Review Article on Artificial Intelligence in Thoracic Disease: from Bench to Bed

Artificial intelligence in thoracic surgery: a narrative review

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Objective: The aim of this article is to review the current applications of artificial intelligence in thoracic surgery, from diagnosis and pulmonary disease management, to preoperative risk-assessment, surgical planning, and outcomes prediction.

Background: Artificial intelligence implementation in healthcare settings is rapidly growing, though its widespread use in clinical practice is still limited. The employment of machine learning algorithms in thoracic surgery is wide-ranging, including all steps of the clinical pathway.

Methods: We performed a narrative review of the literature on Scopus, PubMed and Cochrane databases, including all the relevant studies published in the last ten years, until March 2021.

Conclusion: Machine learning methods are promising encouraging results throughout the key issues of thoracic surgery, both clinical, organizational, and educational. Artificial intelligence-based technologies showed remarkable efficacy to improve the perioperative evaluation of the patient, to assist the decision-making process, to enhance the surgical performance, and to optimize the operating room scheduling. Still, some concern remains about data supply, protection, and transparency, thus further studies and specific consensus guidelines are needed to validate these technologies for daily common practice.

Keywords: Artificial intelligence (AI); thoracic surgery; machine learning; lung resection; perioperative medicine

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Introduction

Artificial intelligence (AI) can be defined as the science of computer algorithms able to perform tasks that imitate human cognitive functions and intelligence (1). AI-based technologies have recently experienced a widespread explosion across many disciplines, and their implementation in healthcare settings is accordingly growing (2).

The applications of AI systems in medicine seem currently endless, ranging from diagnosis generation and risk prediction, to therapy selection and outcome evaluation (3,4). The aim of these techniques is to extract relevant information from massive healthcare data and to assist clinical decision-making, thus reducing medical errors, and enhancing the quality and efficiency of care (5).

AI devices mainly fall into two major categories, natural language processing (NLP) methods and machine learning (ML) techniques, even if some overlapped features are common to both technologies (3). NLP methods can obtain useful information from unstructured data, such as clinical reports, operative notes, and discharge summaries, turning narrative texts into data that can be processed by computer programs (6). ML techniques construct analytical algorithms to iteratively analyze titanic amount of structured information, such as imaging and genetic data; they can extract meaningful patterns and create

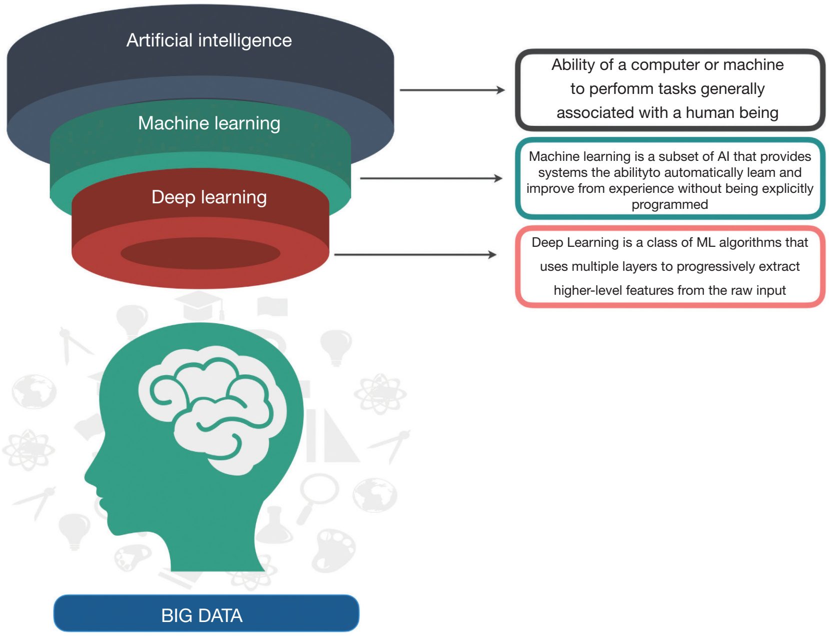

Figure 1 Definitions and relationships of artificial intelligence-based techniques.

prediction models about input variables (7,8) *(Figure 1)*. There are three subtypes of ML that have been applied to medicine: supervised learning, unsupervised learning, and reinforcement learning (RL) (*Table 1*).

