The Role of Artificial Intelligence in Healthcare

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# Table of Contents

I. Abstract .................................................................................................................. 1
II. Introduction ........................................................................................................... 1
III. Current Applications ............................................................................................ 3
   A. Prevention
   B. Treatment
     1. Imaging
     2. Treatment management in chronic and infectious diseases
     3. Intensive care unit organizational model
     4. Antibiotics
IV. Challenges and Limitations .................................................................................. 19
   A. General Overview
   B. Ethical Concerns
   C. Legal Implications
     1. Regulations
     2. Tort
     3. Intellectual Property
     4. Privacy
V. Conclusion ............................................................................................................ 25
VI. Acknowledgements ............................................................................................... 25
References .................................................................................................................. 26
Appendix ...................................................................................................................... 29
Abstract

Artificial intelligence (AI) refers to a machine with the ability of simulating the cognitive functions of humans. Specifically, within healthcare, AI plays a significant role both in prevention and in treatment of diseases. In terms of prevention, AI is useful in identifying multifactorial causes of disease emergence, which include biological and epidemiological factors, along with tracking disease spread by integrating real-time updates from digital media reports. Regarding treatment, AI has a foot in imaging, treatment management of infectious diseases, intensive care unit organization, and antibiotics. Although healthcare has benefited greatly from the incorporation of AI, it does come with limitations and challenges, including quantity, quality, and heterogeneity of the data and privacy and ownership of the developer. Although the benefits provided by the incorporation of AI into healthcare are considerable, the technology still has a long way to go.

Introduction

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law

(Asimov, 1950)

The Three Laws of Robotics were introduced by Isaac Asimov in his series “I, Robot” in the 1950s and later adapted by Will Smith in his movie, which took the same title. The Three Laws of Robotics were designed to guarantee human safety, which later (“spoiler alert”) proved not to be foolproof. Thus, the idea of artificial intelligence (AI) is not a new
phenomenon. Although AI has been around for a while both in the entertainment and healthcare industries, its prevalence and influence are on the rise in the healthcare industry.

The uninformed public tends to associate AI with science fiction: a Star Wars-like feature that is only seen in movies or in technology of the future; an apocalypse in which robots take over the world. When applied to healthcare, people again tend to associate AI with the science fiction concept of robots taking over and completely replacing physicians. Although AI does play a role in the discipline of surgical robotics, it is also being implemented on a much more basic level, aiding in screening and data analyses. The reality is that AI is a current technology that already plays a significant role in everyday life: cellphones, concierge services (i.e., Siri for the iPhone), self-parking and self-driving cars, and thermostats that learn from our routines (i.e., Nest), just to name a few. Humans exhibit a natural tendency to resist change, which stems from a feeling of satisfaction within a comfort zone and from a fear of the unknown. When we encounter something that is unfamiliar to us, such as AI, it can be very frightening. To make it less frightening, we ascribe a different name to it, as with AI, and thus cease to think of it as what it really is.

It is difficult to pinpoint exactly when AI was created. There are texts as far back as the ancient Greeks that make reference to AI (Tian, 2017). Some say the first intelligent machine was El Ajedrecista (The Chess Player), an automaton built by Leonardo Torres y Quevedo in 1912 that was capable of playing chess against a human. Since then, AI has evolved past the gaming industry and has spread throughout every field. Among these fields is healthcare, which is increasingly benefitting in the areas of diagnosis, imaging, micro-
surgery, biomedical engineering, and much more. Like every change, it comes with many obstacles and challenges. Just as the Three Rules of Robotics was written so that robots would not harm humans, it is up to us to create the guidelines and boundaries for AI so that we can maximize the benefit from this technology.

AI is “an entity (or collective set of cooperative entities), able to receive inputs from the environment, interpret and learn from such inputs, and exhibit related and flexible behaviors and actions that help the entity achieve a particular goal or objective over a period of time” (Faggella, 2017). In other words, machines are provided a series of instructions and/or guidelines which rule their subsequent actions. The terms “machine learning” and “deep learning” also get thrown into the mix, but what do they really mean? Is a machine really able to learn, or is it following a designated algorithm? Is it really an intelligent being, or is it just programmed to seem that way? The term machine learning provides a way to describe the “development” of these intelligent machines. More specifically, machine learning explains the ability of AI (a) to constantly process new data, (b) to learn from its experiences and (c) to analyze and to respond to questions it was not specifically programmed to answer.

Current Applications

A physician encounters a patient with certain symptoms or signs and then, based on knowledge and past experiences, develops a hypothesis regarding the cause of the ailment. Like a physician, AI achieves its goals on knowledge and past “experiences,” but it is able to do so at a much faster rate, with greater efficiency and efficacy. It can combine variables,
such as medical causation and statistical prediction, to help achieve its goal, whether that be aiding in diagnosis or in establishing a course of treatment. Machine learning plays a large role in healthcare in terms of its ability to effectively use prediction in prevention, treatment, and policy guidelines (Kleinberg et al., 2015).

