



■ EDITORIAL

Artificial intelligence, machine learning and the evolution of healthcare

A BRIGHT FUTURE OR CAUSE FOR CONCERN?

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First proposed by Professor John McCarthy at Dartmouth College in the summer of 1956,¹ Artificial Intelligence (AI) – human intelligence exhibited by machines – has occupied the lexicon of successive generations of computer scientists, science fiction fans, and medical researchers. The aim of countless careers has been to build intelligent machines that can interpret the world as humans do, understand language, and learn from real-world examples. In the early part of this century, two events coincided that transformed the field of AI. The advent of widely available Graphic Processing Units (GPUs) meant that parallel processing was faster, cheaper, and more powerful. At the same time, the era of ‘Big Data’ – images, text, bioinformatics, medical records, and financial transactions, among others – was moving firmly into the mainstream, along with almost limitless data storage. These factors led to a dramatic resurgence in interest in AI in both academic circles and industries outside traditional computer science. Once again, AI occupies the zeitgeist, and is poised to transform medicine at a basic science, clinical, healthcare management, and financial level.

Terminology surrounding these technologies continues to evolve and can be a source of confusion for non-computer scientists. AI is broadly classified as: general AI, machines that replicate human thought, emotion, and reason (and remain, for now, in the realm of science fiction); and narrow AI, technologies that can perform specific tasks as well as, or better than, humans. Machine learning (ML) is the study of computer algorithms that can learn complex relationships or patterns from empirical data and make accurate decisions.² Rather than coding specific sets of instructions to accomplish a task, the machine is ‘trained’ using large amounts of data and

algorithms that confer it the ability to learn how to perform the task. Unlike normal algorithms, it is the data that ‘tells’ the machine what the ‘good answer’ is, and learning occurs without explicit programming. ML problems can be classified as supervised learning or unsupervised learning.³ In a supervised machine learning algorithm, such as face recognition, the machine is shown several examples of ‘face’ or ‘non-face’ and the algorithm learns to predict whether an unseen image is a face or not. In unsupervised learning, the images shown to the machine are not labelled as ‘face’ or ‘non-face’.

Artificial Neural Networks (ANN)⁴ are one group of algorithms used for machine learning. While ANNs have existed for over 60 years, they fell out of favour during the 1990s and 2000s. In the last half-decade, ANNs have had a resurgence under a new name: deep artificial networks (or ‘Deep Learning’). ANNs are uniquely poised to take full advantage of the computational boost offered by GPUs, allowing them to crunch through data sets of enormous sizes. These range from computer vision tasks, such as image classification, object detection, face recognition, and optical character recognition (OCR), to natural language processing and even game-playing problems (from mastering simple Atari games to the recent AlphaGo victory against human grandmasters).⁵

ANNs work by constructing layers upon layers of simple processing units (often referred to as ‘neurons’), interconnected via many differentially weighted connections. ANNs are ‘trained’ by using backpropagation algorithms, essentially telling the machine how to alter the internal parameters that are used to compute the representation in each layer from the representation in the previous

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layer. As such, deep learning can be largely automatic once set in motion, learning intricate patterns from even high-dimensional raw data with little guidance⁶ and continuously improving.

How might machine learning and deep learning transform the current medical, and specifically the musculoskeletal, landscape? Search engines, spam filters, voice recognition software, and autonomous driving vehicles all depend on ML technologies and are now part of our daily lives, irrespective of the industry sector we occupy. Medicine seems particularly amenable to ML solutions and has been the focus of much interest in thriving technological economies, such as Silicon Valley.

The impact of AI can be considered in two main themes: first, extracting meaning from 'Big Data' in the research domain; and second, aiding clinicians in delivering care to patients.⁴ Using machine learning to extract information on treatment patterns and diagnoses has already been used in large digital databases of Electronic Health Records in the United Kingdom, and has enabled data-driven prediction of drug effects and interactions, identification of type 2 diabetes subgroups, and discovery of comorbidity clusters in autism spectrum disorders.⁷

In the United States, the IBM Watson Health cognitive computing system (IBM Corp., Armonk, New York) has used machine learning approaches to create a decision support system for physicians treating cancer patients, with the intention of improving diagnostic accuracy and reducing costs using large volumes of patient cases and over one million scholarly articles.

