Michael C. Dalsing, MD, SECTION EDITOR

Artificial intelligence in abdominal aortic aneurysm

Juliette Raffort, MD, PhD,[a,b] Cédric Adam, PhD,[c] Marion Carrier, PhD,[c] Ali Ballaith, MD, PhD,[d] Raphael Coscas, MD, PhD,[e,f] Elixène Jean-Baptiste, MD, PhD,[b,d] Réda Hassen-Khodja, MD, PhD,[b,d] Nabil Chakfé, MD, PhD,[g] *and* Fabien Lareyre, MD, PhD,[b,d] *Nice, Paris, Boulogne, Versailles, and Strasbourg, France*

ABSTRACT

Objective: Abdominal aortic aneurysm (AAA) is a life-threatening disease, and the only curative treatment relies on open or endovascular repair. The decision to treat relies on the evaluation of the risk of AAA growth and rupture, which can be difficult to assess in practice. Artificial intelligence (AI) has revealed new insights into the management of cardiovascular diseases, but its application in AAA has so far been poorly described. The aim of this review was to summarize the current knowledge on the potential applications of AI in patients with AAA.

Methods: A comprehensive literature review was performed. The MEDLINE database was searched according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. The search strategy used a combination of keywords and included studies using AI in patients with AAA published between May 2019 and January 2000. Two authors independently screened titles and abstracts and performed data extraction. The search of published literature identified 34 studies with distinct methodologies, aims, and study designs.

Results: AI was used in patients with AAA to improve image segmentation and for quantitative analysis and characterization of AAA morphology, geometry, and fluid dynamics. AI allowed computation of large data sets to identify patterns that may be predictive of AAA growth and rupture. Several predictive and prognostic programs were also developed to assess patients' postoperative outcomes, including mortality and complications after endovascular aneurysm repair.

Conclusions: AI represents a useful tool in the interpretation and analysis of AAA imaging by enabling automatic quantitative measurements and morphologic characterization. It could be used to help surgeons in preoperative planning. AI-driven data management may lead to the development of computational programs for the prediction of AAA evolution and risk of rupture as well as postoperative outcomes. AI could also be used to better evaluate the indications and types of surgical treatment and to plan the postoperative follow-up. AI represents an attractive tool for decision-making and may facilitate development of personalized therapeutic approaches for patients with AAA. (J Vasc Surg 2020;72:321-33.)

Keywords: Artificial intelligence; Machine learning; Deep learning; Aneurysm; Abdominal aortic aneurysm; Open repair; Endovascular aneurysm repair; EVAR

Abdominal aortic aneurysm (AAA) represents a life-threatening disease.[1,2] Curative treatment relies on surgical repair, which can be performed by open surgery or endovascular aneurysm repair (EVAR).[3,4] Guidelines of the Society for Vascular Surgery and the European Society for Vascular Surgery have defined recommendations for the management of patients with AAA, and the decision to treat relies on the evaluation of the balance between surgical risk and the risk of AAA growth and rupture.[3,4] Even though large initial maximal diameter is a well-established independent risk factor for AAA rupture, other factors for rupture, including general characteristics of the patients (such as female sex, hypertension, or smoking) and factors related to the aneurysm itself (including AAA growth rate, wall stress, wall stiffness, wall tension, and rapid increase of intraluminal thrombus), have been identified.[3] In practice, the risk of progression and rupture can be difficult to predict, and the decision-making strategy for AAA repair and its management varies widely between countries despite common guidelines from professional societies.[5] This underlines the need to develop a more personalized therapeutic approach that could take into account the patients' general and clinical characteristics as well as a detailed characterization of AAA geometry and morphology.

The application of data science to medicine has provided novel insights in the era of precision medicine, aiming to propose care that is tailored to the individual

From the Clinical Chemistry Laboratory,[a] and Department of Vascular Surgery,[d] University Hospital of Nice, and the Université Côte d'Azur, CHU, Inserm U1065, C3M,[b] Nice; the Laboratory of Applied Mathematics and Computer Science (MICS), CentraleSupélec, Université Paris-Saclay, Paris[c]; the Department of Vascular Surgery, Ambroise Paré University Hospital, Assistance Publique-Hôpitaux de Paris (AP-HP), Boulogne[e]; Inserm U1018 Team 5, Versailles-Saint-Quentin et Paris-Saclay Universities, Versailles[f]; and the Department of Vascular Surgery and Kidney Transplantation, University Hospital of Strasbourg, and GEPROVAS, Strasbourg.[g]

Author conflict of interest: none.

Additional material for this article may be found online at www.jvascsurg.org.

Correspondence: Fabien Lareyre, MD, PhD, Department of Vascular Surgery, University Hospital of Nice, 30 Ave de la Voie Romaine, 06001 Nice, France (e-mail: fabien.lareyre@gmail.com).

The editors and reviewers of this article have no relevant financial relationships to disclose per the JVS policy that requires reviewers to decline review of any manuscript for which they may have a conflict of interest.

0741-5214

https://doi.org/10.1016/j.jvs.2019.12.026

patient. Artificial intelligence (AI) corresponds to the ability of a computational program to perform tasks that are commonly associated with intelligent beings. Among AI programs, machine learning allows us to uncover patterns and to make decisions from large data sets without the need of explicit instructions or a priori assumptions. Numerous algorithms can be used, and machine learning is in general classified into two main categories: unsupervised and supervised learning.[6,7]

In supervised learning, the program is trained to learn associations between inputs and outputs in a database in which the outcomes of interest are labeled and defined by a human supervisor. It uses a selection of features that are processed and weighted. Once the associations have been identified on the basis of existing data, they can be used to predict new data.[8,9] It is generally used to develop models of prediction and classification or to identify which variables are most relevant to the outcomes.

In contrast, unsupervised learning does not require any labeled or annotated data. The program aims to identify consistent patterns in the data instead of trying to fit the data to an outcome.[10] Unsupervised learning allows the exploration of complex relationships among variables in a data set and leads to the identification of hidden patterns without any prior label or annotation available.

The application of machine learning has been investigated in a wide range of medical fields including imaging and biologic analysis and could potentially lead to the development of new approaches for the diagnosis, prognosis, or treatment of patients.[11,12] Several studies have highlighted the interest of AI in cardiovascular diseases.[10,13,14] However, its application in patients with AAA has so far been poorly described. The aim of this review was to summarize current knowledge and potential applications of AI in AAA and to discuss current limitations and future directions.

METHODS

Search strategy and eligibility criteria. A literature search was conducted using PubMed/MEDLINE database according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses. Two authors (F.L., J.R.) independently performed a literature search of articles published between May 2019 and January 2000 using a combination of the following terms: “artificial intelligence,” “deep learning,” “machine learning,” “neural network,” “convolutional neural network,” “segmentation,” “aneurysm,” “aortic aneurysm,” “abdominal aortic aneurysm,” “open repair,” and “endovascular aneurysm repair” (Supplementary Table, online only).

