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From computer-aided to computer-driven medical diagnosis

Science-fiction shows have made it a staple of futuristic civilization that the doctors are either completely replaced by machines, or are mostly reduced to waving around the patient a few tools which do all the work, from diagnosis to treatment. Recent advances in computer-aided diagnosis as well as in computer-aided surgery seem to indicate that we are catching up on the fiction, and that the place of the computer in future medicine might very well soon outgrow that of the human practician. What would be required for the machine diagnosis to truly replace the eye of the diagnostician as a "gold standard"? The question is double : when will the *technology* be ready for such a paradigm switch, and when will the *patients* be ready to entrust their lives into the metaphorical hands of the computers.

The idea that computers could realistically replace the human as primary diagnostician is not a new one. Studies on automated computer diagnostic started as early as the 1960s, although by the 1980s expectations had been lowered to the idea of computer-aided diagnosis (Doi, 2007). As the power of computation and the quality of image analysis algorithms increased, CAD really started to prove useful in radiological diagnosis since the 1990s, and it has since then become a common tool for radiologists. In such applications, the role of computers is twofold : first, the use of image analysis for enhancement, segmentation, registration, or other means of gathering all relevant informations from the image ; second, the use of machine learning to actually produce diagnostic from this information. The performance of the latter strongly depends on the accuracy of the former, yet it is that performance which really determine whether a machine diagnostic system is or isn't able to replace human diagnostic.

Indeed, the requirements for a machine learning system to replace the human should obviously be much stronger than the requirements to simply aid the diagnostician. These requirements have been defined in (Kononenko, 2001) as : "good performance, the ability to appropriately deal with missing data and with noisy data (errors in data), the transparency of diagnostic knowledge, the ability to explain decisions, and the ability of the algorithm to reduce the number of tests necessary to obtain reliable diagnosis." Most of these requirements – except for the good performance – are not so necessary in CAD. But in automated computer diagnostic, it is not only accuracy which is necessary : when dealing with patients, transparency and cost-effectiveness, both in terms of money and in terms of trouble for the patient, must be taken into account.

When talking about whether the *technology* will soon be ready for the paradigm switch, we have to take all those aspects into account. The accuracy is the easiest to measure. A sensible measure of the quality of a machine learning system against a human diagnostician would be : does the computer agree with a majority amongst a group of diagnosticians more often than any individual diagnostician in that group. Of course, when dealing with medical issues, the problem is slightly more complex, and the scope of any mistake should be taken into account. If the computer makes less mistakes than the humans, but each mistake results in the death of a patient, it is clear that human diagnostic should still be preferred. However, this requirement, and in more general terms all requirements which can be put on a quantitative scale, are nothing more than very complex optimisation problems, and it is highly probable that the technology will rise to the complexity. If the only question was : “at what point does computer diagnostic provide better results than the human eye”, the answer would probably be “very soon”. Recent advances in machine learning (Halpern 2011, Alkim 2012) show that we already are at the turning point. But the accuracy is only part of the problem.

The public, the patients, have a right to more than just a diagnostic and an estimation of the error. The main obstacle to the adoption of automated computer diagnosis, therefore, is that of accountability. A similar issue is right now appearing in completely different area of machine learning and artificial intelligence : the self-driving cars. The Google self-driving car has received a Nevada licence plate, and Nevada law has been changed to allow self-driving cars in traffic (with many restrictions) (BBC, 2012). There is few doubt that a switch to a self-driving model for personal cars would dramatically reduce the number of accidents on the road. However, no computer system is perfect, and mistakes on a self-driving car have the potential to be as fatal as mistakes in a medical system. It will therefore be interesting to follow the reaction of the public, as well as the changes in the rules, to this new development in technology. Will the public accept to release control of their vehicle to a computer? Who will be responsible in an accident? These questions are far from resolved, and it will most certainly take some time before the self-driving car hit the mainstream.

Accountability is important. When something goes wrong, people have a right to know why, to understand what happened, and to hold someone responsible. What is true for the self-driving car is also true for medical systems. In case of an error, who will pay for any damage done, or any further treatment necessary? Just as self-driving car would reduce the number of accidents, and have huge financial benefits in cutting insurance and reparation costs, automated diagnostic systems will probably be able, at some point, to have a better accuracy, at a lower cost, and with less tests required on the patient than what we have now. But the need for accountability makes very unlikely that such systems would replace the human diagnostic.

What we should look for isn't a drastic change in the “gold standard”, from human to machine, but rather a slow transition from a diagnostic framework where the human diagnostician takes most decisions with the help of computer data, to a framework where the computer effectively gives the diagnostic and takes the decision, with a human diagnostician being given the last word – to validate the computer's decision, or to use his own judgement. From computer-aided diagnostic to computer-driven diagnostic, with the eye of the diagnostician still being used to catch any mistake – or to make one of its own.

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