A supervised ML algorithm uses a dataset that has to be labeled by humans, building a relationship between the input variables and the outcomes of interest, when the outcomes are known. Due to the proficiency to provide the best results, supervised techniques such as linear regression, logistic regression, Support Vector Machine (SVM), random forest, naïve Bayes, decision tree, and neural network (3,9), are frequently used in healthcare applications. Although considered a subcategory of supervised learning, deep learning should be mentioned as an independent part, due to its wide application in healthcare setting. This system is made of a series of inputs which go through multiple interconnected layers of neurons (neural networks), that recognize different features independently, and makes predictions on a large quantity of information, finally providing an output. The use of deep learning techniques in medicine have been especially effective if applied to images detection and classification.

In unsupervised ML algorithm, conversely, the only inputs are raw features, and the outcomes are unknown, therefore the method can be used to find hidden patterns in data without human feedback. Principle Component Analysis (PCA) and cluster analysis are the main methods of unsupervised learning successfully used in healthcare to discover new phenotypes of a multifactorial disease (10).

Finally, RL techniques are a family of algorithms that maximize return and are the core technique at the heart of robotic surgery. RL algorithms iteratively try different series of actions until a system can achieve an appropriate performance. They can be used to train a surgical robot to perform a series of actions promoting positive actions and discouraging negative ones, by means of a reward function (11).

The creation and application of a ML method depends on four crucial steps: the collection and preparation of data, the choice and training of the algorithm according to the objective to pursue, the implementation of the software, and the analysis and validation of the system for its proper use *(Figure 2)*.

Despite the promising results of AI implementation in thoracic surgery, its widespread diffusion is far to be a common practice. The aim of this article is to review the current applications of AI to thoracic surgery, exploring the influence of AI-based technologies on each step of the clinical pathway, from diagnosis to the Operating Room (OR), including the legal and ethical aspects related to AI in healthcare *(Figure 3)*.

We present the following article in accordance with the Narrative Review reporting checklist (available at: https://

Table 1 ML algorithms mainly used in healthcare

Algorithm	Definition
Supervised learning	Training a model from input variables and their corresponding labels, using a dataset that has to be labeled by humans
Regression models	Simple models, can provide great insight into linear relationships
Support vector machine	Fast and flexible, its goal is to find an optimal decision boundary between 2 or more classes that put the maximum margin between the 2 groups
Random forest	A collection of short height data structures called random decision trees, that uses different combination of explanatory variables to predict the outcome of interest
Naïve bayes	Family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features
Deep learning	Neural network with many hidden layers, able to handle complex data with various structures to create a prediction. The commonly used deep learning algorithms in medicine include convolution neural network, recurrent neural network, deep belief network and deep neural network
Unsupervised learning	Training a model to find hidden patterns in an unlabeled dataset. Principle component analysis and cluster analysis are the main methods used in healthcare
Reinforcement learning	Group of algorithms that iteratively try different series of actions until the system is able to appropriately perform a reward function

ML, machine learning.

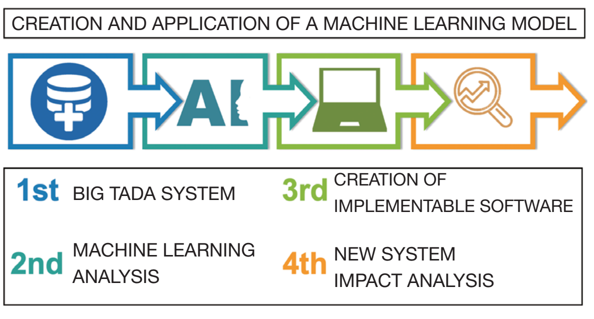

Figure 2 Architectural structure of creation and validation of a machine learning model, designed in four points.

