Artificial Intelligence in Healthcare: Foundations, Opportunities and Challenges

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1 Introduction

In recent years, artificial intelligence (AI) has started to change our lives in a way that humanity has never seen before. We now take speech recognition, personalized pricing and autonomously driving cars (just to name a few AI applications) for granted. All of these functionalities are now available for free—or for very little cost—at any time and anywhere in the world. Given the increased level of automation of human or manual tasks through AI, productivity and customer experience have started to skyrocket. AI has also started to disrupt healthcare. This chapter provides an introduction to the field of AI. It also discusses recent applications in healthcare, opportunities and challenges and examines possible solutions. Other chapters of this book present further AI applications in healthcare. This chapter therefore also enables readers with the necessary foundations in order to get the most out of those chapters.

2 Artificial Intelligence

Most people have encountered the term “artificial intelligence” for the first time only a couple of years ago. However, AI has been an academic discipline since the mid-1950s (McCarthy et al. 1955), while some of its roots date to the late 1930s or even before. This chapter provides a brief introduction to the field of AI, presents recent developments and discusses challenges and how this field may evolve in the coming years and decades.

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2.1 Foundations

Ever since the 1950s, AI methods have typically been distinguished into two fundamentally different disciplines: expert systems and machine learning. On the one hand, expert systems incorporate rules that were manually derived by gathering and generalizing the knowledge of domain experts. These rules are then applied to inputs in order to make predictions or decisions. The concept of expert systems is depicted in Fig. 1.

On the other hand, models based on machine learning\(^1\) do not directly incorporate expert knowledge. Instead, these models examine examples and then find (also referred to “learning” or “training” as) underlying patterns in and among these examples. These patterns are typically being found through statistical methods. In order to make predictions or decisions, these patterns are then applied to inputs. The concept of machine learning is depicted in Fig. 2.

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\(^1\)Historically, the term “data mining” was often used. However, that term usually describes a somewhat larger discipline. During the last decade, that term has lost relevance and tends to be used less frequently nowadays. Instead, the term “data science” has become more popular in recent years. That field aims to apply machine learning models to solving real-world problems.
Generally, neither expert systems nor machine learning is generally better. The choice of methodology depends on use case-specific constraints such as availability and quality of data, computational resources, tolerated prediction errors and others. Both, expert systems and machine learning, have their respective advantages and disadvantages: Expert systems, on the one hand, have the advantage that they are understandable and interpretable and that their decisions are therefore comprehensible. On the other hand, it often takes a great deal of effort, or sometimes it even turns out to be impossible to understand and describe complex problems in detail.

Example 1 Spam filtering To illustrate this difficulty, an example of spam filtering is very helpful: First, the variance of the vast amount of spam emails is enormous. Second, spam emails do not necessarily use languages and grammar correctly, which can cause inaccuracies and ambiguities. Third, the type of spam that is being sent out by spammers is dynamic and changes over time. Creating an expert system for spam filtering is thus a challenge.

The three factors of complexity, uncertainty and dynamics occur in a variety of fields and often prove to be a common limiting factor when building expert systems. Machine learning has the advantage that often less knowledge about a problem is needed as the algorithms learn patterns from data. However, that data is sometimes not available or data quality may be a limiting factor. In contrast to expert systems, however, machine learning often leads to a black box whose decisions are often neither explainable nor interpretable. Nonetheless, over the decades, machine learning has gained popularity and largely replaced expert systems.

2.2 The Three Pillars of Machine Learning

The field of machine learning can broadly be separated into three so-called pillars: supervised learning, unsupervised learning and reinforcement learning. An interconnection can be made between each pillar and human learning: Imagine when you were a kid, you walked through the park with your parents. Your parents then pointed at various animals, say a cat, a dog and a bird. You perceived the visual and audio signals from your eyes and ears, respectively. In addition, you got an explanation of what type of animal you were seeing. That pillar is called supervised learning, in which you get an explicit explanation or “label”. Mathematically speaking, supervised learning uses pairs \(\{(x^{(1)}, y^{(1)}) , (x^{(2)}, y^{(2)}), \ldots , (x^{(m)}, y^{(m)})\}\), where \(x^{(i)}\) is the input vector and \(y^{(i)}\) the label. The goal is to learn a function \(f: y^{(i)} = f(x^{(i)})\) that infers the label from the input. This is also called function induction, because rules from examples are derived. In any case, the labels \(y\) give an unambiguous “right answer” for the inputs \(x\).