**Prevention**

Preventive medicine, including the early detection of disease, is an area that has become particularly relevant in healthcare. AI enables a physician to identify a patient at risk of a particular illness or disease before its onset. Dr. Israel Zighelboim (personal communication, August 13, 2018), a gynecologic oncologist at St. Luke’s University Health Network and chairman of the Department of Obstetrics and Gynecology at the Lewis Katz School of Medicine, Temple University, provides an example of this situation:

“certain genetic cholesterol metabolism disorders that begin in childhood are known to increase future risk of early coronary disease (angina and myocardial infarctions). However, cholesterol levels are typically not checked in children. If large genetic screenings were applied to large populations, we could identify children at risk and initiate cholesterol lowering drugs early and hopefully prevent those early and serious cardiac conditions which shorten those individuals life expectancy.”

Zighelboim hopes that preventive measures, such as the one described above, will be implemented in the near future, as they have the capacity to save and to better many lives. Although admitting that AI will have to advance much faster for this to happen anytime soon, Zighelboim foresees that AI will eventually be used to identify patients at risk of obstetrical complications, including preterm labor and pre-eclampsia.

As changes in and spread of diseases represent a constant threat to public health, effective disease prevention and subsequent management are likewise crucial aspects of
preventive medicine. One approach to tackling the issue of disease transmission is the accurate prediction of disease outbreaks. Intelligent machines can compare cases of disease onset in order to establish underlying factors contributing to the outbreak. One such system, termed the Data Integration and Predictive Analysis System (IPAS), “collects and integrates comprehensive datasets of previous disease incidents and potential influencing factors to facilitate multivariate, predictive analytics of disease patterns, intensity, and timing.” This establishes correlations between certain epidemiological conditions and the specific disease so that, when these conditions are observed, researchers can be prepared for a potential outbreak. Some of the information analyzed by the system includes “knowledge about the location, timing, peak intensity, and potential number of infected” (Erraguntla et al., 2017). Having this information allows public health workers to devise subsequent containment and action plans. Unlike AI, physicians rely on data collected from individual patients. This often limits the physician's ability to see the big picture and also hinders accuracy and consistency. Isolated instances are insufficient to establish patterns or correlations, thereby preventing public health agencies from implementing effective disease management policies. Erraguntla et al. (2017) concluded that systems such as IPAS provide a major contribution in epidemiological data collection, integration, and analysis as it “automates the data collection and aggregation, thereby reducing the burden on biosurveillance and epidemiology analysts currently spending thousands of hours.” Thus, it serves as an effective tool that can help predict disease outbreaks more accurately and efficiently.

Olson et al. (2015) found similar results regarding the efficiency of AI in predicting disease outbreaks, but further stressed the importance of identifying multifactorial causes to
disease outbreaks. AI has the ability to integrate data from physicians, the public, news reports, and more, thereby providing a more wholesome report regarding what may cause a disease to epidemic proportions. One method used in preventive medicine is establishing biomarkers for particular diseases, which can help physicians identify and diagnose the disease at an earlier stage, maybe even before any symptoms manifest themselves. Another method involves the identification of conditions that may lead to the development of infectious diseases (antecedent conditions) that can alert the public to a potential threat and develop a course of action. In the case of unusual infectious diseases, it is said that these “events occur when an underlying mix of antecedent epidemiologic drivers provide the necessary conditions for a pathogen to emerge in susceptible populations.” Thus, to determine whether an unusual infectious disease is likely to emerge in a certain population, it is important to evaluate both biological and epidemiological factors, such as environmental conditions and socioeconomic status which may facilitate the outbreak of the disease. Early detection has become a priority in healthcare as it is easier to treat or prevent the spread of a disease when caught early (Olson et al., 2015).

Olson et al. (2015) refer to digital disease detection or epidemic intelligence as a growing field that stresses the importance of early detection and awareness. Although this study acknowledges the importance of isolated patient symptoms, it emphasizes the role of identifying multifactorial causes of infectious disease development. For example, in terms of research on Ebola, the scientific question shifted from “What causes Ebola?...[to]...Why does an Ebola outbreak occur at a particular time or location?” If AI can establish early warning tools for disease outbreaks, this will help the health sector to recognize conditions that foster...
disease emergence events. Once these conditions are identified for specific diseases, it will be easier to prevent or at least contain future outbreaks. In the 1940s, there was a malaria epidemic which, in hindsight, “resulted from the convergence of poverty, commerce, and agricultural and land-use changes; lack of malaria prevention and treatment services; and resulting shifts in local mosquito ecology” (Olson et al., 2015). Had these factors been identified as contributors to malaria emergence, the epidemic may have been predicted and thus prevented or contained.