Inclusion criteria for article selection were publications written in the English language including patients with AAA in which a technique related to AI was used. AI was defined as a computational program able to perform tasks that are characteristics of human intelligence, including image and pattern identification, recognition, analysis, learning from past experience, problem solving, and decision-making. Titles and abstracts of the publications identified using the search strategy were reviewed. Eligibility was independently checked by two authors (F.L., J.R.) and confirmed with two other authors (C.A., M.C.) in case of disagreement. Case reports and unpublished data were excluded. The flow chart depicting the process for literature search and selection is presented in the Fig.

Data management. The aim of the study and its design, the number of patients and their clinical and procedural characteristics, the material, the methodology, and the techniques related to AI were extracted and analyzed from each published study. Given the wide variety of aims, study designs, and techniques, a narrative literature review was performed. The studies were classified into three main topics: image segmentation and automation, characterization of AAA geometry and fluid dynamics, and prediction and prognosis of patients with AAA (Fig). The detailed list of selected articles is presented in Table I.

Terminology. The definitions of general and technical terms related to AI used in this review are summarized in Table II.

IMAGE SEGMENTATION AND AUTOMATION

Imaging is a key step for the diagnosis of AAA. Computed tomography (CT) imaging remains the most commonly used technique for operative planning as it provides a complete data set of the entire aorta and access vessels, allowing examination of the extent and morphology of the AAA as well as identification of coexistent occlusive disease.[3,4] Image segmentation corresponds to the process of partitioning a digital image into multiple segments (sets of pixels). The pixels are assigned a label so that pixels with the same label share similar properties. It is generally used to process medical images, allowing the tagging of regions of interest, analysis of sets of contours, and creation of three-dimensional (3D) reconstructions.

Aneurysm segmentation. Several methods have been proposed for aneurysm segmentation. de Bruijne et al[17] proposed an interactive method for aneurysm sac segmentation from a data set of CT angiography (CTA) obtained from 23 patients. The method was inspired from the active shape model segmentation, which consists of combining the statistical knowledge of object shape and variations with a local appearance model near the object contours. After manual segmentation of the first slice, the method automatically detects the contour in subsequent slices, allowing rapid processing of the entire volume of the AAA. The method exhibited accurate segmentation, with manual intervention required in only

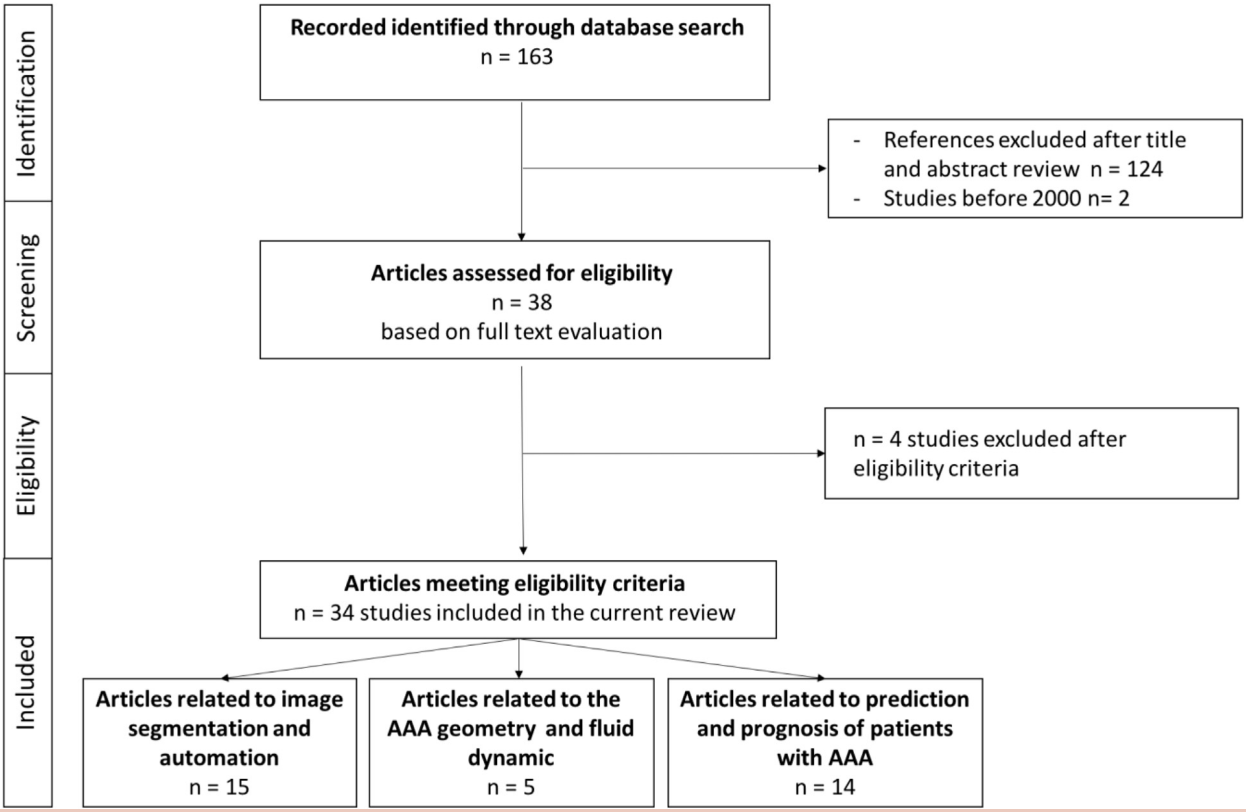

Fig. Flow chart depicting the process for the literature search and selection of the studies. *AAA*, Abdominal aortic aneurysm.

one of six slices, thereby laying the groundwork for a semiautomatic approach helping to reduce the time for expert segmentation. Other investigators proposed a semiautomatic method requiring minimal user assistance for 3D segmentation of AAA from CTA images.[15] A two-step segmentation, first for the inner and then for the outer border, was performed. A 3D-deformable model was implemented with level set algorithms and used to measure the aneurysm area. The results of this semiautomatic segmentation were then compared with manually corrected methods and exhibited relative errors close to those obtained with human experts.

The gain of time obtained from these methods led investigators to go further and to propose methods to allow the measurement of volume and morphologic aspects of AAA. The proposed method by Zhuge et al[19] relies on five main steps (preprocessing, global region analysis, surface initialization, local feature analysis, level set segmentation) and was tested on a database of 20 CTA images of patients. The "gold standard" was established by collecting the results of manual tracing of three experts. The mean volume overlap was 95.3% ± 1.4%, and the mean segmentation time per patient was reduced to 7.4 ± 3.8 minutes vs 20 to 30 minutes per patient with the human manual method. These results are encouraging to further use of this kind of approach in clinical practice for an accurate, precise, and reproducible segmentation of AAA from CT images. Other authors presented a finite element analysis-based approach to analyze AAA images.[24] This software allows an automatic analysis of CT or magnetic resonance images but nevertheless requires a semiautomatic segmentation of the AAA and the intraluminal thrombus.