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Methods

We performed a narrative review of the literature on Scopus, PubMed and Cochrane databases. All the relevant studies published in the last ten years, until March 2021 were included. The research string comprised various combinations of "artificial intelligence", "machine learning", "lung cancer", "esophageal cancer", "pathology", "risk assessment", "thoracic surgery", "robotics", "deep

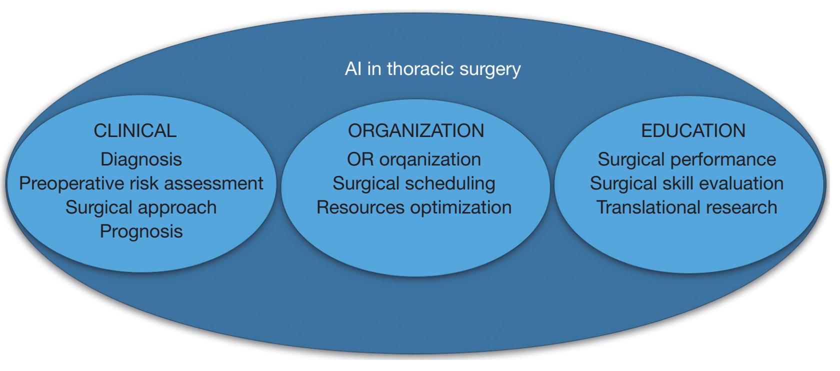

Figure 3 Main fields in which artificial intelligence application has provided the most encouraging results, in both clinical, organizational, and educational settings of thoracic surgery. AI, artificial intelligence; OR, operating room.

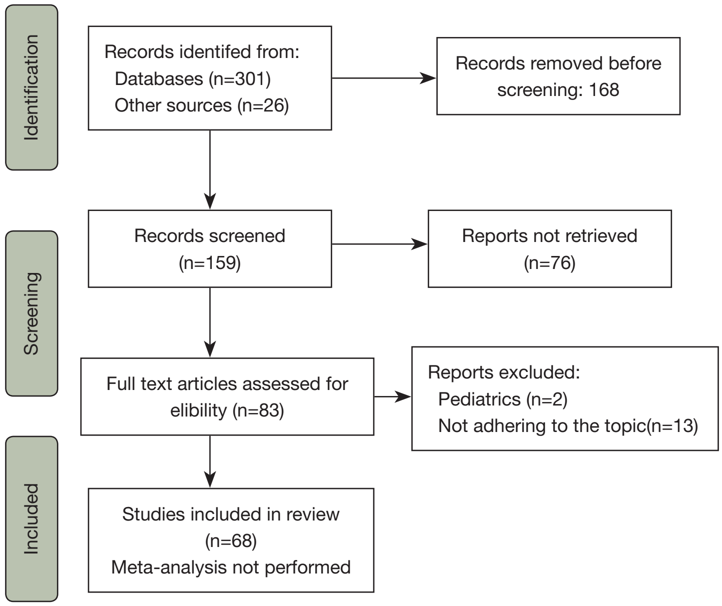

Figure 4 Article selection flow diagram.

learning". Papers concerning children and animals, studies published after March 2021 or written in languages other than English were excluded. Articles of interest that had been cited by the articles identified in the initial search were also included *(Figure 4)*.

Thoracic lesions management

Due to the weight of early detection of lung malignancies on the survival rates, pulmonary nodule management has been one of the main fields to be influenced by the implementation of AI-based technologies. In fact, the substantial variability reported among radiologists in the detection of lung nodules and the high false-positive rate in screening programs (12), bared the need of tools assisting the radiologist in nodule identification, measurement, risk-stratification, and monitoring.