More recently, digital media reports were used as sources of information on disease outbreaks, thereby increasing the volume of data available for integration and analysis. Specifically, real-time monitoring of diseases via social media, active surveillance, and digital surveillance has helped researchers track the spread of diseases. Sources of these real-time reports include cellphones, internet, Facebook, Twitter, Flu Near You, Influenzanet, and more (Olson et al., 2015). Real-time data has made an important contribution in the field of disease prevention, as it allows for rapid access to and for incorporation of newly disclosed information. To the naked the eye, these digital media reports may seem like isolated incidents, such as a person in Vienna, Austria reporting a debilitating cough. An intelligent machine, on the other hand, integrates this report from Vienna with a similar one from Bratislava, Slovakia (a neighboring country) and derives patterns and predictions that can ultimately be used for preventive medicine. As people report personal details about their lives, AI can integrate this information to track the progression of diseases. A person may post a “tweet” on Twitter saying: “still getting worse. Temp is still 103. Went to the Dr. The first test was wrong. It is the flu. They put me on Tamiflu and Zithromax.” A report such as
this one may seem like an unimportant, isolated event, but, through data integration, AI can determine which region is being affected and establish a pattern to predict where it may spread (Signorini et al., 2011).

According to Signorini et al. (2011), the main goal of the Twitter-based model, in contrast to other approaches, is not to forecast influenza activity, but rather to provide real-time estimates of a disease as it spreads. Twitter, which is a free social media platform, has almost 200 million users who tweet over 50 million total tweets per day (140-character maximum per tweet). Due to the magnitude of the network and the high level of activity, the content can be used to track an event if the information is analyzed carefully. In terms of disease prevention, Twitter’s most relevant features are that it is open to the public, that it can be assigned to a specific location, and that it happens in real-time. When real-time tweets about a flu outbreak were compared to statistics provided by the Center for Disease Control (CDC), the results were astonishingly similar. Signorini et al. used search engines to find tweets that contained particular keywords, such as flu, outbreak, and Tamiflu, which allowed them to track the evolving public sentiment with respect to H1N1, or swine flu, and to measure actual disease activity. As people can generate tweets from their handheld devices, tweeting is a fast and efficient way for information to spread. In just the United States, close to 10 million of the total 100 million internet users tweet daily for health-related issues. The level of attention and buzz that a particular topic gets, which is represented by the amount of people and the level of frequency that it is tweeted, reflects the level of concern and interest of the general public on that matter. AI is able to read past the “noise” (general chatter, user-to-user conversations, links to news/content, or spam and self-promotion) to find the relevant
information. Moreover, since the information is generated from an internet protocol (IP) address, which identifies devices connected to computer networks, geographical patterns can also be established. A dynamic map pinpointing where each tweet is coming from provides real-time updates and exact locations, framing the disease activity within a geographical and timely context. Traditional models are unable to keep up with the variability of the outbreak: the different strains of virus from season-to-season, the extent of pathologic effects, the regions affected, how rapidly it’s spread, and more. An AI system based on a tweet-stream is capable of determining this information efficiently, as long as the machine is taught to collect data accurately.

This method does have its limitations. For one, Twitter’s demographics are not representative of the general population, as younger generations are overrepresented. Also, since the tweets come from a large variety of places and people, establishing a uniform standard is the key. For example, California produces more tweets per person than Oklahoma, so more people tweeting about influenza in California is not indicative of an increased prevalence. Nonetheless, if this standard can be established, a Twitter-based surveillance effort may provide an important and cost-effective supplement to traditional disease surveillance systems, especially in areas where Twitter density is high. Eventually, if this consistency is established and the influx of information controlled, it may be possible to use AI for forecasting and prediction.

Other search engines and social media platforms have attempted similar studies and although they may also be useful in tracking the spread of diseases, the scientific potential of
Twitter supersedes that of the others due to Twitter’s large user-base, easy and public access, and real-time updates. Current studies show that Twitter is the most effective internet service in predictive medicine to date. However, “big data,” which is a term used to denote the rapid growth and large volume of information, generated from other areas of the internet, such as searches on Google and Wikipedia, along with self-reporting apps, such as Influenzanet (Europe), Flutracking (Australia), and Flu near You (United States), have shown great potential in predicting disease activity. Moreover, integration of this information could be used to coordinate multinational activities and responses to emerging infectious disease threats.

**Treatment**

Researchers studying breast cancer have introduced the innovative methods of using computer algorithms to serve as a “second opinion” to physicians’ expertise, thereby diminishing the detrimental effects of human error and superfluous treatment, such as radiation or surgery. Mammograms are widely used as a routine clinical practice for breast cancer detection. As Computer-Aided Diagnosis (CAD) has become a valuable tool in the differential diagnosis of many types of abnormalities, many physicians now rely on CAD to accurately interpret the scanned body images. The CAD algorithm “consists of several steps, which may include image processing, image future analysis, and data classification by use of tools, such as Artificial Neural Networks (ANN); these may be referred to as artificial intelligence.” This system uses differential imaging, the ability to “train” the computer to detect and quantify changes in scans (CTs, radiographs, full-body scans), to improve medical decision-making and to reduce the time that healthcare professionals spend deciphering
imaging changes. This can be applied to specific organ or whole-body scans. Instead of having the radiologist engage in a “masking procedure” (using a previous image as a mask image to detect changes in current images), modern medicine relies on the implementation of the temporal subtraction method. This method is especially useful when monitoring and identifying disorders, such as skeletal metastases, bone tumors, etc., since the bone scan examination is a highly sensitive and very time-consuming ordeal. The temporal subtraction method is useful in that it can assist the radiologist in the detection of tumors and in the quantification of changes between scanned images (see Appendices 1-4). Also, CAD and other conceptually similar techniques are used for a more meticulous distinction between benign and malignant pulmonary nodules. Not only can CAD detect and quantify the growth of a lung nodule, but it can also identify whether or not it is malignant. ANN integrates information obtained from multiple images and is able to distinguish between images, even those that produce very similar radiographic patterns (Shiraishi et al., 2011).

