Chapter 4
Artificial Intelligence in Medical Management

Giovanni Briganti

Abstract This chapter will introduce the reader to the current state of artificial intelligence in medicine and its applications for modifying how healthcare is delivered.

Keywords AI · Digital medicine · Medical management · Hospital innovation

4.1 Introduction

Artificial intelligence (AI) is an innovative field of research that is gaining more and more ground in science and society, because of many possible applications. In medicine, since the approval by the Food and Drug Administration (FDA) of several medical technologies exploiting AI in the last decade, a new field is emerging that tries to integrate these technologies into clinical practice: augmented medicine, which is already revolutionizing the hospital world in developed countries (Briganti and Le Moine 2020).

This development in medicine risks bringing about substantial changes in the very functioning of clinical practice and healthcare, and therefore requires relevant awareness-raising among doctors, hospital managers, and anyone contributing to the healthcare sector, so that we can continue to provide patients with high-quality, cutting-edge healthcare.

In this work, we first review the basic concepts of AI; second, we review the present fields of application as well as the future perspectives of medical AI; and third, we discuss the challenges that this area will have to solve in the short and medium term.

G. Briganti (✉)
School of Medicine, Université libre de Bruxelles, Brussels, Belgium
e-mail: giovanni.briganti@ulb.be

H. Shen et al. (eds.), *Regionalized Management of Medicine*, Translational Bioinformatics 17, https://doi.org/10.1007/978-981-16-7893-6_4

4.2 AI: Definitions

The origins of AI can be traced back to Alan Turing, a famous English computer scientist who in 1950 invented a test (now known as the Turing Test) in which a certain level of intelligence is required by the machine to trick a human into believing they are having a conversation with another human: this was called the Imitation Game (Turing 1950). Even if this level of intelligence has not yet been reached by machines, a simple conversation with a virtual assistant (e.g., Siri) can serve as an example to show how far research in AI has evolved in recent decades.

AI is commonly understood as the part of computer science that is able to handle complex problems with a large amount of data and relatively little theoretical input. It is a set of computations that are able to perceive, reason, and act. The two most widely used areas of AI in medicine are machine learning and deep learning.

Machine learning is defined as a set of computations that improve through experience: it is divided into supervised learning, where the data used is labeled by the observer, and unsupervised learning, where the data is not labeled (Niel and Bastard 2019). Two techniques frequently used in medical research since the 2000s and deriving from machine learning are random forests (comparable to decision trees) and artificial neural networks (ANN), organized with hidden layers with a number n of neurons per layer, where each neuron plays a particular role in a general reasoning process that has to transform an input (data) into an output. In the last decade, it is rather the techniques of community detection (clustering) that are gaining ground in research, in order to determine congruent groups of patients, symptoms, or treatments in specific situations (Yang and Bang 2019).

Deep learning derives from machine learning but requires less computational power since generally the number of neurons per layer of the neural network decreases over time. Deep learning is optimal for the analysis of temporal data and large databases (big data). In medicine, deep learning is therefore used, for example, for diagnosis based on images in radiology, pathology, and endoscopy (Liu et al. 2019; Campanella et al. 2019).

Along with classical AI, the past few decades have seen the concomitant emergence of Bayesian AI. Bayesian methods and the reasoning on which they are based are less known to the general public: yet Bayesian models in AI directly represent real-world entities and allow their cause-effect relationships to be investigated (Scutari and Denis 2015).

4.3 Applications of AI in Medicine

The medical world is primarily interested in AI in four of its fields of application: monitoring, prediction, diagnosis, and personalized medicine. AI, on the other hand, is only one of the areas of "augmented medicine." For more details on the applications of AI in medicine, the reader is referred to detailed and recent works (Briganti and Le Moine 2020). All these domains of application have important repercussions on how we imagine and manage healthcare delivery and will therefore greatly impact how healthcare institutions work.

4.3.1 Monitoring

Patient monitoring is a relatively simple but heavy task for the medical and paramedical professions and having great added value in clinical settings. Modern medical technologies allow the emergence of continuous medical monitoring, with the aim of recording certain parameters of the individual and being able to alert the caregiver or relatives when a value considered to be abnormal is recorded. Three medical conditions currently benefit from FDA-approved technologies for continuous medical monitoring: arrhythmia, diabetes, and epilepsy.