When you continued your walk through the park, you perceived more cats, dogs and birds of different colours and sizes. However, that time you did not get any supervision from you parents. Instead, you intuitively learned how to distinguish
cats, dogs and birds regardless of their individual attributes. That is an example of **unsupervised learning**, which aims to find hidden structures in unlabelled data \( \{x^{(1)}, x^{(2)}, \ldots, x^{(m)}\} \).

In many problems, it is essentially impossible to provide an explicit supervision to a learning problem. In **reinforcement learning**, we mainly think in terms of states, actions, transition between states and rewards or penalties you get subject to your performance. That is how humans actually learn most of the time. One great example of how humans learn in a reinforced way is riding a bicycle. It is awfully difficult to explain someone else how to ride a bicycle. Instead, as kids, we tried out how to ride it. If we did the wrong moves, we got hurt. Concretely, we were in different states and tried to find the right transitions between states in order to remain on the bicycle.

### 2.3 Recent Developments

Since 2006, the field of neural networks has seen a number of advances. A neural network is depicted in Fig. 3.

Multi-layer neural networks are now often referred to as deep learning (LeCun et al. 2015; Goodfellow et al. 2016). This term describes that (deep) neural networks have many hidden layers. This type of architecture has proven to be particularly helpful in detecting hidden relationships in inputs. Although this was already the case in the 1980s, there was a lack of practical and applicable algorithms for training these networks from data first and, second, the lack of adequate computing resources. However, today there is much more powerful computing infrastructure available. In addition, significantly better algorithms for training this type of neural network have been available since 2006 (Hinton et al. 2006).

As a result, many advances in AI research have been made (Iansiti and Lakhani 2020). Examples are autonomously driving cars or the computer program AlphaGo. Go is a board game that is especially popular in Southeast Asia, where players have a much greater number of possible moves than in chess. Traditional methods, with which, for example, the IBM program Deep Blue had beaten the then world chess champion Garry Kasparov in 1997, do not scale to the game of Go, since the mere increase of computing capacity is not sufficient due to the high complexity of this problem. It was only until a few years ago the prevailing opinion within the AI

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**Fig. 3** Neural network connecting input nodes (left column) to output nodes (right column). Source: author
community that an AI, which plays Go on world level, was still decades away. The UK company Google DeepMind unexpectedly revealed their AI AlphaGo to the public in 2015. AlphaGo beat South Korean professional Go play Lee Sedol under tournament conditions (Silver et al. 2016). This success was partly based on deep learning and led to an increased awareness of AI worldwide. Of course, in addition to the current breakthroughs of AI mentioned in this section, there have been a lot of further success stories and we are sure that more will follow soon.

Aside from technological advances, the access to AI knowledge has fundamentally changed. This process started in around 2011, when Stanford professors Andrew Ng, Sebastian Thrun and others made their courses available to everyone through online platforms (Ng and Widom 2014). This type of platform is often referred to as massive open online courses (MOOCs). Popular MOOC platforms include Coursera, Udacity and edX. Until 2011, one could usually only learn AI through a few selected university courses and books. That knowledge was also mainly available in developed countries, and potential learners in emerging markets struggled to access corresponding sources. The so-called democratization of AI knowledge has started to fundamentally change how we learn, a trend that is currently also being further accelerated due to COVID-19. The democratization of AI knowledge has also been identified as a massive accelerator of the Chinese AI leadership (Lee 2018).

3 Applications in Healthcare

AI has started to disrupt healthcare by providing better patient care while cutting waiting times and costs. Early works on applying AI in healthcare started in the 1970s. For example, MYCIN (Shortliffe and Buchanan 1975) is an expert system that identifies bacteria causing severe infections, such as bacteraemia and meningitis. It recommends antibiotics treatment and adjusts the dosage for patient’s body weight. MYCIN is based on Dendral (Lederberg 1963), which is considered the first expert system. It was mainly applied to problems in organic chemistry. Further early uses of artificial intelligence in medicine have been surveyed in the literature (Clancey and Shortliffe 1984; Miller 1994).

