Artificial intelligence application in vascular diseases

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Artificial Intelligence (AI) and machine learning (ML) technologies are rapidly revolutionizing the healthcare system and patient management. Various AI applications have been developed to solve critical problems currently facing the healthcare system. It is of paramount importance for healthcare providers and insurance companies to understand the state of AI technologies and how these can be used to improve the efficiency and safety of, and access to, healthcare services to achieve cost-effectiveness in healthcare status.[1] Recently, the American Medical Association defined the role of AI in healthcare as "augmented intelligence," stating that AI should be designed and used to enhance human intelligence rather than to replace it.[2] Thus, AI can be used to aid in the following[1,2]:

- Unlock the power of big data
- Support evidence-based decision-making to improve quality, safety, and efficiency, coordinate care, and foster communication
- Improve patients' experience and outcomes
- Optimize delivery of value in services and reduce costs
- Optimize healthcare system performance

A recent analysis of ML studies reported 358 studies registered at the ClinicalTrials.gov website up to 2020.[3] The number has been constantly increasing from 6 in 2011 to 149 in 2020. Most of the reported studies had investigated ML for imaging studies but also included biopsy tissue sampling, clinical record evaluation, training in medical education, with the aim of high-performance, data-driven medicine. They also encouraged further development of medical device-related regulations and governance.[3]

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REGULATORY VIEWPOINT FOR AI AND ML TECHNOLOGIES

AI and ML software programs have been recognized as medical products in many regulatory areas, including the United States and the European Union.[4] Thus, software such as ML algorithms could also be subjected to the associated regulatory requirements, including conformity assessment, registration, clinical evaluations, and/or postmarket surveillance.[3] The European Medical Device Regulations recognized software as a medical device with a new regulation published in April 2017 and enforced beginning in May 2021.[5] The regulation reads, in part, as follows: "when specifically intended by the manufacturer to be used for one or more [. . .] medical purposes [. . .], independent of the software's location or the type of interconnection between the software and a device".[5]

The U.S. Food and Drug Administration recently published the "Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan."[6] The plan includes proposals and will be constantly updated in the following fields:

- Tailored regulatory framework for AI/ML-based software as a medical device
- Good ML practice
- Patients should be the center of interest, with transparent administrative procedures
- Regulations for scientific methods associated with algorithm bias and robustness
- Real-world experience

The TRIPOD (transparent reporting of a multivariable prediction model for individual prognosis or diagnosis) criteria are the current standard for reporting predictive models and research-derived risk indexes.[7] However, the TRIPOD criteria have important limitations when applied to ML models using observational data. Thus, data validity is an issue and the need exists to repeat or retest validation tests to ensure model calibration. Another issue in ML models is data availability, outcome ascertainment, and biases in the documentation of the predictor and adjuster variables. Thus, adaptations could be needed if the TRIPOD criteria were to be applied to the evaluations of ML models, which are constantly evolving.

BIOETHICAL VIEWPOINT

The design of the decision support systems that are based on ML software is technically challenging. In addition, a major issue is adherence to bioethical principles. Thus, with the evolution of AL and ML technology, bioethical frameworks must be developed to confront the challenges that these evolving systems might pose. Automated systems should also be adapted to include bioethical principles.

Balancing the benefits and risks and, in particular, finding methods to minimize the ethical risks are all of paramount importance. Although the use of AI can improve healthcare delivery and the quality of patient care quality, it can also threaten patient privacy and confidentiality, the informed consent process, and patient autonomy.[8]

It has been postulated that in addition to the principles of clinical ethics, such as beneficence, nonmaleficence, autonomy, and justice, an additional principle is required in the era of AI usage. This additional principal is the explicability of the AI or ML software, which includes both the epistemological sense of intelligibility (answering the question of "how does it work?") and the ethical sense of accountability (answering the question of "who is responsible for how it works?").[9] Some have been argued that the properties of *explicability* have been well-described by the four bioethical principles.[10,11] Therefore, the core issue becomes how these principles are interpreted and, consequently, implemented, making of paramount importance the harmonized guideline development efforts with essential ethical analysis and adequate application strategies.[12]

In addition, from a medical viewpoint, not only does validation in clinical practice have an important role, but also the ability to explain the ML findings will play an important role in the clinical setting of using ML software. The ability to explain could allow for decisions regarding any disagreements between an AI system and human experts, transcending any error from either side. However, random errors will be much more difficult to identify and could remain unseen in the case of agreement between the AI tool and the physician or could result in disagreements and lead to possible malpractice.[13]

