WARWICK

THE UNIVERSITY OF WARWICK

warwick.ac.uk/lib-publications

Artificial Intelligence in Cardiology: Applications, Benefits & Challenges

Panos Constantinides
Warwick Business School
University of Warwick
Coventry
CV4 7AL
Panos.constantinides@wbs.ac.uk

David A. Fitzmaurice
Unit of Academic Primary Care
Warwick Medical School
University of Warwick
Coventry
CV4 7AL
d.fitzmaurice@warwick.ac.uk

The introduction of such digital technologies as robotic implants, home monitoring devices, wearable sensors and mobile apps in healthcare have produced significant amounts of data, which need to be interpreted and operationalized by physicians and health care systems across disparate fields (Free et al 2013). Most often, such technologies are implemented at the patient level, with patients becoming their own producers and consumers of personal data, something which leads to them demanding more personalized care (Kirchhof et al 2014).

This digital transformation has led to a move away from a "top-down" data management strategy, "which entailed either manual entry of data with its inherent limitations of accuracy and completeness, followed by data analysis with relatively basic statistical tools… and often without definitive answers to the clinical questions posited" (Chang 2016, p. 91). We are now in an era of a "bottom-up" data management strategy that involves real-time data extraction from various sources (including apps, wearables, hospital systems etc), transformation of that data into a uniform format, and loading of the data into an analytical system for final analysis (Chang 2016).

All this data, however, poses a serious challenge for physicians: the challenge of limitless choice. According to a white paper by Stanford Medicine (2017, p.4), "the sheer volume of health care data is growing at an astronomical rate: 153 exabytes (one exabyte = one billion gigabytes) were produced in 2013 and an estimated 2,314 exabytes will be produced in 2020, translating to an overall rate of increase at least 48 percent annually." With so much data on the daily decisions of millions of patients about their physical activity, dietary intake, medication adherence, and self-monitoring (e.g., blood pressure, weight), to name but a few, physicians are at a loss as to which data to focus on, to search for what, and for which desired outcome?

Increased data storage, high computing power and exponential learning capabilities together enable computers to learn much faster than humans and address the challenge of limitless choice. Artificial intelligence (AI) is the development of intelligent systems, capable of taking "the best possible action in a given situation" (Future Advocacy 2018, p.8). To develop such intelligent systems machine learning algorithms are required to enable dynamic learning capabilities in relation to changing conditions. Machine learning takes many different forms and is associated with many different schools of thought including philosophy, psychology, and logic (with learning algorithms based on inverse deduction), neuroscience and physics (with learning algorithms based on backpropagation), genetics and evolutionary biology (with learning algorithms based on genetic programming), statistics (with learning algorithms based on Bayesian inference) and mathematical optimization (with learning algorithms based on support vector machine) (Domingos 2015). Each of these schools of thought can apply their learning algorithms for different problems. However, none of these algorithms are perfect in solving all possible problems and none have reached a level of "superintelligence" (Bostrom 2016) that will be able to predict, diagnose and give recommendations for treating complex medical conditions. Still, when competently combined – and provided they are fed the appropriate data to learn from – these algorithms can generate what has been called a "master algorithm", which could potentially solve much more complex problems that humans can (Domingos 2015).

Machine learning can positively impact cardiovascular disease prediction and diagnosis by developing algorithms that can model representations of data, much faster and more efficiently than physicians can. For example, currently, a physician who wishes to predict the readmission of a patient with congestive heart failure needs to screen a large but unstructured electronic health record (EHR) dataset, which includes variables such as the International Classification of Diseases (ICD) billing codes, medication prescriptions, laboratory values,

physiological measurements, imaging studies, and encounter notes. Such a dataset makes it extremely difficult to decide a priori which variables should be included in a predictive model and what type of methods should be applied in the model itself (Johnson et al 2018).