CT and magnetic resonance imaging are two complementary imaging modalities. CT offers a better visualization of calcifications; magnetic resonance imaging allows a more precise distinction of soft tissues and intraluminal thrombus.[49] Multimodal imaging can combine the advantages of both techniques. In this setting, Wang et al[28] proposed the use of neural network fusion to allow a shared representation of aorta in both CT and magnetic resonance images. This approach could improve training speed and allow performance of multimodal AAA image segmentation.

Finally, Lareyre et al[29] recently proposed a fully automated pipeline to detect the aortic lumen and to characterize the AAA, including the presence of intraluminal thrombus and calcifications. The method was tested on a set of 40 patients with CTA images and demonstrated a good correlation with results obtained from manual segmentation by human experts, with a computational time of <1 minute per patient.

Table I. List and year of publication of the selected articles

Topic	Title	Year	Reference
Image segmentation and automation	3-D image analysis of abdominal aortic aneurysm	2000	15
	Adapting active shape models for 3D segmentation of tubular structures in medical images	2003	16
	Interactive segmentation of abdominal aortic aneurysms in CTA images	2004	17
	Segmentation of thrombus in abdominal aortic aneurysms from CTA with nonparametric statistical grey level appearance modeling	2005	18
	An abdominal aortic aneurysm segmentation method: level set with region and statistical information	2006	19
	Three-dimensional thrombus segmentation in abdominal aortic aneurysms using graph search based on a triangular mesh	2010	20
	3D segmentation of abdominal aorta from CT-scan and MR images	2012	21
	Geometrical methods for level set based abdominal aortic aneurysm thrombus and outer wall 2D image segmentation	2012	22
	A proposal of texture features for interactive CTA segmentation by active learning	2014	23
	BioPARR: a software system for estimating the rupture potential index for abdominal aortic aneurysms	2017	24
	Generic thrombus segmentation from pre- and post-operative CTA	2017	25
	Fully automatic detection and segmentation of abdominal aortic thrombus in post-operative CTA images using deep convolutional neural networks	2018	26
	Abdominal aortic aneurysm calcification: trying to identify a reliable semiquantitative method	2018	27
	Neural network fusion: a novel CT-MR aortic aneurysm image segmentation method	2018	28
	A fully automated pipeline for mining abdominal aortic aneurysm using image segmentation	2019	29
Characterization of AAA geometry and fluid dynamics	Three-dimensional geometrical characterization of abdominal aortic aneurysms: image-based wall thickness distribution	2009	30
	Semiautomatic vessel wall detection and quantification of wall thickness in computed tomography images of human abdominal aortic aneurysms	2010	31
	Quantitative assessment of abdominal aortic aneurysm geometry	2011	32
	Hemodynamic flow modeling through an abdominal aorta aneurysm using data mining tools	2011	33
	Machine learning approach for predicting wall shear distribution for abdominal aortic aneurysm and carotid bifurcation models	2018	34
Prediction and prognosis of patients with AAA	Ruptured abdominal aortic aneurysm: a novel method of outcome prediction using neural network technology	2000	35
	Analysis and computer program for rupture-risk prediction of abdominal aortic aneurysms	2006	36
	Informed prognosis [corrected] after abdominal aortic aneurysm repair using predictive modeling techniques [corrected]	2006	37
	Evaluation of texture for classification of abdominal aortic aneurysm after endovascular repair	2012	38

Table I. Continued.

Topic	Title	Year	Reference
	Bayesian neural network approach for determining the risk of re-intervention after endovascular aortic aneurysm repair	2014	39
	An artificial neural network stratifies the risks of reintervention and mortality after endovascular aneurysm repair; a retrospective observational study	2015	40
	Prediction of in-hospital mortality after ruptured abdominal aortic aneurysm repair using an artificial neural network	2015	41
	Patient-specific numerical simulation of stent-graft deployment: validation on three clinical cases	2015	42
	Deployment of stent grafts in curved aneurysmal arteries: toward a predictive numerical tool	2015	43
	Using machine learning methods for predicting inhospital mortality in patients undergoing open repair of abdominal aortic aneurysm	2016	44
	Patient-specific simulation of endovascular repair surgery with tortuous aneurysms requiring flexible stent-grafts	2016	45
	Using multiple classifiers for predicting the risk of endovascular aortic aneurysm repair re-intervention through hybrid feature selection.	2017	46
	Feature selection through validation and un-censoring of endovascular repair survival data for predicting the risk of re-intervention	2017	47
	Applied machine learning for the prediction of growth of abdominal aortic aneurysm in humans	2018	48

Manual segmentation is tedious and time-consuming; it requires a trained and experienced operator and is subject to interoperator and intraoperator variations. Automated segmentation would be of great interest to reduce analysis time, to alleviate the burden of performing repetitive tasks, and to improve reproducibility. Vascular segmentation is challenging as vessels and AAA exhibit high variability of morphology, size, and curvature. The AAA characteristics can be difficult to assess because of the existence of concomitant occlusive disease, calcifications, intraluminal thrombus, pre-existing grafts, or close localization with the surrounding tissues. Finally, technical considerations, including acquisition methods, contrast agent used, resolution, and presence of noise and artifacts, may interfere with image analysis. Machine learning approaches in AAA imaging analysis are currently being developed.[23] These methods may facilitate image acquisition, measurements, and reporting; they may improve image interpretation and potentially reduce cost.[10] We truly believe that major advances are to be expected within the next few years, although further research will be required before their use in daily clinical practice. Such innovative techniques need to be compared with the gold standard and the trusted evaluation provided by human experts to evaluate their accuracy and their safety. In addition, the generalizability of the results is another major concern that requires external validation on large multicenter and international cohorts. Meanwhile, these methods can be applied in research settings to optimize segmentation, to reduce computational time, or to provide detailed quantitative analysis under the supervision of a medical expert.

Intraluminal thrombus segmentation. Intraluminal thrombus is a factor contributing to AAA development, and its increase correlates with the aneurysm sac and rupture.[50] A precise and quantitative volumetric analysis of the thrombus would be useful to better assess the risk of AAA rupture. Thrombus segmentation is a challenging task as its borders are irregular and not well defined because of the presence of adjacent structures with similar intensity values and regions of low boundary contrast.