WHY VASCULAR SURGEONS SHOULD PAY ATTENTION TO AI

AI and its applications could benefit vascular physician in both the clinical and the administrative levels. The application of AI in clinical practice has shown promising results in predicting the health course of patients, suggesting specific management, directing surgical care, following up patients, and supporting population health management. Additionally, administrative AI tools have led to a decrease of provider burden and increased productivity with the use of digital records, optimizing interventions, and automating difficult tasks. The level of maturity and application of those tools differs, ranging from emerging to broadly applied.[14]

In particular, AI and ML models can be used to identify and diagnose disease and provide supplementary support in disease prevention, treatment decisions, and long-term outcomes. In addition, advanced data science methods can be used to characterize long-term treatment safety in a real-world setting, including questions not likely to be addressed in clinical trials.[15] By developing tailored interventions, ML-based decision support systems can help prioritize lifestyle changes for patients in a personally meaningful way. Chi et al[16] used data from the ARIC (atherosclerosis risk in communities) study to develop an ML model that identifies lifestyle changes necessary to maximally reduce an individual's 10-year risk of cardiovascular disease.

Challenges for AI implementation are also apparent. The U.S. Government Accountability Office has highlighted the difficulties regarding the use of AI tools that could hinder their widespread application[14]:

- Obtaining data
- Bias
- Scaling and integration
- Lack of transparency
- Privacy
- Uncertainty over liability

TEACHING FOR AI COMPETENCY

Another important issue is that physicians must learn how to work constructively with AI technology and other systems to best serve their patients' needs. However, medical schools do not yet have faculties with the demanding experience required to educate students about AI and ML and their applications and adoption in medicine. Thus, a need exists for an increase in joint efforts among healthcare experts and engineering and computer science faculties.[17] Future directions in teaching programs should include ensuring that their students will be able to understand AI tools and their applications and are prepared to adapt their work in healthcare environments transformed by the use of AI systems.[18] Medical students must understand the four "V's" of big data (ie, volume, variety, velocity, veracity) and competency in the aggregation process, analysis, and personalization in the context of decision-making.[17]

APPLICATIONS IN VASCULAR DISEASES

Abdominal aortic aneurysmal disease. As was recently described in a systematic review of the literature, international guidelines have provided specific indications regarding the treatment of abdominal aortic aneurysms (AAA), all of which, without exception, were based solely on the AAA diameter.[19] This fact illustrates two important remarks: (1) the important role of the AAA diameter; and (2) the absence of any other reliable marker of AAA disease progression.

The evolution of technology in deep learning (DL, and, in particular, U-Net architecture, has revolutionized the analysis of the aorta in segments and has a potential application in monitoring the AAA size.[20] In a recent study, algorithms based on AI were suggested as a method to support the use of "opportunistic" screening instead of routine imaging examinations. A number of ML techniques have been assessed and showed potential benefit in the characterization and risk prediction of AAAs and their progression using computed tomography and magnetic resonance imaging.[21]

One ML technique to predict for future AAA growth was applied in the OxAAA (Oxford abdominal aortic aneurysm study), a prospective study of AAA patients treated using the routine National Health Service management pathway.[22] The algorithm predicted an individual AAA diameter to within a 2-mm error in 85% and 71% of patients at 12 and 24 months, respectively, highlighting the important role of ML techniques for AAA research in the current and future eras of vascular medicine.[22]

Developing multifunctional ML platforms that include clinical data and data aggregation, extraction, management, and analysis could assist physicians by stratifying patients with efficiency, optimizing decision-making.[23] AI application could also be of use for predicting postoperative outcomes. In a recent study, ML models precisely predicted the occurrence of early postoperative complications such as acute renal failure and paraplegia in patients who had undergone complex aortic aneurysm repair.[24]

The current international guidelines have highlighted the importance of follow-up for patients with treated AAAs, recommending regular imaging examinations at specific intervals.[19] It is a clinical issue of paramount importance to predict which patients will require closer follow-up and potentially reintervention to prevent postoperative complications. Recently, in a comprehensive literature review, Raffort et al[25] reported that AI is a useful tool in the interpretation and analysis of AAA imaging studies by enabling automatic quantitative measurements and morphologic characterization. The administration of data based on AI could assist in predicting AAA growth and, potentially, the risk of rupture and procedural outcomes. The use of AI could also represent a method for determining the indications and optimal surgical treatment and could also assist in planning postoperative monitoring. The use of AI could also expedite the development of personalized decision-making and treatment for patients with AAAs.[25]