Such predictive models can be produced with "supervised learning" algorithms that require a dataset with predictor variables and labeled outcomes (Johnson et al 2018). For example, a recent study investigated the predictive value of a machine-learning algorithm that "incorporates speckle-tracking echocardiographic data for automated discrimination of hypertrophic cardiomyopathy (HCM) from physiological hypertrophy seen in athletes" (Narula et al 2016, p. 2287). The study's results showed a positive impact of machine-learning algorithms in assisting in "the discrimination of physiological versus pathological patterns of hypertrophic remodelling... for automated interpretation of echocardiographic images, which may help novice readers with limited experience" (Narula et al 2016, p. 2287).

A separate set of algorithms used in cardiology are called "unsupervised learning" algorithms which focus on discovering hidden structures in a dataset by exploring relationships between different variables (Johnson et al 2018). For example, one study investigated the use of such learning algorithms to identify temporal relations among events in EHR; these temporal relations were then examined to assess whether they improved model performance in predicting initial diagnosis of heart failure (Choi et al 2016). Thus, results from unsupervised learning algorithms can feed into supervised learning algorithms for predictive modelling.

A third set of algorithms are reinforcement learning algorithms, which "learn behavior through trial and error given only input data and an outcome to optimize" (Johnson et al 2018, p. 2677). Designing dynamic treatment regimes such as, managing the rates of reintubation and regulating physiological stability in intensive care units is one area where the application of reinforcement learning algorithms may hold great potential (Weng et al 2017).

Evidently, the potential benefits of AI in cardiology are enormous. However, such benefits are not without challenges. First, there are clear benefits for improving work productivity. There are currently fewer physicians to care for an ever-increasing aging population (WHO 2016). AI can support, rather than replace physicians, generating time- and cost-saving benefits for them and their patients and enabling more compassionate and thorough interactions. However, as more tasks become automated, there are possibilities that fewer physicians will be required to work or that fewer will do so on a full-time basis, since many tasks could be delivered through platforms by part-time, freelancer physicians. This may impact the relationship between patients, physicians and administrative staff in healthcare systems (see Taylor et al 2016).

Second, as discussed earlier, machine learning algorithms can scan through larger volumes of health data enabling faster identification of predictive, diagnostic, as well as treatment options for different cardiovascular diseases. This feeds into the current demand for more personalized care. At the same time, however, many patients now express the need for more transparency about the types of data shared, who it is used by and for what purpose. With the General Data Protection Regulation (GDPR) now in full force across Europe, there are important implications for the security and privacy of data that machine learning algorithms need to keep evolving. The recent scandal involving Google DeepMind and the Royal Free London NHS Foundation Trust, which led to the transfer of identifiable patient records across the entire Trust without explicit consent (Powles and Hodson 2017), is a case to be avoided. The architecture of the digital infrastructure supporting AI and machine learning across different localities and between applications and platforms needs to be carefully designed (see Constantinides et al 2018), in order to maintain the security and privacy of healthcare data.

Beyond the issue of seeking consent before any access and use of data, there also are issues around the transparency of algorithmic objectives and outcomes (how do algorithms

work and to what end) and of the accountability for the potential misuse of data. As a recent report has pointed out, informed consent by all possible patients may not always be possible because of the way data are shared across platforms and for different purposes; algorithmic transparency, even though sought for, may be difficult to achieve because of the dynamic learning and evolution of algorithms; and accountability for data use may raise challenging ethical questions if in the end such data use leads to improved patient outcomes (Future Advocacy 2018). What matters the most is the *clinical efficacy* of algorithms and their use of data (Future Advocacy 2018).

Finally, although both AI and physicians can make errors in their clinical judgment, either because of not having seen a particular case before or because of bad training, in combining the two—AI and human expertise—the number of clinical errors can be reduced. In this context, there are opportunities for revisiting the training of individual physicians, as well as multi-disciplinary teams to learn to interact with AI. We believe this is of paramount importance and new policies should be developed towards an improved and enhanced training of physicians, which will also enable more effective and efficient clinical judgment.