Several semiautomatic approaches have been proposed for thrombus segmentation. de Bruijne et al[16] developed a method that adapted both the shape and the appearance model of the original active shape model formulation. The evaluation of the method on 23 acquired CTA images demonstrated a better accuracy for thrombus segmentation compared with the conventional active shape model. Other investigators generated

Table II. Definition of technical terms related to artificial intelligence (*AI*)

General terms
AI: Ability of a machine or a device to display properties of human intelligence.
Machine learning: Subdiscipline of AI whereby a set of techniques is used to give the machine the ability to learn.
Deep learning: Type of machine learning method based on a neural networks architecture with several hidden layers. The large number of hidden layers (the "depth" of the algorithm) requires a large quantity of training data.
Data mining: Interdisciplinary subfield between computer science and statistics that aims to discover patterns in large data sets.
Pipeline: Term used in software engineering that corresponds to a chain of processing elements that transform input elements into outputs and where the output of one element is the input of the next one.
Segmentation: Term used in computer vision that corresponds to the process of partitioning a digital image into multiple segments (sets of pixels).
Technical terms
Active shape model: Model-based method that makes use of a prior model of what is expected and iteratively attempts to find the best match position between the model and the data.
Back-propagation network: Supervised learning algorithm for training artificial neural networks.
Bayesian networks: Type of probabilistic graphical model used to build models from data or expert opinion. (3D) Deformable model: Geometric object that can move under the influence of internal forces defined by the model itself and external forces computed from the data.
Feature selection: A process of selecting a subset of original features according to certain criteria, frequently used as a reduction technique for data mining.
Finite element analysis: Numerical method for solving problems of engineering and mathematical physics.
Graph-cut method: Method to solve a class of energy minimization problems in graphs, such as image segmentation.
Support vector regression: A supervised-learning approach to approximate a real-value function with error control.
Multiple logistic regression: Estimation of the parameters of a logistic model (based on a logistic function) to approximate data through classification. This problem can be solved through a support vector machine (see support vector regression).
(Artificial) Neural network: Computing systems inspired by biologic neural networks that process data through layers of mathematical functions (the neurons). Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules.
Multilayer perceptron: Common architecture of artificial neural network. This architecture is very resource and learning data consuming.
Multiple classifier: A machine learning architecture based on the fusion of several classifier outputs for better accuracy and classification.
Convolutional neural network: Popular neural network architecture. Convolutional neural networks use a variation of multilayer perceptron designed to require minimal preprocessing. They are easier to train and generally more effective than multilayer perceptron.
Deep convolutional neural network: A convolutional neural network with more than one layer (ie, belonging to deep learning techniques). It takes advantage of the hierarchical pattern in data and assembles more complex patterns using smaller and simpler patterns. It is most commonly applied for visual image analysis.
Radial basis function networks: An artificial neural network architecture that uses radial basis functions in its neurons. They have many uses, including function approximation, time series prediction, classification, and system control.

a semiautomatic segmentation algorithm based on the application of geometric methods to the boundary curves obtained by a level set method.[22] The comparison with manual segmentation from an expert on 10 CTA images showed a mean overlap for the outer wall boundary of 94.6% and a mean relative error of 15.84% for the measurement of wall thickness. Olabarriaga et al[18] developed a deformable model-based method for 3D thrombus segmentation from CTA images. A study of 17 patients with AAA showed the agreement of the method with manual segmentation, with the advantage of reducing user interaction. Another 3D deformable model-based approach requiring minimal user interaction was developed and demonstrated accurate results compared with manual delineation, with an average processing time of 8.2 ± 3.5 seconds.[25]

Finally, other semiautomatic approaches based on modifications of the graph-cut method were used.[20,21] In a set of 44 patients with magnetic resonance and contrast-enhanced CT images, Duquette et al[21] demonstrated reproducible evaluations of lumen interface and aortic wall with their method, with results similar to those obtained with a human operator. Other investigators developed a method based on double-surface 3D graph search using a triangular mesh, offering another alternative to facilitate thrombus segmentation from CTA images.[20] Whereas these results are encouraging for an accurate and easily available measurement of the intraluminal thrombus to be obtained, all of the methods described require minimal user interaction. Based on a deep convolutional neural network, Lopez-Linares et al[26] developed fully automatic approaches for thrombus detection. The pipeline was trained, validated, and tested in 13 postoperative CTA images of patients with AAA, and segmentation quality was evaluated by comparing results obtained from the automatic method with the manually delimited volume. Even if the mean relative volume significantly differed between the two approaches, these results are encouraging as the automatic method could be improved by training the network with more data sets.

Segmentation of aortic calcifications. The presence of aortic calcifications has an impact on AAA development and risk of rupture as they may cause severe tissue overstretching in surrounding tissue areas. A higher aortic calcification score was significantly associated with the development of symptomatic and ruptured AAA.[51] AI may offer the opportunity to develop software that enables a rapid and objective quantitative assessment of calcifications in a large data set of patients.

Several semiquantitative computerized methods have been developed to segment aortic calcifications,[27] some of them derived from the Agatston score.[52] An evaluation in a cohort of 102 patients with AAA who underwent elective repair demonstrated the correlation between the different methods, offering interesting perspectives on their use in research settings.[27] To go further in the understanding of the link between vascular calcifications and cardiovascular diseases, some authors aimed to develop a fully automated pipeline to compute aorta morphology and calcification measures in CT images.[53] The detection performance of the algorithm for calcifications was compared with manually detected calcifications, and of the 424 calcified regions marked by the expert, the algorithm successfully detected 96% of them correctly. The pipeline was then applied to a cohort of 2500 patients with chronic obstructive pulmonary disease and identified correlations between calcification volume and aorta width and mean radius.[53] A machine learning approach using convolutional neural networks was recently applied to develop a fully automated vascular calcification algorithm.[54] The method was tested in a data set of 9914 CT scans obtained from consecutive adults who underwent colonography screening, and the results were compared with the Agatston score obtained with semiautomated methods. For the 812 scans compared, the r^2 agreement value was 0.84, suggesting the reliability of the method.

CHARACTERIZATION OF AAA GEOMETRY AND FLUID DYNAMICS

The characterization of AAA geometry and the material properties of the arterial wall is a critical step to assess the risk of rupture.[3,4] The wall thickness plays a central role in AAA pathogenesis, and several studies aimed to develop algorithms based on neuronal networks for the accurate quantification from CT images.[30,31] In a set of 20 contrast-enhanced AAA image data sets, Shum et al[31] demonstrated a good agreement of their method with the manual assessment performed by vascular surgeons, with average coefficients of variation of 10.59% for ruptured AAA and 13.02% for nonruptured AAA. Ruptured aneurysms exhibited significantly thicker walls than nonruptured AAA (1.78 mm vs 1.48 mm; $P = .044$), underlining the potential of this quantitative assessment for the risk of AAA rupture.