In the following decades, we have witnessed improvements of computing power (Koomey et al. 2010), the abundance of data thanks to the Internet (Rajaraman and Ullman 2011) and noticeable advances in the fields of computer vision (Dougherty 2009) and natural language processing (Banko and Brill 2001; Mikolov et al. 2013; Brown et al. 2020). These have led to a large number of applications of AI in healthcare, including, but not limited to, in radiology (Li et al. 2020; Chockley and Emanuel 2016), screening (Patcas et al. 2019; McKinney et al. 2020), psychiatry

http://www.coursera.org.
http://www.udacity.com.
http://www.edx.org.
(Graham et al. 2019; Fulmer et al. 2018), primary care (Blease et al. 2019; Liyanage et al. 2019), disease diagnosis (Alić et al. 2017), telehealth (Pacis et al. 2018), analysis of electronic health records (Bennett et al. 2012), prediction of drug interactions and creation of new drugs (Bokharaeian et al. 2016; Christopoulou et al. 2020; Zhou et al. 2018), prediction of injuries of football players (Borchert and Schnackenburg 2020) and others.

In addition, other chapters of this book discuss further applications. There are also a number of surveys on AI in healthcare (Jiang et al. 2017; Tomar and Agarwal 2013; Yu et al. 2018; Reddy et al. 2019; Davenport and Kalakota 2019).

We now also present one of our own works in greater detail. Surgeries are one of the main cost factors of healthcare systems. To reduce the costs related to diagnoses and surgeries, we have previously proposed a system for automated segmentation of medical images in order to segment body parts like liver or lesions (Trestioreanu et al. 2020). The model is based on convolutional neural networks, for which we showed promising results on real computed tomography scans. The deep learning algorithm is part of a larger system that aims to support physicians by visualizing the segments in a Microsoft HoloLens, an augmented reality device as depicted in Fig. 4.

Our approach depicted in Fig. 5 allows physicians to intuitively look at and interact with the holographic data rather than using 2D screens, enabling them to provide

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**Fig. 4** 3D visualization of liver segmentation in a Microsoft HoloLens (left): the segmented liver volume (right) was separated from the input volume—a scanned torso (centre) (Trestioreanu et al. 2020). Source: author

**Fig. 5** System architecture (Trestioreanu et al. 2020). Source: author
better healthcare. Both, the machine learning algorithm and the visualization, utilize high-performance graphical processing units (GPUs) in order to enable physicians to interact efficiently with our system.

4 Opportunities

AI has the potential to skyrocket healthcare by providing more personalized patient care while cutting waiting times and costs. This section discusses some opportunities, and other chapters of this book discuss further opportunities.

Various studies have started to make predictions of what the hospital of the future may look like (Gebreyes et al. 2020; Savino and Latifi 2019). Due to shrinkage of technology and its reduction of costs, a transformation of inpatient treatment to outpatient treatment looks likely for patients because the technology needed to care is becoming more mobile. Physicians and nurses will then be supported by AI-driven technology 24/7 and come to the patients’ homes when needed. Rooms will also likely become more flexible and can be adopted to patient-specific needs.

Nurses spend a lot of their time in moving patients on hospital beds from one room to another, for example from the patients’ rooms to examination rooms or treatment rooms. However, they are trained specialists and could allocate their time better to actually providing care to patients. Given the advances of autonomously driving cars (Yurtsever et al. 2020), it seems likely that hospital beds will become autonomous in the near future. They could then autonomously move patients from one room to another. There is no need to create detailed and costly maps of hospitals, as simultaneous localization and mapping (SLAM) algorithms (Bresson et al. 2017) can learn those while exploring the hospital and become increasingly better over time.

AI also looks promising to advancing personalized medicine, i.e. selecting appropriate or generating optimal therapies from the context of a patient’s disease, their genetic content and other molecular or cellular analysis (Hamburg and Collins 2010). Doing so would particularly help to reduce cancer mortality (Chin et al. 2011). Initial steps of employing AI and big data-driven approaches towards personalized medicine have been made (Cirillo and Valencia 2019). AI is expected to make further progress in that direction in the coming years. Quantum computers could play a crucial role in these kinds of high-dimensional optimization problems. An excellent introduction to quantum computing for the general audience is provided in Akenine (2020).

Overall, it seems unlikely that a large number of physicians or nurses would be made redundant by AI in the foreseeable future. Instead, AI will support them by providing better assistance in decision making and automating other tasks. Doing so will allow them to better allocate their time to interaction with patients and examining or treating challenging cases.
5 Challenges

AI has recently started to disrupt healthcare. It has, furthermore, the potential to skyrocket healthcare in the foreseeable future. In this section, we address a number of challenges, technical and non-technical, that need to be solved in order to make this possible. We also discuss how these challenges could be solved.