In conclusion, it is important that we avoid placing "exaggerated hope" on the potential impact of AI, but also not to fall victims of "exaggerated fear" because we cannot identify with the technology (Bryson et al 2011). "The real dangers of AI are no different from those of other artifacts in our culture: from factories to advertising, weapons to political systems. The danger of these systems is the potential for misuse, either through carelessness or malevolence, by the people who control them" (Bryson et al 2011, p. 1641). The possibilities of improving clinical efficacy and healthcare outcomes through AI are enormous, but we need to be aware of the associated risks and challenges and try to minimize those through multidisciplinary research, and renewed legal and ethical policies**.**

References

Bostrom, N. 2016. *Superintelligence: Paths, Dangers and Strategies*. OUP Oxford

Bryson, J.J., Kime, P.P. and Zürich, C., 2011, July. Just an artifact: why machines are perceived as moral agents. In *IJCAI proceedings-International joint conference on artificial intelligence.* 22(1), pp. 1641-1646.

Choi, E., Schuetz, A., Stewart, W.F. and Sun, J., 2016. Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association*, *24*(2), pp.361-370.

Constantinides, P., Henfridsson, O., and Parker, G.G. 2018. Platforms and Infrastructures in the Digital Age. *Information Systems Research*, Articles in Advance, pp. 1-20.

Domingos, P., 2015. *The master algorithm: How the quest for the ultimate learning machine will remake our world*. Basic Books.

Free, C., Phillips, G., Watson, L., Galli, L., Felix, L., Edwards, P., Patel, V. and Haines, A., 2013. The effectiveness of mobile-health technologies to improve health care service delivery processes: a systematic review and meta-analysis. *PLoS medicine*, *10*(1), p.e1001363.

Future Advocacy. 2018. *Ethical, Social, and Political Challenges of Artificial Intelligence in Health.* Available at http://futureadvocacy.com/ai-think-tank/#ai-publications

Johnson, K.W., Soto, J.T., Glicksberg, B.S., Shameer, K., Miotto, R., Ali, M., Ashley, E., Dudley, J.T. 2018. Artificial Intelligence in Cardiology. *Journal of the American College of Cardiology,* 71(23), pp. 2668-2679

Kirchhof, P., Sipido, K.R., Cowie, M.R., Eschenhagen, T., Fox, K.A., and Katus, H., 2014. The continuum of personalized cardiovascular medicine: a position paper of the European Society of Cardiology. *European Heart Journal*, *35*(46), pp.3250-3257.

Narula, S., Shameer, K., Omar, A.M.S., Dudley, J.T. and Sengupta, P.P., 2016. Machine-learning algorithms to automate morphological and functional assessments in 2D echocardiography. *Journal of the American College of Cardiology*, *68*(21), pp.2287-2295.

Powles, J. and Hodson, H., 2017. Google DeepMind and healthcare in an age of algorithms. *Health and Technology*, *7*(4), pp.351-367.

Stanford Medicine (2017) *Health Trends Report: Harnessing the Power of Data in Health.* Stanford Medicine. Available at: https://med.stanford.edu/content/dam/sm/sm-news/documents/StanfordMedicineHealthTrendsWhitePaper2017.pdf

Taylor, M., Marsh, G., Nicol, D. and Broadbent, P. (2017) *Good work: The Taylor Review of Modern Working Practices*. RSA. Available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/627671/good-work-taylor-review-modern-workingpractices-rg.pdf

Weng, S.F., Reps, J., Kai, J., Garibaldi, J.M. and Qureshi, N., 2017. Can machine-learning improve cardiovascular risk prediction using routine clinical data?. *PloS one*, *12*(4).

WHO. 2016. *Global strategy on human resources for health: workforce 2030.* World Health Organization. Available at: http://www.who.int/hrh/resources/pub_globstrathrh-2030/en/