A precise characterization of AAA geometry was developed by combining different algorithms for image segmentation and wall thickness detection, leading to the calculation of 25 size and shape indices.[30,32] In this study, a decision tree algorithm was created using an open source machine learning software on 76 contrast-enhanced CT scans, and the population was divided into ruptured (n = 10) and nonruptured AAA (n = 66). The decision tree model based on a combination of indices was trained and demonstrated an average prediction accuracy of 86.6%. These results demonstrate the feasibility of AI and machine learning to precisely characterize AAA geometry to define patterns of higher risk of rupture.

Last, fluid dynamics are considered to play a critical role in AAA formation and progression.[55] Blood flow induces wall shear stress (WSS), which contributes to the risk of rupture in AAA. By combining computational fluid dynamics with data mining methods, some investigators estimated WSS on the basis of geometric parameters and demonstrated the potential interest of this approach to development of a predictive system.[33] An alternative machine learning-based approach was also proposed for the calculation of WSS and demonstrated its interest to predict WSS distribution at different cardiac cycle time points.[34]

PREDICTION AND PROGNOSIS OF PATIENTS WITH AAA

Prediction of AAA growth and rupture. The application of AI has offered interesting perspectives for image segmentation, automation, and characterization of the AAA, facilitating and improving data acquisition and quantitative measurements in large data sets of patients. A combination of these advances may help to better evaluate the prognosis of patients and predict the risk of AAA growth and rupture (Table III). A first study investigated the feasibility of predicting future AAA growth using a set of benchmark learning technique.[48] The algorithm, based on support vector regression using two features (flow-mediated dilation and AAA diameter) accurately predicted the individual's AAA diameter within a 2-mm error in 85% of patients at 12 months and 71% at 24 months. Another computer program integrating eight biomechanical factors was created to predict the risk of AAA rupture.[36] The software calculated a patient-specific severity parameter and provided a patient status classified as low risk, observation, elective repair, or imminent rupture. The method was tested in three clinical cases and correctly classified the patient's status. Machine learning has the ability to compute large and heterogeneous data sets and to identify patterns between variables even if their

Table III. Use of artificial intelligence (AI) for prediction and prognosis of patients with abdominal aortic aneurysm (*AAA*)

Predicted factor	Study population	Method	Main results	References
AAA evolution				
Growth	94 patients with AAA followed up at 12 months 79 patients with AAA followed up at 24 months	Benchmark learning technique using nonlinear kernel support vector regression with 2 features and hyperparameter optimization using nested fivefold cross-validation	Average AAA growth: 3.4% at 12 months and 2.8% per year at 24 months Algorithm predicted the individual's AAA diameter to within 2-mm error in 85% and 71% of patients at 12 and 24 month	Lee et al,[48] 2018
Rupture	3 clinical cases	Calculation of a time-dependent specific parameter based on 8 biomechanical parameters	Specific parameter value classified the patient's status correctly in all cases	Kleinstreuer and Li,[36] 2006
Postoperative outcomes				
In-hospital mortality	125 patients admitted for emergent ruptured AAA repair: 108 open repair, 17 EVAR	4-variable ANN Comparison with multiple logistic regression and Glasgow Aneurysm Scale score	Results derived from multiple regression logistic regression, ANN, and aneurysm score models: • AUROC of 0.85 ± 0.04, 0.88 ± 0.04, and 0.77 ± 0.06 • Pearson r^2 values of 0.36, 0.5,2 and 0.17	Wise et al,[41] 2015
	57 attributes from 310 cases	3 machine learning algorithms tested: multilayer perceptron, radial basis function networks, and Bayesian networks	For Bayesian networks: sensitivity of 73%, specificity of 92.6% For radial basis function networks: sensitivity of 52.1%, specificity of 96.1% For multilayer perceptron: sensitivity of 65.2%, specificity of 96.1%	Monsalve-Torra et al,[44] 2016
	1751 patients with AAA who underwent open repair: 1205 elective, 546 emergency	4-variable ANN Comparison with multiple logistic regression analysis and clinicians' prediction	ANN prediction tended to overestimate the risk of low-risk cases and to underestimate the risk of high-risk patients Clinicians tended to underestimate the risk of high-risk cases Multiple regression model had the best internal validity	Hadjianastassiou et al,[37] 2006
30-day mortality	102 patients operated on for ruptured AAA	4-variable ANN	ANN correctly predicted survival in 82.5% of patients Sensitivity and specificity values: 86.4%; 79.3% Positive and negative predictive values: 82.6%; 88.5%	Turton et al,[35] 2000
Endograft complications	761 patients who underwent EVAR with a mean follow-up of 36 ± 20 months	ANN created from aorta morphologic features to class patients in high or low risk	ANN predicted endograft complications and mortality with discrimination between low-risk and high-risk	Karthikesalingam et al,[40] 2015

Table III. Continued.

Predicted factor	Study population	Method	Main results	References
		Assessment of aortic or limb complications	groups Comparison of values between the low- and high-risk groups in the validation data set: • 5-year freedom from aortic complications: 95.9% vs 67.9% • 5-year freedom from limb complications: 99.3% vs 92% • 5-year freedom from all endograft complications: 96.5% vs 85.6% • 5-year freedom from mortality: 87.9% vs 79.3%	
Reintervention after EVAR	146 patients who underwent EVAR from 2 distinct centers	Bayesian network and back-propagation neural network to class patients in high or low risk Assessment of reintervention	Center 1 neural network model for prediction of center 2 patients • AUROC of the trained model in center 1: 0.9498 • AUROC of the trained model in center 2: 0.666 • *P* value (log-rank test): .00037 The model succeeded in differentiating the low- and high-risk groups	Attallah and Ma,[39] 2014
	457 and 286 patients from 2 distinct centers	Multiple classifier combining support vector machine, multiple layer perceptron neural network, and K-nearest neighbor classifiers	Multiple classifier outperformed individual classifiers to predict the risk of reintervention after EVAR	Attallah et al,[47] 2017
	457 and 286 patients from 2 distinct centers	Feature selection method with ANN	The method outperformed other methods in distinguishing the high- and low-risk groups of reintervention after EVAR	Attallah et al,[46] 2017
Aneurysm evolution after EVAR	70 patients who underwent EVAR	3-layer back-propagation neural network based on texture features of the intraluminal thrombus: GLCM, GLRLM, GLDM Assessment of aneurysm evolution • Favorable: reduction of AAA diameter • Unfavorable: growth of AAA diameter or presence of endoleaks	Good ability of GLCM, GLRLM, and GLDM features to discriminate between favorable and unfavorable evolutions Classification accuracy of GLCM, GLRLM, and GLDM: 93.41%; 90.17%; 81.98%	Garcia et al,[38] 2012
Stent graft deployment after EVAR	3 patients undergoing EVAR	Simulation of stent graft final deployed shapes using finite element analysis Comparison of the simulation results with the real deployed geometry of stent graft after surgery	Matching between simulated and real deployed stent graft geometries Stent locations along the vessel centerlines were within a few millimeters of real stents' locations	Perrin et al,[42] 2015

ANN, Artificial neural network; *AUROC*, area under the receiver operating characteristic curve; *EVAR*, endovascular aneurysm repair; *GLCM*, gray level co-occurrence matrix; *GLDM*, gray level difference method; *GLRLM*, gray level run length matrix.

relationships are complex and nonlinear.[10] Clinical, biologic, and imaging characteristics of patients with AAA can be combined, analyzed, and used for prediction and decision-making. Even if validation on larger cohorts is required, that kind of approach may lead to the development of prognostic scores that may help improve precision medicine and develop patient-specific guidelines.