Within musculoskeletal medicine, machine learning and active shape modelling have proven influential in understanding biomechanics, orthopaedic implant design,⁸ bone tumour resection,⁹ prediction of progression of osteoarthritis based on anatomical shape assessment,^{10,11} and robotic surgery.¹² The analysis of complex physiological data via ML has been used in patients with spinal degenerative changes. Hayashi et al¹³ focused on gait analysis as a classification method to improve diagnostic accuracy in patients with multilevel spinal stenosis. By identifying gait characteristics of those with confirmed L4 or L5 radiculopathy, support vector machine (SVM) analysis was used to contrast patient motion with normal controls, allowing the development of a gait model to aid diagnosis. Similar work has been done with knee osteoarthritis, using ML to analyze massive data inputs from complex gait analysis to develop models that provide an estimation of the presence of disease.¹⁴ This engineering approach to a medical diagnostic problem is not isolated. In the lower limb, deformable joint contact models can be used to estimate loading conditions for cartilage-cartilage, implant-implant, human-orthotic, and foot-ground interactions. However, contact evaluations are often so expensive computationally that they can be prohibitive for simulations or optimizations requiring

thousands or even millions of contact evaluations. Eskenazi et al¹⁵ created an ANN-based contact model of the tibiofemoral joint using over 75 000 evaluations of a fine-grid elastic foundation (EF) contact model. The contact model computed contact forces and torques about 1000 times faster than a less accurate coarse grid EF contact model, removing an important computational bottleneck from musculoskeletal simulations incorporating deformable joint contact models. Similar approaches have been used in the analysis of preoperative images to help the surgeon define intraoperative bone resection levels in upper limb arthroplasty.¹⁶

Major improvements have been seen in all stages of the medical imaging pathway, from acquisition and reconstruction to analysis and interpretation. Segmentation, the division of digitized images into homogeneous partitions with respect to specific borders of regions of interest, is commonly used in the assessment of cartilage lesions. Traditionally performed manually, it is a difficult and time-consuming task with limited standardization. Fully automated ML analysis segmentation of hip, knee, and wrist cartilage MRI images¹⁷ have transformed this process and promise to bring automated segmentation into the mainstream of research and clinical practice. Complex, user-dependent image analysis techniques, such as ultrasound for developmental dysplasia of the hip, are particularly amenable to deep learning techniques.¹⁸ Individuals in geographically underserved or remote locations can be imaged by unskilled users, accurately diagnosed, and then directed to expert care at an earlier stage in the natural history of disease, potentially transforming outcomes.

As both the number of imaging studies and the number of images per study grows, radiology has become threatened by its own success: the workload of radiologists has increased dramatically, the number of radiologists is limited, and healthcare costs related to imaging continue to increase. With 40 million mammograms and 38 million MRI scans¹⁹ performed each year in the United States alone, and a trend to extend the indications for scans containing huge amounts of data,²⁰ ML has and will continue to have an important role to play in image interpretation. Several studies have suggested that the incorporation of computer-aided detection (CADE) systems into the diagnostic process can improve the performance of image interpretation by providing quantitative support for clinical decision-making, particularly the differentiation of malignant and benign tumours.²¹ CADE provides an effective way to reduce reading time, increase detection sensitivity, and improve diagnosis accuracy, thus supporting rather than usurping the need for specialist musculoskeletal radiologists. In the future, these technologies may progress from clinical decision support use to diagnostic decision-making (computer-aided diagnosis (CADx)). Currently, regulatory bodies such as the United States Food and Drug Administration do not

permit this, and it is unlikely that doctor's representative groups will embrace it enthusiastically either. However, as the accuracy and speed of the technology increases, clinicians should consider their role in repetitive manual tasks that involve pattern recognition and reporting, and understand how they can incorporate technology into their practice rather than resist it.

Not all commentators share unbridled enthusiasm for adoption of AI technologies. Professor Stephen Hawking, in 2016 declared AI to be "either the best, or the worst thing, ever to happen to humanity".²² The Royal Society, in an attempt to address public concern on the topic, commissioned a report on AI and specifically on Machine Learning. While championing the role of the technology in the management of Big Data, it also highlighted legitimate anxiety regarding the implications for governance of data, as well as the role of AI in automation, and subsequently the future of work and employment.²³ What does the future hold for clinicians and researchers as ML and DL technologies advance? Data will continue to increase and there can be little doubt that machine learning will be integral to interpretation and utilization. While it is easy to consider medicine a rational, evidence-based activity focused on well-defined conditions, in reality it is ambiguous and emphasizes relationships, advice, and reassurance. So, while medicine is much more than simply a diagnosis and treatment algorithm, machine learning looks set to both transform and complement the way we deliver care.

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Conflicts of Interest Statement

- Two authors (DG and RM) declare shares in or take a salary from an artificial intelligence company. None of the authors declare any conflicts of interest relevant to this paper.

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