Machine doctor (MD): The threat to human medical doctors' job security from deep learning

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Abstract

The age of "Big Data" has arrived with the liberation of large amounts of digital and analog data. The data can be used to help deep learning algorithms develop sophisticated layers of computerized "neural networks" that generate increasingly accurate clinical gestalt refined over numerous iterations. Combined with the simultaneously advancing clinical capabilities of computers, autonomous "machine doctors" might begin to offer financial and operational advantages over human medical care. However, taking up such a technology should be weighed against the machine's lack of ethical transparency and inability to improve health equity.

Introduction

The exponential growth of computing power has ushered in the era of "Big Data". This term took off around 2010 and is defined by voluminous data in the order of exabytes spanning various fields such as social media, blogs, videos, and images generated at an astounding hourly rate of petabytes.[1-3] Combined with the deep learning technology that has become vastly more powerful since 2006,[4] the replacement of human physicians by machine doctors (MDs) might be near.

Deep Learning—a more "organic" learning method for machines

Each refinement of a medical trainee's diagnostic or therapeutic plan improves some cognitive shortcomings. The iteratively selective reinforcement increases or decreases the weight of certain clinical features in the learner's mind. These key factors and their associated weights form the essence of a learner's neural network.[5]

This learning process has been adapted for machines. After being exposed to large amounts of unsorted data, the machine can derive an optimal solution by proposing several factors that are iteratively optimized in number, quality, weight, and layers to arrive at the most accurate solution possible.[5,6] For example, attempting to classify television by including objects with eight edges, a shiny screen, and a cord might inadvertently include computers. The subsequently corrected criteria might include the lack of a mouse or keyboard.

The accurate processing of non–traditional data such as images, speech patterns, sentiment, and languages can be combined with the data from clinical trials, electronic health records, social media, and personal devices to unlock the full power of deep learning algorithms.[7-21]

Current medical advances with deep learning

One medical application of deep learning comes from the "C-Path" algorithm. After training with several hundred pathology slides, the algorithm achieved an 89% accuracy in independently diagnosing breast cancer, and even determined novel prognostic features.[22]

Another algorithm, based on the GoogleNet Inception v3 Convoluted Neural Network (CNN), was trained with 129,450 images to determine "keratinocyte carcinomas versus benign seborrheic keratosis; and malignant melanomas versus benign nevi."[23] The CNN performed as well as 21 board–certified dermatologists in both tasks.[23]

The famous Watson supercomputer created by IBM is yet another example of machine learning. It has been used to assist the world–renowned oncologists at the Memorial Sloan Kettering Cancer Center by directly interpreting medical charts to understand a case and synthesizing the latest research to devise the optimal course of antineoplastic therapy.[24]

Deep learning in medicine leading to computerized clinicians

Experts have already suggested that machines will soon compete against pathologists and radiologists.[25,26] Even though no direct displacement has taken place yet, the famous Silicon Valley investor Vinod Khosla suspects that even Siri might provide a more accurate diagnosis than an average family doctor in 10–15 years.[27]

A clinician's job begins with holding an appropriate conversation for an accurate history. After successfully identifying the scene,[28] objects,[29,30] and human subject(s),[31] a MD can conceivably begin to elicit history with pre–determined questions. It can then transcribe the audio input for accurate analysis of denotations, as well as sociocultural or emotional connotations.[32-34] During the conversation, the machine can also adjust its questions around the human sentiments identified.[35-36] Even though machines cannot yet hold a conversation, current technologies already take orders in natural language forms [37] and might be conversational by the year 2020.[38]

Analysis of waveforms from the heart and lungs are well under way.[39-41] Although the engineering community has only recently moved beyond computer aids for palpation to automated palpation,[42-45] defining the appropriate pressure resistance to delineate a mass or elicit tenderness will be relatively straightforward.

Combining these ongoing advances in computerized clinical skills with the abstract reasoning abilities from deep learning algorithms might soon yield machines capable of autonomously proposing personalized diagnoses and management plans for each patient encounter. This will be the era of autonomous MDs.

The threat to human physicians' jobs—pros and cons

The MDs might threaten the job security of modern physicians who practice and train in an environment that de–emphasizes humanity in favour of routine biomedical diagnostic or therapeutic approaches.[46-50] Without the need for costly and prolonged training, the MD workforce can scale up much more cheaply and quickly;[51] unbridled by humans' lifestyle, location, or income preferences, MDs can aid underserved areas; freed from emotional and physiological fatigue, MDs' work hours can overshadow that of human doctors'. Patients can also

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receive the most up–to–date care, thanks to patch updates that can be automatically disseminated and installed.

The transition to robotic services has already started in surgery, where an independent suturing machine recently outperformed expert surgeons.[52] In medical laboratories also, automation has replaced postdoctoral researchers in routine tasks,[53] leading to a 30–fold decrease in operational cost.[54]

The disadvantages of adopting MDs, however, extend beyond losing control over the machines[55] or sacrificing therapeutic relationships with human doctors. The long–term cost saving requires large upfront investments into infrastructures. Whereas machines excel in repetitive tasks, they might flounder in novel situations without humans' reasoning ability.[56] At least in the near future, machines will also require help from human innovators to improve their algorithms,[27] leading Khosla to suggest that there is "still need to leverage the top 10 or 20% of doctors (at least for the next two decades) to help [the] bionic software get better at diagnosis."[27] The age–old concern around the lack of ethical principles guiding machines remains valid,[57] especially because MDs' opaque decision trees preclude the possibility to understand—let alone influence—the machines' ethical principles.[58] Such a technocratic advance also misses opportunities to tackle social determinants through proactive policies[59] or combat the perverse political and economic incentives that continuously drive health inequity.[60,61]

Conclusion

The collision between "Big Data" and deep learning might very well usher in MDs that are capable of forming personalized clinical decisions for routine diagnoses and therapeutic plans. Even though the practical advantages and the mechanistic framing of modern medicine make machine replacement of human doctors a financially and logistically attractive alternative, further developments ought to consider the machines' inaccessible ethical framework and inability to improve health equity.

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