Prediction of postoperative outcomes. AAA is associated with high mortality rates, and several risk prediction scores have been established in patients undergoing AAA repair.[56] Although a large number of models have been developed, their performances are not optimal and not always adapted for each patient as the prognosis may differ widely according to the procedure (open or EVAR) and its context (elective, emergency, ruptured or nonruptured AAA). Several studies aimed to apply AI for development of predictive mortality scores in patients undergoing AAA repair (Table III). Two studies used a four-variable artificial neural network (ANN) model to evaluate in-hospital[41] and 30-day mortality[35] in patients admitted for ruptured AAA repair and demonstrated the feasibility of this approach. Another study involving patients who underwent open repair compared the performance of ANN with multiple logistic regression analysis and clinicians' prediction for in-hospital mortality.[37] In this study, the ANN prediction tended to overestimate the risk of low-risk cases and to underestimate the risk of high-risk patients.[37] Finally, three other machine learning algorithms, including multilayer perceptron, radial basis function networks, and Bayesian networks, were tested to predict in-hospital mortality and exhibited variable results in terms of sensitivity and specificity.[44]

EVAR has become a well-established alternative to open repair.[3,4] However, its long-term success and surveillance remain a challenge as patients may develop postoperative complications such as endoleaks, endotension, stent graft migration, or stent graft iliac limb thrombosis or stenosis.[3] Several studies aimed to apply AI to predict the risk of postoperative outcomes after EVAR (Table III). An ANN based on AAA morphologic features demonstrated its ability to correctly discriminate patients at low or high risk of aortic complications (including rupture, endoleaks, graft migration, and sac expansion) or limb complications (occlusion or stenosis requiring a reintervention).[40] In another study, a back-propagation network was used to successfully discriminate AAA with unfavorable evolution (defined as growth of intraluminal thrombus).[38] Attallah and Ma[39] demonstrated the ability of a back-propagation neuronal network to correctly discriminate patients at high or low risk of reintervention after EVAR. They further developed a hybrid feature selection and used a multiple classifier to predict the risk of reintervention after EVAR.[46,47] In time, these approaches may be useful in clinical practice for better assessment of aneurysmal evolution and long-term surveillance after AAA repair.

The preoperative planning of EVAR is a critical step to prevent and to anticipate postoperative complications.[3] Using finite element analysis, some investigators developed a program to simulate final deployed shapes of stent grafts on preoperative CTA.[42] A comparison with the actual stent graft shape and localization in patients who underwent EVAR demonstrated the agreement of the method, even in patients with curved or tortuous arteries.[42,43,45] Such tools may be useful in clinical practice to optimize the planning and sizing of stent grafts and to anticipate post-EVAR complications.

CURRENT LIMITS AND FUTURE DIRECTIONS

The current literature brings interesting perspectives to the use of AI for clinical practice. AI-derived software may improve image segmentation and analysis. This will allow investigators to more easily detect the aneurysm; to characterize its anatomic characteristics (including the presence of calcifications and intraluminal thrombus); and to automatically calculate the diameters, lengths, distances, and volumes of the aneurysm and vessels. In the future, this kind of approach could help the surgeon in preoperative planning and sizing of endografts. In addition, data derived from automatic analysis of AAA images could be combined with clinical and biologic characteristics of patients to develop multiple-variable scores, allowing identification of predictive patterns and better assessment of the prognosis of patients. This kind of approach will help the vascular surgeon to better assess the balance between the operative risk and the risk of aneurysm growth and rupture. This will create a more personalized therapeutic approach.

However, several pitfalls and limitations have to be overcome before these techniques and approaches can be used in daily clinical practice. External validation is required, and the generalizability of results may need multicenter registries taking into account a broad spectrum of patient demographics.

The first concern relates to the availability of data and privacy protection. Indeed, machine learning approaches require large databases for learning and training. Data sharing is subject to ethical and legal considerations, making it extremely difficult to develop publicly available, large multicentric registries. Second, such techniques require adapted platforms and infrastructures with sufficient computational power. In addition, a huge effort of standardization regarding data quality, storage, sharing, and analysis is necessary. Indeed, the type of medical data available is diverse and heterogeneous, including manual clinical notes, electronic medical records, laboratory test results, and medical imaging. Thus, data are generated by various manufacturers and are stored in diverse manual or electronic repositories with a wide variation of quality, formats, resolutions, dimensions, and scales.

Other interrogations relate to the economic aspect. Such approaches are expensive to develop but may improve the quality of patients' care, representing a real interest in terms of public health and potentially a return on investment. The incorporation of AI may modify clinical practice, and one may wonder how such changes would be perceived by both the patients and the clinicians. Some clinicians may fear that their profession will be replaced by a machine. Some patients may fear that automation affects the physician-patient relationship and the quality of the care provided. AI has the potential to be a useful tool for the clinician but will never replace the physician's expertise and decision-making, taking into account not only the patient's health status but also the patient's environment and the clinician's own judgment.

Future directions should be oriented toward improving collaboration and teamwork between clinicians, biomedical informatics scientists, and experts. Economic and institutional support would be a step forward in developing such projects, which could in time lead to major advances in both clinical research and practice.

CONCLUSIONS

Although the field is still in its infancy, AI appears to offer various potential applications in medical practice for patients with AAA. It may help in the interpretation and analysis of AAA imaging by enabling automatic quantitative measurements and a precise characterization of AAA morphology, geometry, and fluid dynamics as well as of the presence of intraluminal thrombus and calcifications. Although further studies are required, it could lead to the development of new software to help surgeons in preoperative planning and sizing of endografts. With use of AI, the combination of clinical, biologic, and imaging characteristics of patients would allow development of robust and accurate predictive and prognostic scores of AAA evolution and risk of rupture. That kind of approach could help surgeons to better evaluate the indications for surgical repair. Finally, it would also help to better predict the postoperative outcomes and to adapt the surveillance of patients undergoing AAA repair. Such approaches may improve precision medicine and allow a personalized therapeutic approach to be proposed.