Low specificity of infectious disease imaging poses a challenge for health care providers. It makes it difficult for a physician to discern differences in CTs of varying infectious and inflammatory diseases, such as the differences in the images of patients with H1N1, fibrosis, Mycobacterium avium complex (MAC), and parainfluenza; it is also difficult for physicians to identify the degree of severity of the disease. Thus, a practical addition to a clinical team would be an intelligent machine that can detect and even quantify the difference between infections. A machine can accomplish this by way of a texture-based system, as “texture analysis quantifies an image by identifying statistical relationships among the pixels’ densities, which can be used to identify lesions and quantify the volume of an organ
manifesting those patterns associated with lesions” (Yao et al., 2011). Different infections may manifest themselves with different texture features in CTs and can thus be differentiated by AI. The actual method involves segmentation of the image of the organ(s), in this case the lungs, and then subdivision into texture blocks. The computer is taught texture patterns of different kinds of lungs (normal lungs, lungs affected by influenza, lungs with nodules, etc.) so they can be later compared with “abnormal” patterns. A pixel-based scoring system is incorporated in the algorithm to help compare the lung images. The texture analysis method proved to be successful in differentiating abnormal from visually normal areas of the lungs (see Appendices 5-7).

AI has also been useful in improving diagnostic accuracy in medical imaging, such as in aiding dermatologists in skin cancer detection. Not only has AI been used by physicians to aid in diagnosis, but a form of AI termed Convolutional Neural Network (CNN) was shown to outperform experienced dermatologists at diagnosing certain skin cancers. As compared to dermatologists, this neural network was more sensitive and specific in its diagnoses, meaning that it detected more skin cancers and that it produced less misdiagnoses. First, CNN was “trained.” It was presented with thousands of images of both malignant skin cancers and benign moles; the diagnosis of each image was also indicated. The increased accuracy in diagnosis by CNN may help produce earlier diagnoses as well as decrease the amount of unwarranted procedures, such as mole removal (European Society for Medical Oncology, 2018). More recently, however, an article in the Washington Post (2018) suggested that these results may be misleading. Although CNN outperformed physicians, the study was too specific, and the data cannot be generalized to assert that AI is more effective than
physicians. First of all, CNN only identified those cancers for which it was trained. Therefore, diagnoses were dependent on the accurate and complete training of the intelligent machines. The article suggested that CNN was trained to distinguish between benign and malignant moles, but not between other melanoma mimickers. Secondly, the training was further limited in that it did not include many abnormal moles. Thirdly, CNN was trained with images of predominantly light-skinned patients, limiting its ability to identify melanomas in darker-skinned patients. Thus, the CNN was unable to provide the holistic examination that a dermatologist could provide (Nelson et al., 2018). The study was also flawed to pin man against machine, when, in reality, “human-computer symbiosis provides a valuable lens through which to view the appropriate role of artificial intelligence in medicine. As AI becomes more powerful, rather than fostering competition, we should develop solutions that can be integrated into our practice” (Nelson et al., 2018). To provide the greatest benefit and service to patients, man and machine must work together. Dr. Zighelboim shared this belief, as he observed that “in the past, some feared that AI would try to ‘replace doctors’ or ‘make better and earlier diagnoses.’ Nowadays, I feel most of us that have seen the evolution of this field trust this would be a very positive adjunct technology to make physicians and healthcare in general better” (personal communication, August 13, 2018).

Furthermore within the field of dermatology, AI has aided in the post-diagnosis decision making process. Specifically, CNN can help physicians devise a course of action for a patient, whether to pursue follow-up tests, perform biopsies, cease testing, etc. Digital dermoscopy is a common system for documentation and follow-up in the field, so CNNs
could be used to evaluate stored images for a “second opinion.” Although a thorough clinical
examination is still considered to be the best diagnosis tool, imaging technology will
revolutionize cancer diagnosis and will provide a more standardized level of accuracy and
treatment (European Society for Medical Oncology, 2018).

As the use of AI has increased physicians’ understanding of disease, it has also
facilitated a shift in patient care to more personalized treatments. As explained by Dr. Israel
Zighelboim (personal communication, August 13, 2018),

“Currently, cancer therapies ideally are ‘targeted’ at specific molecular events or
derangements in specific tumors occurring in a specific individual. In the old days, we treated everyone with the same treatments. Now, we understand that two individuals with histologically ‘identical’ cancers, will respond very differently to different therapies. This is due to molecular differences in the tumors and also due to genetic differences among those individuals. Those realizations have been possible only due to ‘big data’ analysis which has allowed [us] to detect such differences and to identify the targets.”