The detection of an abnormal heart rhythm by connected device was the first FDA-approved medical device case with AI. Approved devices allow recording of ECGs with an algorithm to recognize, for example, atrial fibrillation (Turakhia et al. 2019). These technologies have great added value in the elderly and/or isolated at risk of developing arrhythmias without anyone being able to alert the emergency services.

Subcutaneous devices connected to an app are able to continuously record blood sugar levels (Christiansen et al. 2017) and report low or high blood sugar levels. By adding AI, these devices are able to predict these adverse events by getting to know the patient. These technologies have a significant impact on a pathology such as diabetes which strongly affects the social life of citizens and which, in addition to improving the quality of life by reducing adverse events, also reduces the stigma associated with these adverse events.

Epilepsy is another example of a disease that strongly affects the quality of life and stigmatizes those who have it, especially children of school age. Connected devices can measure the body's electrical activity to detect acute episodes (e.g., absences) and notify the caregiver, loved one, but also the teacher with the child in their class; in the future, this technology will also be able to predict epileptic episodes (Regalia et al. 2019).

4.3.2 Prediction and Diagnosis

Structured or unstructured information encoded in electronic medical records (EHR) are invaluable for developing models capable of predicting the occurrence of certain disorders: this is the case of cardiovascular risk, renal failure, and digestive disorders (Briganti and Le Moine 2020). The only obstacle encountered for the development of these models is the paucity of solutions for the exploitation of unstructured data, currently constituting a greater proportion of the content in EHR. One potential solution to restructuring this data is another AI technique, natural language processing (NLP), which automatically analyzes sentences in medical reports to derive structured information. NLP is relatively new in medicine and is enabled in particular by the international coding language SNOMED CT.

Diagnostic AI also extends into a number of areas and is deeply embedded in Bayesian causal reasoning. Thus, it is possible to infer a diagnosis from databases made up of symptoms, parameters (as in the case of ECGs for arrhythmias), medical imaging, endoscopy, and histopathology sections: these last three specialties are not surprisingly the more revolutionized by the wave of new technologies.

4.3.3 Personalized Medicine

AI is particularly effective for high-dimensional data (the number of variables is much greater than that of patients), as in genetics (one patient for thousands of genes) and for temporal data (endoscopy, imaging). This strongly contributes to its innovative and disruptive side since these data were difficult to analyze before. This has resulted in the development of personalized medicine, which is enabled by the collection and analysis of personal data on smartphones. For example, we can denote the clinical trial initiatives relocated on smartphones, as well as applications dedicated to personal parameters (somatic and related to mental health).

4.4 Present and Future Challenges of Integrating AI in Healthcare Delivery

Monitoring technologies, as well as those for prediction and diagnosis, have and will have important repercussions on the way care is provided. For example, reference hospitals for the technologies mentioned in this work have all revised their care process according to the working time saved in the absence of administrative overload and being able to solve easier cases while leaving more complicated ones to experienced physicians, while other institutions delegate part of the diagnostics in imaging or pathological anatomy to the software itself, with subsequent validation by the doctor. Others outsource history taking at home when possible, through applications that automatically provide questions as they might have been asked by a clinician. The field of reinventing hospital care with smart technologies is so vast that it has quickly become a fertile research field in medical management.

Even if initially interested in monitoring in the context of diseases, a larger part of the medical technology industry quickly became interested in the concept of "quantified self," that is to say the measurement of repeated individual parameters without a medical reason: for example, the quantification of physical exercise, diet, and weight. The reason is simple: the quantified self allows for greater market capture because more people can benefit from it, so the data collection there is exponentially greater and several different types of data are collected. The quantified self, however, introduces a significant bias in the data: many more young people will adopt connected devices, which has the effect of “distorting” the vision of a “healthy” individual. This is all the more important as entire states are beginning to enter into agreements for the mass distribution of connected devices to improve the hygiene of their citizens’ lives.