We acknowledge Dr Andrew Sage (Department of Cardiovascular Medicine, University of Cambridge) for his careful proofreading of the final manuscript.

AUTHOR CONTRIBUTIONS

Conception and design: JR, FL
Analysis and interpretation: JR, CA, MC, NC, FL
Data collection: JR, CA, MC, AB, RC, EJB, RHK, FL
Writing the article: JR, FL
Critical revision of the article: JR, CA, MC, AB, RC, EJB, RHK, NC, FL
Final approval of the article: JR, CA, MC, AB, RC, EJB, RHK, NC, FL
Statistical analysis: Not applicable
Obtained funding: Not applicable
Overall responsibility: FL

REFERENCES

1. Nordon IM, Hinchliffe RJ, Loftus IM, Thompson MM. Pathophysiology and epidemiology of abdominal aortic aneurysms. Nat Rev Cardiol 2011;8:92-102.
2. Golledge J, Muller J, Daugherty A, Norman P. Abdominal aortic aneurysm: pathogenesis and implications for management. Arterioscler Thromb Vasc Biol 2006;26:2605-13.
3. Wanhainen A, Verzini F, Van Herzeele I, Allaire E, Bown M, Cohnert T, et al. Editor's choice—European Society for Vascular Surgery (ESVS) 2019 clinical practice guidelines on the management of abdominal aorto-iliac artery aneurysms. Eur J Vasc Endovasc Surg 2019;57:8-93.
4. Chaikof EL, Brewster DC, Dalman RL, Makaroun MS, Illig KA, Sicard GA, et al. The care of patients with an abdominal aortic aneurysm: the Society for Vascular Surgery practice guidelines. J Vasc Surg 2009;50(Suppl):S2-49.
5. Beck AW, Sedrakyan A, Mao J, Venermo M, Faizer R, Debus S, et al. Variations in abdominal aortic aneurysm care: a report from the International Consortium of Vascular Registries. Circulation 2016;134:1948-58.
6. Narayanan A, Keedwell EC, Olsson B. Artificial intelligence techniques for bioinformatics. Appl Bioinformatics 2002;1:191-222.
7. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436-44.
8. Panch T, Szolovits P, Atun R. Artificial intelligence, machine learning and health systems. J Glob Health 2018;8:020303.
9. Loh BC, Then PH. Deep learning for cardiac computer-aided diagnosis: benefits, issues & solutions. Mhealth 2017;3:45.
10. Dey D, Slomka PJ, Leeson P, Comaniciu D, Shrestha S, Sengupta PP, et al. Artificial intelligence in cardiovascular imaging: JACC state-of-the-art review. J Am Coll Cardiol 2019;73:1317-35.
11. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med 2019;380:1347-58.
12. Ngiam KY, Khor IW. Big data and machine learning algorithms for health-care delivery. Lancet Oncol 2019;20:e262-73.
13. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M, et al. Artificial intelligence in cardiology. J Am Coll Cardiol 2018;71:2668-79.
14. Henglin M, Stein G, Hushcha PV, Snoek J, Wiltschko AB, Cheng S. Machine learning approaches in cardiovascular imaging. Circ Cardiovasc Imaging 2017;10:e005614.
15. Subasic M, Loncaric S, Sorantin E. 3-D image analysis of abdominal aortic aneurysm. Stud Health Technol Inform 2000;77:1195-200.
16. de Bruijne M, van Ginneken B, Viergever MA, Niessen WJ. Adapting active shape models for 3D segmentation of tubular structures in medical images. Inf Process Med Imaging 2003;18:136-47.
17. de Bruijne M, van Ginneken B, Viergever MA, Niessen WJ. Interactive segmentation of abdominal aortic aneurysms in CTA images. Med Image Anal 2004;8:127-38.