5.1 Methodological Advances in Artificial Intelligence Research

While AI has recently made a lot of progress in terms of applications, its underlying methodology has not made that much progress (Milne 2020). Currently, there are a number of methodological and technical challenges that need to be addressed in order to make considerable progress in AI and its applications in healthcare. This section discusses some of the most critical ones.

The recent focus on deep learning has created the impression that deep learning models may generally be more powerful than others. However, the “no free lunch theorem” (Wolpert 1996), which is to our surprise largely unknown both in industry and academia, shows that this is impossible. Rather, deep learning models usually excel in some disciplines like big data-driven computer vision or natural language processing, while they do not excel in others (Marcus 2018). Deep learning models also come with an enormous need for resources, such as the number of training examples, training time (Brown et al. 2020) or electricity. As a consequence, it may cost millions of dollars to train a model from scratch (García-Martín et al. 2019). Instead, humans learn efficiently from just a few examples while using substantially less energy (Spicer and Sanborn 2019).

Most machine learning models only learn correlations between inputs and outputs. However, such correlations may actually be spurious (Calude and Longo 2017) and thus be of limited usefulness. The literature presents a vast number of spurious correlations, such as between the people who drowned after falling out of a fishing boat and the marriage rate in Kentucky (Vigen 2015). As a consequence, interpretability, i.e. understanding why a (black box) machine learning model makes a certain prediction, is challenging. Nonetheless, progress in interpreting models has been made in recent years (Ribeiro et al. 2016). Instead, we are actually interested in identifying causal relationships (Schölkopf 2019). It has long been known that correlations do not imply causations. Learning causations would substantially improve interpretability and reduce the impact of biases (Glauner et al. 2018), i.e. learning from unrepresentative data sets, of models. An example of a bias is depicted in Fig. 6. By learning causations instead, models would become more reliable. Subsequently, stakeholders, such as physicians, patients and healthcare providers, would then be willing to place more trust in them.

Further challenges that IBM’s AI division, known as IBM Watson, encountered in healthcare are discussed in Strickland (2019).
5.2 Impact of Artificial Intelligence on Our Society

When looking at the rapid progress of AI, the question arises as to how the field of AI will evolve in the long term, whether one day an AI will exceed the intelligence of a human being and thus potentially could make mankind redundant. The point of time when computers become more intelligent than humans is referred to in the literature as the technological singularity (Shanahan 2015). There are various predictions as to when—or even if at all—the singularity will occur. They span a wide range, from a period in the next 20 years, to predictions that are realistic about achieving the singularity around the end of the twenty-first century, to the prediction that the technological singularity may never materialize. Since each of these predictions makes various assumptions, a reliable assessment is difficult to make. Overall, today it is impossible to predict how far away the singularity is. The interested reader is referred to a first-class and extensive analysis on this topic and a discussion of the consequences of the technological singularity in Shanahan (2015).

In recent years, various stakeholders have warned about the so-called killer robots as a possible unfortunate outcome of AI advances. What about that danger? Andrew Ng has set a much-noticed comparison (Williams 2015): Ng’s view is that science is still very far away from the potential killer robot threat scenario. In his opinion, the state of the art of AI can be compared to a planned manned trip to Mars, which is currently being prepared by researchers. Ng further states that some researchers are also already thinking about how to colonize Mars in the long term, but no researcher has yet tried to explore how to prevent overpopulation on Mars. Ng equates the scenario of overpopulation with the scenario of a killer robot threat. That danger would also be so far into the future that he was simply not able to work productively to prevent it at the moment, as he first had to do much more fundamental work in AI research. Ng also points to potential job losses as a much more tangible threat to people by AI in the near future.

These fears need to be addressed by researchers, product developers and educators. Otherwise, a lot of stakeholders, such as patients and physicians, may not adopt AI-driven healthcare products or services.
Furthermore, data protection regulation frameworks such as the General Data Protection Regulation (GDPR) (European Commission 2012) could severely limit AI applications in healthcare (Przyrowski 2018). GDPR was also intended to limit the power of major international tech companies. It has been argued that, however, exactly the opposite has happened as small companies do not have adequate resources for becoming GDPR compliant (Yueh 2020). Policy makers and regulators should therefore rethink GDPR and other data protection frameworks in order to find a better trade-off between data protection and innovation (Larrucea et al. 2020).

5.3 Education and the Need for Data Literacy

A few years ago, one of our managers made a very interesting statement:

When solving a problem, we first need to use our human intelligence. Only then AI is able to add value later on.