Cerebrovascular disease. ML and DL technology can offer automated techniques for use in identifying and measuring the carotid intima media thickness and plaque area on carotid vascular images. Supervised learning has been implemented for ML and DL techniques both (ie, learning from "ground truth" images with transformation of test images that were not a part of the training images).[26]

Analysis of the carotid intima media thickness and/or plaque area using AI technology has been applied to monitoring of cerebrovascular disease and stroke risk and could expand to the clinically known parameters for atheromatosis assessments using carotid ultrasound.[26] The currently available ML image segmentation, disease risk prediction, and pathology quantitation methods have shown sensitivities and specificities >70% compared with expert manual analysis and invasive quantitation.[27] AI models have previously been applied to magnetic resonance imaging, computed tomography, and ultrasound. ML and DL can be used to differentiate the types of carotid plaque by signal processing and feature strengths. This technology could offer a solid and vigorous method of tissue characterization and risk classification for carotid plaque for all three imaging modalities.[28] Additionally, AI solutions incorporating image-derived features into a vascular risk stratification tool could offer computer-aided prediction of stroke, which could help in the prevention of cerebrovascular events.[29]

Peripheral arterial disease. Although the application of these technologies to peripheral artery disease (PAD) is in its infancy, the potential is tremendous. In a recent review, the investigators highlighted the important concepts in the fields of ML and AI that have been applied to PAD.[15] The use of AI-based tools seems promising in the correct identification of patients with unstable PAD using existing clinical information and, thus, supplementing clinical decision-making.[30] AI algorithms, in particular, ML algorithms, have been increasingly used in the diagnosis of PAD. A recent study showed that they might be more effective than logistic regression and the ankle brachial index for the diagnosis of PAD in an elderly cohort.[31] In another study, ML was used to identify undiagnosed PAD in a clinical trial of patients who had presented for elective coronary angiography. Of the 1755 patients included in the study, 17% had had PAD, and PAD had been undiagnosed for 68% of these patients at study enrollment, confirming that PAD is underrecognized. Integrating disparate data variables spanning sociodemographic data, medical history, genetic factors, and coronary angiography findings might allow for a classification model trained to identify cases of PAD that were previously undiagnosed.[15]

ML models can also assist in mortality risk assessments for patients with PAD and in building a risk stratification model that could accurately identify which patients with PAD will be most likely to subsequently experience a major adverse cardiovascular event before such an event occurs.[32] AI could also be used to identify patients with a high risk of surgical site infections after lower extremity revascularization or, in the near future, might offer supporting reliable model prediction of amputation and acute limb ischemia.[33]

ECONOMIC VIEWPOINT

A positive economic impact is another key factor in deciding in favor or against supporting economic AI technology for the healthcare industry. The cost of healthcare is considered one of the most important issues for healthcare leaders and stakeholders to consider, in addition to the pharmaceutical and medical technology sectors.[34] However, reported evidence is lacking regarding the economic effects of AI solutions for the healthcare system. In a recent meta-analysis, none of the included studies had performed a methodologically complete analysis of the cost-effectiveness of the use of AI technology. That study showed that the existing impact assessments possessed methodologic deficits and that more comprehensive economic analyses are required to before deciding for or against implementing AI technology in healthcare.[34]

CONCLUSIONS

AI is a collection of technologies that combines data, algorithms, and computing power in an effort to assist decision-making by mimicking multiparametric analysis of complex cognitive problems. Flaws could be inherent in the overall design of the AI system or in its use without correcting potential biases, especially in the first stages of AI system use, known as the "latency" of the learning period. Completely anticipating such flaws in the AI design phase still seems challenging and could be difficult to correct in the initial phases of its use. Although the upsurge in AI use is expected to provide benefits to all citizens in their daily activities, to services of public interest, and to business development, it remains of paramount importance for the use of AI, ML, and DL to be in accordance with the fundamental rights of European and Western civilizations such as human dignity and privacy protection. This consideration should apply, not only from an individual perspective, but also from a societal perspective.

AUTHOR CONTRIBUTIONS

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