18. Olabarriaga SD, Rouet JM, Fradkin M, Breeuwer M, Niessen WJ. Segmentation of thrombus in abdominal aortic aneurysms from CTA with nonparametric statistical grey level appearance modeling. IEEE Trans Med Imaging 2005;24:477-85.
19. Zhuge F, Rubin GD, Sun S, Napel S. An abdominal aortic aneurysm segmentation method: level set with region and statistical information. Med Phys 2006;33:1440-53.
20. Lee K, Johnson RK, Yin Y, Wahle A, Olszewski ME, Scholz TD, et al. Three-dimensional thrombus segmentation in abdominal aortic aneurysms using graph search based on a triangular mesh. Comput Biol Med 2010;40:271-8.
21. Duquette AA, Jodoin PM, Bouchot O, Lalande A. 3D segmentation of abdominal aorta from CT-scan and MR images. Comput Med Imaging Graph 2012;36:294-303.
22. Zohios C, Kossioris G, Papaharilaou Y. Geometrical methods for level set based abdominal aortic aneurysm thrombus and outer wall 2D image segmentation. Comput Methods Programs Biomed 2012;107:202-17.
23. Maiora J, Papakostas GA, Kaburlasos VG, Grana M. A proposal of texture features for interactive CTA segmentation by active learning. Stud Health Technol Inform 2014;207:311-20.
24. Joldes GR, Miller K, Wittek A, Forsythe RO, Newby DE, Doyle BJ. BioPARR: a software system for estimating the rupture potential index for abdominal aortic aneurysms. Sci Rep 2017;7:4641.
25. Lalys F, Yan V, Kaladji A, Lucas A, Esneault S. Generic thrombus segmentation from pre- and post-operative CTA. Int J Comput Assist Radiol Surg 2017;12:1501-10.
26. Lopez-Linares K, Aranjuelo N, Kabongo L, Maclair G, Lete N, Ceresa M, et al. Fully automatic detection and segmentation of abdominal aortic thrombus in post-operative CTA images using deep convolutional neural networks. Med Image Anal 2018;46:202-14.
27. Dias-Neto M, Neves E, Sousa-Nunes F, Henriques-Coelho T, Sampaio S. Abdominal aortic aneurysm calcification: trying to identify a reliable semiquantitative method [published online ahead of print February 8, 2018]. J Cardiovasc Surg (Torino). doi: 10.23736/S0021-9509.18.10132-7.
28. Wang D, Zhang R, Zhu J, Teng Z, Huang Y, Spiga F, et al. Neural network fusion: a novel CT-MR aortic aneurysm image segmentation method. Proc SPIE Int Soc Opt Eng 2018: 10574.
29. Lareyre F, Adam C, Carrier M, Dommerc C, Mialhe C, Raffort J. A fully automated pipeline for mining abdominal aortic aneurysm using image segmentation. Sci Rep 2019;9:13750.
30. Martufi G, Di Martino ES, Amon CH, Muluk SC, Finol EA. Three-dimensional geometrical characterization of abdominal aortic aneurysms: image-based wall thickness distribution. J Biomech Eng 2009;131:061015.
31. Shum J, DiMartino ES, Goldhamme A, Goldman DH, Acker LC, Patel G, et al. Semiautomatic vessel wall detection and quantification of wall thickness in computed tomography images of human abdominal aortic aneurysms. Med Phys 2010;37:638-48.
32. Shum J, Martufi G, Di Martino E, Washington CB, Grisafi J, Muluk SC, et al. Quantitative assessment of abdominal aortic aneurysm geometry. Ann Biomed Eng 2011;39:277-86.
33. Filipovic N, Ivanovic M, Krstajic D, Kojic M. Hemodynamic flow modeling through an abdominal aorta aneurysm using data mining tools. IEEE Trans Inf Technol Biomed 2011;15: 189-94.
34. Jordanski M, Radovic M, Milosevic Z, Filipovic N, Obradovic Z. Machine learning approach for predicting wall shear distribution for abdominal aortic aneurysm and carotid bifurcation models. IEEE J Biomed Health Inform 2018;22:537-44.
35. Turton EP, Scott DJ, Delbridge M, Snowden S, Kester RC. Ruptured abdominal aortic aneurysm: a novel method of outcome prediction using neural network technology. Eur J Vasc Endovasc Surg 2000;19:184-9.
36. Kleinstreuer C, Li Z. Analysis and computer program for rupture-risk prediction of abdominal aortic aneurysms. Biomed Eng Online 2006;5:19.
37. Hadjianastassiou VG, Franco L, Jerez JM, Evangelou IE, Goldhill DR, Tekkis PP, et al. Informed prognosis [corrected] after abdominal aortic aneurysm repair using predictive modeling techniques [corrected]. J Vasc Surg 2006;43: 467-73.
38. Garcia G, Maiora J, Tapia A, De Blas M. Evaluation of texture for classification of abdominal aortic aneurysm after endovascular repair. J Digit Imaging 2012;25:369-76.
39. Attallah O, Ma X. Bayesian neural network approach for determining the risk of re-intervention after endovascular aortic aneurysm repair. Proc Inst Mech Eng H 2014;228: 857-66.
40. Karthikesalingam A, Attallah O, Ma X, Bahia SS, Thompson L, Vidal-Diez A, et al. An artificial neural network stratifies the risks of reintervention and mortality after endovascular aneurysm repair; a retrospective observational study. PLoS One 2015;10:e0129024.
41. Wise ES, Hocking KM, Brophy CM. Prediction of in-hospital mortality after ruptured abdominal aortic aneurysm repair using an artificial neural network. J Vasc Surg 2015;62:8-15.
42. Perrin D, Badel P, Orgeas L, Geindreau C, Dumenil A, Albertini JN, et al. Patient-specific numerical simulation of stent-graft deployment: validation on three clinical cases. J Biomech 2015;48:1868-75.
43. Perrin D, Demanget N, Badel P, Avril S, Orgeas L, Geindreau C, et al. Deployment of stent grafts in curved aneurysmal arteries: toward a predictive numerical tool. Int J Numer Method Biomed Eng 2015;31:e02698.
44. Monsalve-Torra A, Ruiz-Fernandez D, Marin-Alonso O, Soriano-Paya A, Camacho-Mackenzie J, Carreno-Jaimes M. Using machine learning methods for predicting inhospital mortality in patients undergoing open repair of abdominal aortic aneurysm. J Biomed Inform 2016;62:195-201.
45. Perrin D, Badel P, Orgeas L, Geindreau C, du Roscoat SR, Albertini JN, et al. Patient-specific simulation of endovascular repair surgery with tortuous aneurysms requiring flexible stent-grafts. J Mech Behav Biomed Mater 2016;63: 86-99.
46. Attallah O, Karthikesalingam A, Holt PJ, Thompson MM, Sayers R, Bown MJ, et al. Using multiple classifiers for predicting the risk of endovascular aortic aneurysm repair re-intervention through hybrid feature selection. Proc Inst Mech Eng H 2017;231:1048-63.
47. Attallah O, Karthikesalingam A, Holt PJ, Thompson MM, Sayers R, Bown MJ, et al. Feature selection through validation and un-censoring of endovascular repair survival data for predicting the risk of re-intervention. BMC Med Inform Decis Mak 2017;17:115.
48. Lee R, Jarchi D, Perera R, Jones A, Cassimjee I, Handa A, et al. Applied machine learning for the prediction of growth of abdominal aortic aneurysm in humans. EJVES Short Rep 2018;39:24-8.
49. Sakalihasan N, Limet R, Defawe OD. Abdominal aortic aneurysm. Lancet 2005;365:1577-89.
50. Swedenborg J, Eriksson P. The intraluminal thrombus as a source of proteolytic activity. Ann N Y Acad Sci 2006;1085: 133-8.

51. Buijs RV, Willems TP, Tio RA, Boersma HH, Tielliu IF, Slart RH, et al. Calcification as a risk factor for rupture of abdominal aortic aneurysm. Eur J Vasc Endovasc Surg 2013;46:542-8.
52. Agatston AS, Janowitz WR, Hildner FJ, Zusmer NR, Viamonte M Jr, Detrano R. Quantification of coronary artery calcium using ultrafast computed tomography. J Am Coll Cardiol 1990;15:827-32.
53. Kurugol S, Come CE, Diaz AA, Ross JC, Kinney GL, Black-Shinn JL, et al. Automated quantitative 3D analysis of aorta size, morphology, and mural calcification distributions. Med Phys 2015;42:5467-78.
54. Graffy PM, Liu J, O'Connor S, Summers RM, Pickhardt PJ. Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort. Abdom Radiol (NY) 2019;44:2921-8.
55. Canchi T, Kumar SD, Ng EY, Narayanan S. A review of computational methods to predict the risk of rupture of abdominal aortic aneurysms. Biomed Res Int 2015;2015: 861627.
56. Lijftogt N, Luijnenburg TW, Vahl AC, Wilschut ED, Leijdekkers VJ, Fiocco MF, et al. Systematic review of mortality risk prediction models in the era of endovascular abdominal aortic aneurysm surgery. Br J Surg 2017;104: 964-76.

Submitted Aug 14, 2019; accepted Dec 7, 2019.

Additional material for this article may be found online at www.jvascsurg.org.

Supplementary Table (online only). Combination of keywords used for the search strategy in PubMed/MEDLINE database

Combination of keywords		
Artificial intelligence OR		Aneurysm OR
Machine learning OR		Aortic aneurysm OR
Deep learning OR	AND	Abdominal aortic aneurysm OR
Neural network OR		Open repair OR
Convolutional neural network OR		Endovascular repair
Segmentation		