Commercially available computer algorithms have allowed for unique analyses of patients’
tumors, for identifying molecular targets, and for providing potential therapies. Making
treatment more personalized to specific individuals and diseases allows for more effective
patient care. Zighelboim has already witnessed some of the evolution that AI has undergone
and sees the potential it has in his field as an adjunct technology that will positively impact
physicians and healthcare alike.

Price et al. (2017) highlighted the concept of the “precision medicine,” which is the
“convergence of advances in systems medicine, big data analysis, individual measurement
devices, and consumer activated social networks that has led to a vision of healthcare that is predictive, preventive, personalized, and participatory.” These researchers suggested that
data analysis may lead to identification of molecular changes in biological networks in common diseases, may assist in the detection of diseases, and may promote the development of drugs or other treatments intended to halt diseases at earlier stages (see Appendix 10). They evaluated the transition from wellness to disease via a longitudinal study in an attempt to identify early warning signs of diseases. Overall, this system aimed to provide a more holistic approach to patient care, in which multifactorial causes of disease are evaluated, including both genetic and environmental factors. Although the researchers believed this study had great potential to increase the understanding of the transition from wellness to disease, not enough individuals were included in the study to establish definitive biomarkers. Nonetheless, the use of decision-support systems in medicine has demonstrated improved quality of patient care (i.e., better treatment choices) and indicates a well-balanced cost-benefit approach.

The concept of personalized care can be similarly applied in the context of Intensive Care Units (ICUs), in which all critically ill inpatients are grouped together. Managing efficient ICUs presents a challenge to the healthcare system as utilization and costs are on the rise. Furthermore, specialized physicians, more individualized care, and use of advanced technology have proven to yield more effective ICUs but also increased costs considerably. Therefore, organizational interventions, which group patients based on their needs rather than diagnoses, are necessary to offer more efficient care services. This shift in the way ICUs are organized can be implemented by AI, such as by Clustering Analysis, which utilizes “a group of multivariate mathematical algorithms that quantify the similarity between individuals within a population on the basis of multiple specified variables” (Vranas et al., 2017). For
example, patients in the ICU are “classified” based on severity of illness and amount or type of intervention needed at the time. Even within a group of patients with the same diagnoses, a patient’s specific care needs may differ from that of another patient’s care needs. Using an objective data-driven approach that involves having patients grouped by diagnosis, severity of illness, trajectory, and needs will help hospitals prioritize their needs to provide efficient healthcare (Vranas et al., 2017).

AI has also been used to manage infectious diseases in the ICU by helping with decision making processes. A critical aspect of management of infectious diseases in the ICU is early intervention. Clinical competence is essential in diagnosing and treating patients in the ICU in a timely and accurate manner, so computer-based decision-support systems may facilitate and aid in this process. Decision-making support systems and algorithms help classify patients into categories, which may differ from system to system. Computational techniques can detect patterns hidden in medical data, as well as to represent and to manipulate uncertainties. It integrates data from “multiple medical services, such as emergency, pharmacy, radiology, surgery, pathology, nursing, and respiratory therapy, as well as clinical laboratories, including microbiology, within computerized medical records.” Based on the totality of these data, the machines were able to impart the probability of a patient having a particular diagnosis. Thus, by combining multiple sources of data, medical decision support systems are able to predict and to analyze the presence of infections, as well as their possible causes and their treatment actions (Schurink et al., 2005).
Chronic viral diseases, such as those caused by hepatitis B virus and by human immunodeficiency virus (HIV), present another global public health problem that will benefit from the use of AI, aiding in management of treatment in chronic infectious diseases. According to the World Health Organization, chronic diseases “are the leading cause of death and disease burden worldwide” (World Health Organization, 2005). Consequently, any procedure that can help prevent the progression of these diseases is beneficial. An algorithm was devised to provide healthcare providers with current information on screening, diagnosis, and treatment of chronic hepatitis B (CHB). This algorithm “addresses a number of issues (1) which patients are candidates for antiviral therapy; (2) what are the advantages and disadvantages of available treatment options; (3) when should therapy be initiated; (4) when can therapy be discontinued; (5) what is the role of on-treatment monitoring; and (6) which strategies should be used to decrease the risk of antiviral resistance?” (Martin et al., 2015).

Collecting and analyzing data and variables result in a time consuming and sometimes erroneous process. Thus, an algorithm that can explore and consider relevant patient data is an invaluable tool in the decision-making process for patients with chronic diseases. Algorithms have also been used to improve early detection of HIV. Accuracy has been increased and costs deduced by use of alternative algorithms in lieu of expensive, tedious, and labor-intensive supplemental tests (Owen et al., 2008).