Various Computer-Aided Diagnosis (CAD) techniques have been proposed in pulmonary nodule assessment with CT and chest radiography since last decades (13,14). Although CAD has revealed to improve detection and efficiency, its acceptance in routine clinical practice is prevented from the high number of false positives (15).

More recently, due to their ability to increase diagnostic accuracy (16,17), the introduction of deep learning techniques gained sparkling attention. The turning point was the publication of the paper titled "ImageNet Classification with Deep Convolutional Networks" by Krizhevsky *et al.* (18), who first used a multilayered convolutional computational model known as Convolutional Neural Network (CNN) to identify and classify more than one million of images to a level of accuracy never seen before. Even if the use of CNNs in this paper was not in a radiological setting, the manuscript by Krizhevsky *et al.* paved the way for a wide application of the technique. In fact, CNN is a form of neural networks that uses convolution filters to extract features from images (18) and seem able to detect patterns beyond human perception. In comparison to CAD technique, the innovation of CNNs is due to its capacity to learn from verified data, and to self-determine previously unknown features, thus maximizing classification with limited direct supervision (16). Thus, this architecture of feature extraction by convolutional layers proved to be appliable to image classification and segmentation (19-21). Since 2012, CNNs have proven to be a valid tool in radiologist' hands in assisting pulmonary nodule detection, confirming its superior efficacy compared to both human perception and standard CAD techniques (22-25). Specifically, they show a reduction in the false-positive rate, therefore potentially enabling to prevent unnecessary follow-up (26,27). Moreover, recently, deep learning reported significative results in nodule segmentation and characterization, while only few preliminary studies are currently available about the application of these techniques on monitoring and follow-up of pulmonary lesions (28). Despite the high sensitivity of CNNs in detecting and discriminating pulmonary lesions, some limits have still to be overcome. The main advantage of CNNs is the ability to self-learn previously unknown features, but the learning capacity requires a huge amount of high-quality data; moreover, a substantial number of studies has been conducted on the same large database; so, to validate these techniques for routine clinical use, further work is needed (16,27).

Among other supervised ML algorithms, SVM, random forest, and decision tree are the most widely used in the field of diagnosis of thoracic disease (29). SVM has proven to be successful in enhancing the efficiency of diagnosis (30,31), while random forest has been able to correctly classify non-small cell lung cancer (NSCLC) (32) (*Table 2*).

Current literature about AI application on the management of thoracic disease other than pulmonary nodules is to date limited. AI based technologies have been mainly applied in the early and accurate detection of esophageal malignant lesion (33-35), and in the classification of thymic epithelial tumours (36).

Preoperative evaluation and risk- assessment

In last decades, AI gained attention in the field of preoperative risk assessment, resulting in many ML algorithms to predict the risk of major complications and mortality after surgery (37,38).

Due to the high morbidity rates, it is of utmost importance to properly evaluate candidates for a thoracic surgical procedure, to assess their individual risk and prognosis (39). In this regard, AI-based technologies have shown promising results, providing an effective aid in the decision-making process, and in the achievement of overall integrated risk scores (40-45) (*Table 3*). Particularly, in 2002, Esteva *et al.* used four different probabilistic artificial neural network models to estimate post-operative prognosis after lung resection (41). Shortly after, Santos-García *et al.*, similarly, evaluated the prediction of cardio-respiratory morbidity after pulmonary resection for NSCLC (42).

More recently, Bolourani *et al.* identified risk factors for respiratory failure after lobectomy and introduced two machine learning-based techniques to predict respiratory failure for quality review and clinical decision-making settings (43). Encouraging results were obtained by Salati *et al.* who, by means of an innovative ML approach called XGBOOST, developed a model able to define the risk of cardiac and pulmonary complications in the early postoperative period for patients submitted to anatomic lung resection (44). Lastly, an AI prediction model with seven supervised ML algorithms was constructed to predict whether patients could be weaned immediately after lung resection surgery or if they could need a staged weaning with transfer to the intensive care unit (45).