Several challenges relate to diagnostic AI. The first and perhaps most important is the replication crisis of studies aimed at showing the effectiveness of AI in making diagnoses: a meta-analysis (Liu et al. 2019) carried out on the literature shows that most of the results from studies in AI (other than those technologies validated by the FDA) do not have an appropriate design and do not replicate in other source populations: they cannot therefore be translated into clinical practice unless additional studies of primary replication, absent in most cases. To resolve the replication crisis, an obvious path is that of “open science”: making public the methods and data leading to the development of the models at hand.

Second, the models developed so far seem to perform too well on training and testing data (i.e., the data that initially feeds the AI so that it can improve) and poorly perform on data from other source populations: this phenomenon is defined as overfitting. Resolving overfitting requires a great deal of effort, since it is only detected after the model has been adopted by a healthcare institution. To resolve overfitting, it is necessary either to recalibrate the models once adopted on the basis of the target population or to develop models from the outset via larger and more diverse populations: this is difficult for companies developing medical technologies because partnerships with hospitals are extremely rare. New partnerships between hospitals and technology companies are therefore needed to develop better diagnostic models.

Third, most studies of diagnostic AI compare its performance to that of physicians: this is not surprising, since companies pushing medical technologies need to demonstrate their effectiveness. However, this does contribute to the resistance of the medical profession against AI, already strong in view of the absence of an ethical, legal framework and the security concerns associated with the technologies. Also, these studies miss the real wish for doctors, patients, and healthcare institutions, that of offering (and receiving) better quality care: in the next decade, we must therefore observe the emergence of studies, combining the two forces to improve the quality of care. Indeed, caregivers are irreplaceable in the care process for reasons that go beyond the simple human guarantee, one of the only principles emerging in the legal- ethical chasm linked to AI and giving the doctor a role of supervisor of the AI.

Regarding personalized medicine, the biggest concern remains that of data security: in fact, most of the time, the data remains on the servers supporting the given application, which is problematic.

We must also consider the capital importance of educating physicians and future physicians in new technologies, so that they are able to use them, co- develop them, and evaluate them (in the same way as the review by peers carried out in the scientific publication process). For this, courageous initiatives are needed at an international level to allow the emergence of common and effective educational platforms in AI.

4.5 Conclusion

AI must be seen by technology companies as well as caregivers and healthcare institutions as a tool to improve the quality of care. It is necessary to improve the design of development studies, models, and testing their effectiveness so that their implementation is as secure as possible. It is also necessary to study the combined strengths of physicians and RNs before setting up an implementation at the level of healthcare institutions. To do this, we have to build bridges between the industrial and healthcare sectors.

References

Briganti G, Le Moine O. Artificial intelligence in medicine: today and tomorrow. Front Med. 2020;7:27.

Campanella G, Hanna MG, Geneslaw L, Miraflor A, Silva VWK, Busam KJ, et al. Clinical-grade computational pathology using weakly supervised deep learning on whole slide images. Nat Med. 2019;25(8):1301–9.

Christiansen MP, Garg SK, Brazg R, Bode BW, Bailey TS, Slover RH, et al. Accuracy of a fourth-generation subcutaneous continuous glucose sensor. Diab Technol Therap. 2017;19(8):446–56.

Liu X, Faes L, Kale AU, Wagner SK, Fu DJ, Bruynseels A, et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. Lancet Digital Health. 2019;1(6):e271–97.

Niel O, Bastard P. Artificial intelligence in nephrology: core concepts, clinical applications, and perspectives. Am J Kidney Dis. 2019;74(6):803–10.

Regalia G, Onorati F, Lai M, Caborni C, Picard RW. Multimodal wrist-worn devices for seizure detection and advancing research: focus on the Empatica wristbands. Epilepsy Res. 2019;153: 79–82.

Scutari M, Denis JB. Bayesian networks: with examples in R; 2015. Available from: https://www.crcpress.com/Bayesian-Networks-With-Examples-in-R/Scutari-Denis/p/book/9781482225587.

Turakhia MP, Desai M, Hedlin H, Rajmane A, Talati N, Ferris T, et al. Rationale and design of a large-scale, app-based study to identify cardiac arrhythmias using a smartwatch: The Apple Heart Study. Am Heart J. 2019;207:66–75.

Turing AM. Computing machinery and intelligence. Mind. 1950;59(236):433.

Yang YJ, Bang CS. Application of artificial intelligence in gastroenterology. World J Gastroenterol. 2019;25(14):1666–83.