, and alert healthcare professionals (Bates et al., 2003). An example of this would be a patient being admitted with a particular diagnosis, but then having a separate discharge diagnosis. This could indicate that the patient suffered a harmful event while in hospital. This screening would detect a much greater percentage of adverse and possible adverse events, enabling them to be dealt with to ensure maximal patient safety.

There are of course a number of assumptions connected to screening large amounts of data. Associations being discovered must be relevant to hospital staff, and actual sources of causation are being found, not just correlations. This concept is referred to as “dirty data,” which can be a major hiccup in all data mining processes.

Over time with advancements in machine learning, algorithms will be able to evolve to identify a greater range of adverse events continually and in real time. This will dramatically increase identification of substandard medical care throughout healthcare facilities.

**Conclusion**

While the application of machine learning in the medical field is still mainly in the developmental stages, its impact and benefits are already producing some tangible results. Using machine predictively to identify patient risks of developing disease as well as possible substandard health care can assist doctors by dealing with problems before they even arise. Computational thinking can also be used to supplement doctors medical expertise by helping them improve medication prescriptions, as well as diagnose exceptionally rare diseases. It should be noted that although machine learning is constantly improving, there are still many individuals who are sceptical about trusting aspects of their health to a computer, no matter how increasingly accurate they become. This is in large part thanks to debates over healthcare being fraught with emotive arguments and personal experiences. Old ways of thinking can be hard to change, but these concerns can be addressed by ensuring patients that the impact of computer science in medicine is one of assistance to healthcare professionals and should never be solely relied upon. The goal is not to take away final decisions from humans with years of invaluable experience that can never be perfectly coded into a computer, but supplement their knowledge. Another concern is the oversimplification of computer science in the news, which may further fuel assumptions that these developed algorithms are not as rigorously and technically developed and tested as they actually are. While the topics addressed provide evidence that computational thinking can have
a positive impact in medicine, these are just a few of the many ways machine learning can help members of the healthcare community, and over time even more applications will be created as technology continues to advance.

**Limitations**

Computational thinking can have a definite positive impact on medicine, yet there are also some limitations that accompany it. Obtaining precise details outside of those published in studies can be difficult to find. This is due to patient confidentiality concerns and inaccessible data. There are over 100 “Artificial Intelligence Startups in Healthcare,” leading to aggressive competition and unwillingness to disclose data for fear of revealing trade secrets (cbinsight.com, 2017). Without access to raw data it becomes a matter of trust in the rigours of peer reviewed scholarly articles when it comes to collecting information.

**Bibliography**


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