As many patients infected with HIV die from tuberculosis, screening for chronic tuberculosis is highly recommended and beneficial. Nevertheless, current screening approaches are often limited and insensitive, resulting in a vast number of false negative results. Although chest radiography proved to be the best single predictor for establishing or ruling out a diagnosis of tuberculosis, it is considered to be a relatively weak predictor when
used alone. Using a combination of predictors (e.g., cough, fever, night sweats, loss of appetite) increases the likelihood of an accurate diagnosis. Therefore, a screening algorithm and a diagnostic algorithm were developed based on these combinations of predictors to determine whether patients required further evaluation or if they were at risk of tuberculosis, respectively (see Appendices 8 and 9). These algorithms were both accurate and cost-effective in determining the presence of tuberculosis and the subsequent need for treatment. In terms of asking patients questions, it was deemed important to ask simple questions, such as the presence or absence of cough (one predictor), but it was imperative to ask multiple questions that involve a combination of symptoms, thereby generating a combination of predictors. The optimal number of predictors to accurately rule out tuberculosis in a patient with HIV was determined to be three. Furthermore, some predictors and select combinations of predictors increased sensitivity and specificity of diagnoses. The use of these algorithms successfully reduced the number of false negative results considerably (Cain et al., 2010).

Another area of healthcare that could derive benefit from the incorporation of AI is that of antibiotic distribution, which is often erroneous and “has led to the emergence and dissemination of resistant pathogens, [which] has major implications for morbidity in intensive care units” (Nachtigall et al., 2014). Increased antibiotic resistance poses an imminent threat as it prevents the treatment of illnesses that once had effective treatments. Decisions related to antibiotic therapy are usually made following particular guidelines, although sometimes a lack of information makes it difficult to establish proper and timely proceedings. Computer assisted decision support systems (CDSS), which proved to be useful and beneficial, encompass algorithms to establish guidelines for treating infections frequently
found in the ICU. It effectively minimizes the consequences resulting from an inadequate amount of information and limited communication between staff. The use of CDSS has resulted in a significant reduction in antibiotic usage, as well as an increased accuracy of antibiotic selection. It also increased guideline adherence in the use of antibiotics, which resulted in a shorter duration of antibiotic therapy for patients and a lower mortality rate (Nachtigall et al., 2014).

**Challenges and Limitations**

Along with the benefits provided by AI come the many challenges and limitations that must be overcome for it to be truly successful. Firstly, an enormous amount of data is required to create AI algorithms, more than what currently is available. The more information gathered, the more successful the algorithm. As of September 2016, there were about 7.5 billion people in the world; a large percentage of these people do not have primary healthcare, so there is not enough available information for a comprehensive study. In addition to data volume, quality of data presents another obstacle. Furthermore, healthcare data is not homogeneous, rather, it is ambiguous and incomplete. Another complication is rooted in the fact that diseases are constantly evolving and even healthcare providers do not fully understand them, making it difficult to program machines. Due to the high degree of complexity and the quality and quantity of data available, the interpretation of the data represents another obstacle.

On the bright side, all of the challenges referenced above also represent great opportunities in the field. The limited number of patients makes it imperative to develop
machines capable of gathering, analyzing, sharing, and storing as much information as possible from each patient. The integration of such heterogeneous information will be a key factor to consider. Additionally, the data must be shared and integrated without leaking their sources and still maintaining privacy. Creating and developing a secure platform that guarantees this secrecy represents a huge opportunity in the healthcare deep learning field. Considering the fact that the data originates from various sites, there is a need to develop a feature/system capable of standardizing the information and sources (patients). Furthermore, to maximize the data available, it will be extremely valuable to incorporate expert knowledge into the mix, ensuring progress is made in the right direction. Lastly, the constant evolution and change of diseases establishes the need to develop a fast learning machine that can provide timely clinical support.

There are also several ethical concerns regarding machine-learning tools that make decisions for patients on behalf of physicians. Society has already witnessed some of the adverse effects of AI, such as the death of a passenger in a driverless car, which have raised ethical dilemmas. Undoubtedly, many of these concerns also apply to AI in healthcare. If algorithms are created with biased information, the results will be affected as well as the clinical recommendations. Moreover, algorithms may be developed to purposely skew results. Furthermore, physicians must understand the models and algorithms along with their limitations; they must learn to use them without fully depending on them. Lastly, the sensitive relationship between doctors and patients may be complicated by addition of the machine (Spitzer, 2018). Thus, the objective is to create a machine that is able to follow ethical principles, whether implicit or explicit. An implicit ethical agent refers to a machine
that has been programmed to act ethically. This type of machine does not take part in
decision-making, rather, it just abides by an algorithm. The machine’s “decisions” reflect the
decisions of the programmer or designer. An explicit ethical agent, on the other hand, uses
ethical principles to determine its actions; the development of this type of machine is the
ultimate goal of both ethicists and researchers. Beyond gathering and collecting information,
the key here is the decision-making process. Despite the amount of information the machine
can acquire, it still does not guarantee it comprehending whether or not something is ethical.
The challenge here is that, even between researchers and ethicists, there is not yet a uniform,
standardized ethical code that can be programmed into a machine.

