

# Artificial Intelligence: Its future in the health sector and its role for medical education

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## ABSTRACT

The – possibly – imminent AI revolution will, to a great extent, affect the education and training for all knowledge-working professions, and therefore must be considered an important aspect also of CME. This paper reviews some of the misconceptions about AI technology, then turns to point out possible applications of AI in the medical domain and then addresses the question what this will mean for (continuing) medical education.

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## Introduction

No field of digital technology has recently received more attention by the general public than Artificial Intelligence AI. Spectacular results are becoming more and more visible, ranging from (nearly) autonomously driving cars to (almost) natural voices coming from little gadgets built in our new smart home. Since most intelligent humans exhibit the capability of learning, self-reflection and self-improvement, we therefore tend to project these capabilities also on technical AI systems. Therefore, almost every person who is not an expert in digital technology has the impression that the current limits of AI technology, culminating in the innocent words “nearly” and “almost” in the above classification are only temporary limits that may be overcome in a few years, at most. After which, to express this clearly, we would then have a “full” AI that could surpass human intelligence by an yet undefined factor. Clearly, this would be a disruptive challenge to every field of knowledge work (= a domain) that involves information processing and decision making, and thus also the health domain.

Driven by the fact that this perspective has worried many researchers, Russell, Dewey and Tegmark published a paper in 2015 outlining research priorities for AI development, expressing not only possible benefits but also concerns about the unwanted aspects of AI [1]. The corresponding Open Letter to the AI research community was up to now signed by more than 8.000 renowned thinkers, among them scientific visionaries like Stephen Hawking and technological visionaries like Elon Musk [2].

## Some Misconceptions on AI

The Open Letter was initiated by the expectation that a (dangerously) full AI is just around the corner – which, as pointed out above, results from projecting human capabilities on a non-human system. It is only one of the various misconceptions on AI.

## Is AI Something New?

No, it is not. Most of the current paradigms are several decades old, extensive research on AI systems has been going on since its kick-off at the famous 1956 Dartmouth Summer Research Project on Artificial Intelligence, a summer school organised by John McCarthy and Claude Shannon. Rule-Based Systems as well as Neural Networks have been around for 50 years, but they were slow and clumsy to use. Until a few years ago AI systems therefore tended to be isolated lab projects with highly customised computer code.

The first medical AI system MYCIN has been developed in 1972 by Ted Shortliffe [3]. MYCIN comprised a rule-based system that presented suggestions for antibiotic treatment of human patients. Based on lab parameters and involving approximately 450 quite complex rules, it was able to give precise advice to medical practitioners. MYCIN was shown to be as skilled as a medical expert in deriving meaningful suggestions.

## Is There Such a Thing as “The” Artificial Intelligence?

No, it is not. “Intelligence“ comes in completely different flavours, of which four distinct types must be mentioned, each of them represented also in modern computer science by particular approaches:

- (1) Derivation of rules from the analysis of large amounts of data, representing the cognitive task of model building from experience.
- (2) Rule-Based Systems, or semantic technologies that unveil knowledge hidden in collections of existing facts and relations.
- (3) Pattern recognition and classification based on large amounts of training data, but without explicit rules.
- (4) Orchestration of intelligent constituents, possibly also including other specialised AI instances and *humans in the loop*.

It is important to realise that the current very rapid development of AI systems is mainly due to the third type of intelligence mentioned above, e.g. advances in pattern recognition with the aid of so called Artificial Neural Networks (ANNs), in which the behaviour of nervous cells within the human brain is mimicked in software. There are many different types of ANNs. Some of them consist of different layers, where each layer can be seen as a container for a number of connected neurons called units. In Deep Learning the ANNs consist of an input layer, which reads the vectorised input data, various hidden layers and an output layer. Each node has a weight. If the weight exceeds the value the neuron is activated and sends data to the connected neurons of the next layer. The neurons can be connected in different ways, depending on the network type. In Feed-Forward networks, for example the units are connected from one layer to the next, whereas Recurrent Neural Networks allow feedback connections from higher layers to lower ones. Feedback connections are commonly necessary to model temporal problems, like sequence processing and natural language processing. Nowadays one of the most common tasks of neural networks is the classification of pictures.