We therefore need to properly understand problems as well be able to think in terms of data and the underlying statistics before looking at AI. However, it has been reported in the literature that a lot of physicians do not seem to learn statistics, i.e. one of the building blocks of AI, during their studies or tend to forget it later on Gigerenzer (2015). The following problem is meant to test your expertise in statistics.

**Problem: What Does a Positive Test Result Mean?**

0.8% of people have disease $D$. A $D$ test returns a correct positive 98% of the time and a correct negative 97% of the time. The test returns positive for John. Does he have disease $D$?

Have you found the solution? Let us walk through the solution step by step:

**Solution**

We need to think in terms of probabilities and conditional probabilities. From the problem description, we can infer the following:

1. $P(D) = 0.008$, i.e. 0.8% of people have disease $D$.
2. We also know that the conditional probability $P(+|D) = 0.98$ (“The probability of a positive test given the person examined has disease $D$”), which is the correct positive of 98%.
3. Furthermore, we know that $P(−|\neg D) = 0.97$ (“The probability of a negative test given the person examined does not have disease $D$”), which is the false negative of 0.97%.
We are interested in the following probability \( P(D|+) \), i.e., having the disease given a positive test. We cannot directly compute this probability. Instead, we need to apply Bayes’ rule (alternatively Bayes’s law, Bayes’s rule or Bayes’s theorem):

\[
P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(B|A)P(A)}{P(B|a)P(a) + P(B|¬a)P(¬a)},
\]

where \( ¬ \) denotes the logical negation. We assume binary attributes.\(^5\) For a derivation and intuitive explanation, the interested reader is referred to the literature (Gigerenzer 2015).

We can now use Bayes’ rule for our problem:

\[
P(D|+) = \frac{P(+|D)P(D)}{P(+)} = \frac{P(+|D)P(D)}{P(+|D)P(D) + P(+|¬D)P(¬D)}
\]

\[
= \frac{0.98 \times 0.008}{0.98 \times 0.008 + 0.03 \times 0.992} \approx 0.2085 = 20.85\%.
\]

Given the result of 20.85\%, John most likely does not have \( D \) despite the positive test result.

If you struggled to solve this problem, do not feel ashamed. Plenty of physicians in fact incorrectly assume that John definitely had disease \( D \), given the positive test\(^6\) (Gigerenzer 2015). See this as an opportunity to become more literate in data analytics, which is a good step towards understanding the foundations of AI. You will then be able to provide better healthcare to your patients while remaining competitive. You will find plenty of great statistics courses on the MOOC platforms listed in Sect. 2.3.

In recent years, plenty of companies have started to invest in AI in order to remain competitive. However, the sad truth is that some 80\% of AI projects fail or do not add any business value (Nimdzi Insights 2019; Thomas 2019). One of the underlying causes is how AI is taught at universities, which usually only discuss purely methodological aspects of AI (Glauner 2020b). That is a serious limitation. There is clearly an acute need in industry for experts who get the big picture of what needs to be done so that AI adds value to companies. Educators need to address that issue by also enabling students to think in terms of **AI innovation management**. We have started in September 2020 at the Deggendorf Institute of Technology to teach a novel and internationally unique course on this topic (Glauner 2020a) that addresses that need. Students learn a number of challenges, both technical and

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\(^5\) A more general definition for multi-valued attributes is \( P(A|B) = \frac{P(B|A)P(A)}{\sum_{a∈A} P(B|a)P(a)} \).

\(^6\) Note that in real-world medical cases, there is usually more evidence, such as pain or pre-existing diseases, that contributes to a physician’s decision making.
managerial, that companies typically face when becoming AI-driven companies. They also learn respective best practices along the entire data journey and how these lead to deployed applications that add real business value.

## 6 Conclusions

In this chapter, we first provided an introduction to artificial intelligence for the general audience. We looked at its foundations, the three pillars of machine learning, recent developments in and around deep learning as well as the democratization of AI education through massive open online courses (MOOCs). We then presented a number of AI applications in healthcare. Next, we showed opportunities of how AI could skyrocket healthcare in the coming years. However, there are a number of challenges, technical and non-technical, that are currently limiting AI and its applications in healthcare. We discussed these challenges, including hypes around deep learning, the need for learning causal relationships instead of correlations, fears and the lack of statistics training in many medical schools. We also examined how these challenges could be solved in the future.

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