There are three main reasons explaining why ethics are of great concern when it
comes to AI. The first is that due to the role these machines play, both in healthcare
(diagnostics, microsurgery) and in other fields (weapons, vehicle maneuvering), there are
ethical consequences in what they currently do and what they will do in the future. Thus, an
ethical code must be implanted in the decision-making process in order to prevent human
harm. Moreover, there’s a natural fear that, if engineers are able to create a fully autonomous
machine, it may or may not behave ethically. Therefore, safety mechanisms must be
established for protection. Additionally, most researchers believe that studying machine
ethics will advance the world of ethics, in general. In order to program the machines and
design their algorithms, more cases must be studied. The more situations that are analyzed,
the more the general field of ethics will develop. It is said that ethicists do not spend enough
time analyzing cases, but this is not the case in the biomedical field. Ethicists in the
biomedical field have been able to reach a consensus as to what is considered to be ethical
more so than in any other field, which may be due in part to the fact that the health of a patient is more ethically defensible than other areas. Developing machine ethics in the healthcare domain, where the ethics have reached this more general consensus, will help develop other fields in the future (Anderson et al., 2007).

One of the most prevalent fears in AI research involves how to guarantee that the machines will make the “right” decision, especially in non-programmed situations. The creators of the machines, humans, are far from being perfect, ethical role models; humans are naturally selfish beings. Thus, researchers are concerned about whether these explicit machines will start acting selfishly and favor themselves, just as the humans who created and designed them. However, machines have an advantage over human beings in that they are unaffected by instinctual or competitive drives that lead humans to act unethically. This advantage of machine over man was exemplified by the robot from Asimov’s “Bicentennial Man,” who came to be more ethical than the humans who created him (Anderson et al., 2007).

“Big data” requires an increasing level of sophistication of the machine learning techniques. Some have categorized the Big Data phenomenon as the “three Vs”: volume (quantity), variety (heterogeneity), and velocity (access). As information is gathered from several sources, each of which has a different grade of reliability, ranging from social media to high definition imaging, the filtering, analyzing, and storing of this information is no simple task. Black box medicine, which is the name some people give to AI in healthcare due to its opacity, brings enormous benefits to the industry, but not without bringing along a great
deal of challenges too (Price, 2017). Black box medicine is and will continue to revolutionize healthcare as long as the following legal concerns, including regulation, tort, intellectual property, and privacy, are addressed. If these legal issues are successfully resolved, it may spill over into day-to-day healthcare.

As the quality of the algorithms is crucial for the successful outcome, the issue of regulation imparts a legal challenge. The Food and Drug Administration (FDA) regulates all new and existing devices and technology for safety and efficacy. However, there is a debate as to whether the FDA has authority over the algorithms, since they are not medical devices and the FDA does not regulate medical practice. Silicon Valley has a long history of not working closely with regulators. There is no question that black box medicine will have to be regulated; the FDA will need to be more flexible, adapt to the new technology and innovations, create safeguard mechanisms, and validation systems. An alternative may be to include more sophisticated third-party entities to serve as consultant figures or simple auditors. The handling of information is a sensitive topic and developers will be hesitant to share their innovations. If developers do not share their innovations, it will be impossible to regulate the intelligent machines. Thus, a solution may be for the FDA to serve as a third-party in charge of centralizing and sharing the information (Price, 2017).

Furthermore, those developing the algorithms may become liable under the tort law if an algorithm is discovered to have a flaw in its design or if it is not of high quality. The judicial system is trying to determine the extent to which the developer will be liable. The technology they are developing is just meant to aid healthcare professionals in their decision-
making, so they should not be responsible for the making of the decision itself. The final
decision, and therefore liability, is up to the provider, not the black box algorithm. The
flipside of this argument is that it is difficult and maybe even unfair to blame the healthcare
provider as he/she does not fully understand the tool or algorithm at hand. If the black box is
not liable, healthcare providers will start to second guess the algorithms, which will slow
down the process and make it less effective (Price, 2017).

Additional legal challenges arise with the issues of intellectual property and privacy.
Firstly, there’s a conflict between the costs to develop black box medicine \(i.e., \) it requires
developers to generate, analyze, and store tremendous amounts of information, along with
designing and then validating the algorithms) and how the developers can protect ownership.
Although patents may be an option, the Patent Act makes it difficult as the laws of nature
cannot be patented. An alternative may be trade secrecy, but this law “protects from
appropriation of information that is kept secret and gets commercial value from its secrecy.”
The secrecy also generates distrust among the healthcare providers. The intellectual property
concern must be resolved in order to motivate developers. Secondly, the gathering of vast
amounts of information along with the sharing of it generates a major privacy problem. In
addition to a patient’s natural tendency toward secrecy, the Health Insurance Portability
Accountability Act (HIPAA) restricts and regulates the use and disclosure of health
information (Price, 2017).

Conclusion
Although I do not envision AI completely replacing physicians anytime soon, I do believe its capabilities are invaluable in the field of healthcare. The potential of AI spans a great range, whether it be in aiding in diagnoses, serving as a second opinion, helping in disease outbreak prevention, or assisting in the decision-making processes. It is not without its limitations though and must therefore continue to be modified and perfected. As technology develops and becomes increasingly more sophisticated, AI will follow concomitantly and its impacts in healthcare will be increasingly more significant.