### Why Has Neural Network Based AI Made so Much Progress in Recent Years?

Neural networks require lots of linear algebra calculations, where vectors are multiplied by matrices and added to other vectors. On a more basic level: The

calculational step used most often in NN is an operation where a number is multiplied by a second number and the result added to a third number. Moreover, this can be done using integer numbers, not the entity known as floating point numbers in computer science. It now turns out that there is another field of technology where exactly this type of calculations is needed to a great extent: Computer graphics, where a main task is the projection from a (virtual) three-dimensional world on a (real) two-dimensional computer screen. While a scientist could very well wait some seconds for the appearance of a calculated picture on his screen, there is a target group that was (and still is) in huge demand of faster and ever faster multiply-add operations: Gamers, computer game aficionados, have been driving the industrial development of ever faster Graphics Processing Units or GPUs for about three decades. The top models of these chips nowadays exhibit more than 10.000 calculational pipelines that may operate independently on the data, which results in a huge throughput.

Furthermore, industrial driving forces have published open-source frameworks, i.e. freely available libraries of computer code, that make it much easier to write software for NN. Instead of highly customised computer code, modern NN software is easily portable and thus has achieved a democratisation of NN coding. As one of the most prominent examples one has to mention the TensorFlow framework that has been released by the Google Brain Project in 2015 [4]. We will see below how this democratisation of AI software may have a big influence on the future of the health sector.

### Why Can It Be Dangerous to Rely on the Results of AN Classifications?

ANN-type AI are intransparent black box systems: One sees the input, one sees the output – but does not know about the rules connecting them. To express this in pedagogical terms: Machine Learning by a NN is a purely behaviouristic learning, a well-trained NN receives an input and produces an output. If one does not take additional measures, it is hardly possible to understand *why* a certain output was generated.

The particular example of the Wolf vs. Husky classifier has made science history: A NN-type AI was trained with a large number of images depicting either Wolves or Huskies. While according to state-of-the-art knowledge, it should then have been able to classify new pictures accordingly. However, the trained system was unable to recognise a Husky on a snowpatch. Deeper analysis revealed that the training of the NN-

type AI has resulted in a system that identified any animal on snow as a wolf, and everything else as a Husky [5].

Interesting consequences of this deficiency are on one hand that one may produce completely weird and meaningless images that are nevertheless (falsely) classified as proper input. To be mentioned on the other hand, but out of scope for this article, are possibilities to create so-called deep fakes, e.g. video clips showing people speaking words they never used, or acting as they never did.

## Discussion: Possible Future Fields of AI in Medicine

### Diagnostics at the Dialog Level

A key factor of successful medical treatment and most challenging for the health knowledge worker is the proper diagnosis. Symptoms as well as communicative skills can vary fundamentally between patients, anamnesis therefore is often a time-consuming and expensive process even for experienced physicians. Maintaining the communicative touch and establishing a bridge of trust to the patient is nevertheless an important factor. Studies in medical psychology showed that simply listening to patients made them significantly more satisfied [6].

AI applications can make significant contributions here. This starts with rather unspecific voice assistants taking the initial telephone call from patients and scheduling their visit [7]. An intermediate step, and technically even simpler, is an application leading the patient through structured questionnaires to acquire as much patient data by dialogue as possible [8]. A simple test, however, shows that so far these questionnaire applications are much too formal and inhuman to contribute to the desired bridge of trust. In other areas of human-machine interaction Chatbots and *conversational user interfaces* have been established to carry out more natural dialogues [9]. So far this has not been implemented in the medical sector. Two of us (K.G and P.H.) are currently members of a research consortium exploring such informal pathways.

At the top level of this application field for AI, but still a few years in the future, we will find applications that can indeed help the physician to find a proper diagnosis by using anamnesis data to reduce the number of possible conditions. It is nevertheless clear that a proper diagnosis also requires objective measured data. As we will see below, this might also involve specialised AI subsystems. A full AI-based diagnostic assistant therefore must be able to orchestrate different

inputs – and finally present a weighted opinion to a human decider.