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References


when-doctors-compete-with-artificial-intelligence-patients-lose/?noredirect=on&utm_term=.22bbf8b463e7


Overall computerized schemes for the temporal subtraction method in successive whole-body bone scans (Shiraishi et al., 2011).
APPENDIX 2- Temporal Subtraction Method

Concept of nonrigid image warping technique for temporal subtraction method in successive chest radiography (Shiraishi et al., 2011).
Example of temporal subtraction image in 2 sequential chest radiographs. Progression of a lung mass in right lower lung was clearly identified in the temporal subtraction image (Shiraishi et al., 2011).
Example of temporal subtraction image in 2 sequential CTs with 2 small lung nodules (arrow). Because a voxel-matching technique searched matched pixels on neighbors in detail, normal lung structures, such as pulmonary vessels and bronchi, were removed clearly in the temporal subtraction image (Shiraishi et al., 2011).
APPENDIX 5- Image Analysis

Method diagram for image analysis (Yao et al., 2011).
APPENDIX 7- Pixel Classification

The left column (A, C, E) from one patient and the right (B, D, F) from the other patient with pathology and RT-PCR confirmed swine-origin Influenza A/H1N1 infection. A and B are the raw gray scale CT images. C and D are a binary depiction of pixel texture SVM values based on cutoff value of 0.5 in which colorized regions are detected as abnormal by the software. Images E and F are graded maps of the pixel texture SVM values. Graded classification presents subtle areas of abnormality as green and yellow, corresponding to pathology-proven regions of bronchitis (Yao et al., 2011).
APPENDIX 8- Combinations of Predictors

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Negative Predictive Value</th>
<th>Positive Predictive Value</th>
<th>Likelihood Ratio&lt;sup&gt;1&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cough or fever of any duration in previous 4 wk</td>
<td>91</td>
<td>37</td>
<td>96</td>
<td>21</td>
<td>0.23</td>
</tr>
<tr>
<td>Cough in previous 24 hr or fever of any duration in previous 4 wk</td>
<td>88</td>
<td>44</td>
<td>95</td>
<td>22</td>
<td>0.27</td>
</tr>
<tr>
<td>Cough in previous 24 hr or fever of any duration or drenching night sweats for ≥ 3 wk in previous 4 wk</td>
<td>93</td>
<td>36</td>
<td>97</td>
<td>21</td>
<td>0.19</td>
</tr>
<tr>
<td>Cough, drenching night sweats, or loss of appetite of any duration in previous 4 wk</td>
<td>93</td>
<td>35</td>
<td>97</td>
<td>21</td>
<td>0.19</td>
</tr>
<tr>
<td>Cough in previous 24 hr or fever of any duration or drenching night sweats for ≥ 3 wk in previous 4 wk</td>
<td>90</td>
<td>43</td>
<td>96</td>
<td>22</td>
<td>0.23</td>
</tr>
<tr>
<td>Cough in previous 24 hr or drenching night sweats or loss of appetite of any duration in previous 4 wk</td>
<td>89</td>
<td>44</td>
<td>96</td>
<td>22</td>
<td>0.24</td>
</tr>
<tr>
<td>Cough of any duration or fever for ≥ 2 wk or drenching night sweats in previous 24 hr or loss of appetite of any duration in previous 4 wk</td>
<td>93</td>
<td>37</td>
<td>97</td>
<td>21</td>
<td>0.18</td>
</tr>
<tr>
<td>Cough or drenching night sweats or loss of appetite in previous 24 hr or lymphadenopathy of the head or neck in previous 4 wk</td>
<td>88</td>
<td>50</td>
<td>96</td>
<td>24</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Performance characteristics of combinations of predictors (Cain K.P. et al., 2011).
Diagnostic algorithm for tuberculosis in patients with HIV infection. Eligibility for diagnostic screening required a history of cough of any duration, fever of any duration, or night sweats lasting 3 weeks or more in the preceding 4 weeks and includes the 1199 patients who reported one or more 2nd of these symptoms. For patients in group 1, treatment for tuberculosis (TB) is in most cases indicated immediately. For those in groups 2 and 3, clinical judgment should be used to determine whether immediate treatment is needed, followed by confirmatory mycobacterial culture. For patients in group 4, the best course of action is unclear. Ideally, mycobacterial culture would be obtained, but this group has a lower priority than group 2 or group 3. Reevaluation of group 4 at a later date might be a safe alternative to immediate culture, but this strategy has not been tested (Cain K.P. et al., 2011).
Types of longitudinal data collected. (a) Timeline of important events in the P100. (b) Schematic of the data collected every 3 months throughout the study (Price N.D. et al., 2017).
APPENDIX 11- Biomarkers

Cholesterol, serotonin, diversity, IBD, and bladder cancer communities. (a) Cholesterol community. (b) Serotonin community. (c) diversity community. (d) The polygenic score for inflammatory bowel disease is negatively correlated with cystine. (e) The polygenic score for bladder cancer is positively correlated with 5-acetylamino-6-formylamino-3-methyluracil (AFMU) (Price N.D. et al., 2017).