### Diagnostics at the Data Level

Traditionally, medical science is *evidence-based* [10] – but what is the evidence in case of more and more raw data being available for a complete picture of the patient? It has been known for a long time that an overload of the human mind with input data severely cripples its abilities to make good decisions [11,12]. Therefore, the above question has become more and more important, signalling a transformation of medical science from an evidence based to a more *data driven* domain of knowledge. We therefore expect the earliest and most obvious application of AI technology in medical science in this field, helping the physician to deal with large volumes of data.

The main task of a data diagnostic AI therefore is the reduction of input bandwidth to the physician, enabling him to achieve a clearer picture – but in no case to take the decision (=diagnosis) away from him. Apart from the MYCIN AI mentioned already, we point out only two recent successful applications, but will return to a special aspect of *data driven medicine* in subsection D.

Software is much better suited to discover small non-random differences in brightness in a large collection of pixels than the human eye. Therefore, it was clear for several years that there must exist the possibility to employ this ability for the analysis of tomography data. A 2019 paper has shown that indeed an ANN-type AI is not inferior to the average radiologist in detecting female breast cancer [13]. Another system was able to detect acute neurological conditions in human patients 150 times faster than radiologists [14].

### Drug Design

Another field, where AI can be helpful is the development of drugs, usually an expensive process. An ANN-type AI trained with data on existing drugs may search through thousands of possible molecules to find targets or drug candidates [15]. Such an application clearly does not replace laboratory work, but significantly reduces the number of possible candidates needing deeper investigation.

While this may be seen as a top-down approach mimicking the experienced human researcher, the opposite direction of investigation has become an exciting new possibility in 2020. For more than two decades, research teams around the globe have been

competing in the biannual challenge *Critical Assessment of Protein Structure Prediction CASP* to predict the folding structure of amino acid sequences. The 2020 challenge has been won with a huge margin by a neural network type AI called AlphaFold2 from DeepMind [16]. The commercial enterprise DeepMind, now a subsidiary of Google, had become famous among computer scientists already in 2016 for its program AlphaGo that achieved a smashing victory over the world's best human Go player.

Today, the source code of AlphaFold2 and a huge library of protein structures are freely available [17]. Consequently, every computer literate person can participate in the analysis of protein structures, contributing to an understanding of life processes – or in the design of new proteins. We deem it highly necessary to discuss the scientific as well as ethical consequences of this development – as in other domains of knowledge, the democratisation of knowledge can have a negative effect also in the health sector.

Moreover, the tremendous success of AlphaFold2 is a good example for the ambivalence of AI in research: Even though the AlphaFold2 ANN may predict the three-dimensional structure of a particular amino acid sequence with great precision, it does not tell us *why* this structure arises. Of course, the rules behind the folding process are clear – they are just the rules of atomic physics. Ab initio calculations of protein folding therefore are possible – but require really huge amounts of supercomputer time, and are beyond our capabilities for complicated proteins.

Finally, we also indicate the possibility to use an AI system to predict (and also warn the physician of) unwanted (or at least unexpected) interaction of different drugs.

### **Precision Medicine**

In conventional medical approaches one generalises over signs and symptoms to find a treatment, dealing with the patients equally if they share the same symptoms. Decisions about prevention and treatment methods are made by combining the best available external clinical evidence and internal clinical expertise, leading to what a data scientist would call *clinical decision pathways*. Although this practice has been tremendously successful, due to the inherent generalisation, we may call it an “one size fits them all” approach [10].

In contrast, outside the health sector, data-driven technologies have led to an industrial revolution commonly called “industry 4.0”. Today, many types and in the near future almost any type of goods can be produced rationally with a lot size of one. Also, advanced

biosensors are able to provide important real-time data on the human body. Implementing these technologies in the health sector would mean that every patient can be treated differently, thereby deviating from the established practice of clinical decision pathways. Clearly, such advanced methods are entering the health sector even without AI technology, for example as 3D printing of implants [18] or as innovative antibiotics sensor [19]. It is easily envisaged that this may be achieved also in the production of pharmaceuticals, where one may produce customised mixtures of well-established substances, tailored to the needs of an individual patient. Moreover, especially in view of the recent progress in mRNA technologies and gene sequencing, we see the real possibility of creating medication tailored to individual strains of bacteria or viruses, or to individual tumours.

Now add to this the capabilities of a specialised AI to process and analyse large genomic data sets even in clinical practice [20], and also add the progress in medical imagery and in our understanding of molecular biology outlined above. This will lead to complex healthcare units that are tailored much more to the needs of the patient individually and personally than any evidence-based medicine of today. They will be able to identify the molecular events accountable for the condition of the patient and to apply a highly individual and adaptive treatment based on history, current biochemical state and genome of the person to be cured [21]. We may call this *AI controlled data-driven precision medicine*.

### **Conclusion: What Does This Mean for Medical Education?**

The digital healthcare transformation is unavoidable for an effective and professional future medicine. However, already today studies like the survey carried out by the European Health Parliament initiative [22] clearly indicate that the digital competence of physicians could be improved. Sadly this has not changed for more than a decade [23,24], we constitute a severe lag that has become a dramatic problem: Most health professionals have no or insufficient training in digital health technologies, thereby affecting the ability to follow the latest developments outlined above. Since the speed of the changes is ever increasing, the lag becomes more and more prominent.

Another consequence should not be forgotten, which arises because patients are increasingly demanding an improvement of quality in healthcare. Mistakes are not accepted, the attorney is literally always present as a third person in patient–physician relationships. Patients want to be autonomous and manage their health more



independently than ever before, democratisation of knowledge does not stop at the code level. Consequently, they also demand an *assisting* health professional, who guides them through the use of digital assistance [22].

The inclusion of advanced digital skills in medical education therefore is an absolute and urgent necessity. Because of the lag mentioned above, this must affect also CME to a significant extent, where we desperately need to provide educational content for the *digital upskilling* of health professionals. The content for this upskilling process follows from the rather technical analysis in section 3. We were able to identify four fields, with increasing complexity:

- General skills like data protection, problem solving with digital tools and legal considerations in using data and digital tools.
- Digital communication and cooperation with laypersons as well as within a data-driven medicine.
- Data literacy and data analytics skills to initiate, to carry out and to evaluate the input bandwidth reduction explained in subsection 3.B.
- Decision support, as a meta skill enabling the orchestration of interdisciplinary contributors, human as well as AI based.

It is important to realise that this upcoming opening of medical education for interdisciplinary content is hindered by an *ontological mismatch* that has to be overcome. Computer science and medicine use different vocabularies, or more precisely, the two domains use different ontologies.

A very simple example demonstrates this in the scope of the current journal:

The effort to translate these vocabularies back-and-forth is non-trivial and still an ongoing research effort [25]. In part, this may be attributed to the complexity of the standard medical terminology – which, to be honest, by a computer scientist could also be described as full of semantic ambiguity and logical uncleanliness.

A profound consequence of this ontological mismatch is that a new medical profession must (and will) arise very rapidly. We predict a bright future for *data scientists* with application knowledge of the medical and health care domain. Data science, focused on the translational competencies between the world of computer science and an application domain, has already established itself in various other domains. Corresponding study programmes have popped up at many universities, and a huge demand for continuing education has already been registered.

One aspect of the *data-driven precision medicine* goes beyond all technical progress in the sense that it

	<i>digitisation</i> means	<i>digitalisation</i> means
In computer science,	creating a sequence of time-discrete integer numbers from a continuously changing quantity	shifting logic, processes and data from the “analog” world onto digital computers
In medicine,	shifting logic, processes and data from the “analog” world onto digital computers	treating human heart conditions with Digitalis glycosides

affects the nature of medical work. Scientists from different domains, i.e. physicians, biologists, computer scientists must work together to establish an infrastructure for storing, analysing, integrating and visualising large amounts of biological data – offline as well as on the spot in any given medical emergency situation. The capability to manage such interdisciplinary teams, and to orchestrate different “opinions”, be it from fellow scientists or from specialised non-full AI subsystems must also be part of medical education.

Finally, we have to mention another aspect of AI relevant for context of CME that has not been mentioned in section 3. AI technologies together with decade-long experience in E-learning and data collection on learning have resulted in systems called *Adaptive Learning Environments ALE* [26]. In these and based on a few tests as well as the real-time analysis of the learning behaviour, an AI provides a highly individualised learning content to any person. The time of the “one size fits them all” is over also for continuing education.

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