Overall, ML algorithms proved to be effective in a tailored optimization of risk definition, increasing the efficacy of the pre-anesthetic evaluation, suggesting the proper therapeutic planning, and improving the communication with patients and family members.

Surgical performance and planning

To date, implementation of AI-based technologies in the OR is limited. Still, they have a promising future in increasing surgical precision and safety, supporting intraoperative decision-making, and predicting postoperative outcomes (46,47).

In the last two decades, surgical robotics has experienced a relentless growth. Minimally invasive surgery has been shown to decrease length of hospital stay and post-operative complications and is currently considered as a core issue of enhanced recovery programs.

However, even if it is commonly associated with AI, robotic-assisted surgery should not be considered an AI-based technology, and it requires full supervision by human surgeon. The range of robotically assisted thoracic procedures is widening and includes lobectomies, resection of mediastinal malignancy, and esophagectomies. The Da Vinci Robotic Surgical System (Intuitive Surgical Inc. Sunnyvale, CA, USA) is the most used platform. Robotic tele-manipulators provide three-dimensional (3D) and magnified visualization, and are equipped with flexible effector instruments, that have a wide freedom of motion, thus enhancing surgeon's dexterity during the procedure (48). Nevertheless, the lack of tactile feedback might impair surgical outcomes, leading to suture breakage or failure. Dai *et al.* evaluated a biaxial haptic feedback system that effectively warns the user when the tension is approaching the suture's failure point (49). Similarly, in 2016, Shademan *et al.* proved the feasibility of autonomous surgery, evaluating a supervised system compared to robotic, laparoscopic, and manual approach, when performing an intestinal anastomosis (50). Furthermore, ML models were used to develop and enhance contactless interfaces with gesture recognition, decreasing the risk of contamination

Table 2 Artificial Intelligence studies related to pulmonary nodules management

Author	Objective	Algorithm	Application	Main results
Nam JG, *et al.*	To develop and validate a DLAD for malignant pulmonary nodules on chest radiographs and to compare its performance with physicians including thoracic radiologists	Deep learning-based automatic detection algorithm	Outperformance of radiograph classification and nodule detection for malignant pulmonary nodules on chest radiographs	Radiograph classification performances of DLAD were a range of 0.92–0.99 (AUROC) and 0.831–0.924 (JAFROC FOM), respectively
Li W, *et al.*	To design a deep convolutional neural networks method for nodule classification, with the advantage of autolearning representation and strong generalization ability	Deep convolutional neural networks	Pulmonary nodule recognition and classification	Results demonstrate the effectiveness of the proposed method in terms of sensitivity and overall accuracy and that it consistently outperforms the competing methods
Nibali A, *et al.*	To improve the ability of CAD systems to predict the malignancy of nodules from cropped CT images of lung nodules	Deep residual networks	Pulmonary nodule malignancy classification	The system achieves the highest performance in terms of all metrics measured including sensitivity, specificity, precision, AUROC, and accuracy
Eppenhof KAJ, *et al.*	To develop a deformable registration method based on a 3-D convolutional neural network, together with a framework for training such a network	Convolutional neural networks	Pulmonary CT registration	This approach results in an accurate and very fast deformable registration method, without a requirement for parameterization at test time or manually annotated data for training
da Silva GLF, *et al.*	To proposes a methodology to reduce the number of false positives using a deep learning technique in conjunction with an evolutionary technique	Convolutional neural networks	Lung nodule false positive reduction on CT images	The methodology was tested on CT scans with the highest accuracy of 97.62%, sensitivity of 92.20%, specificity of 98.64%, and AUROC curve of 0.955
Naqi SM, *et al.*	To develop a multistage segmentation model to accurately extract nodules from lung CT images	Support vector machine	Lung nodule segmentation method	The classification is performed over GTFD feature vector, and the results show 99% accuracy, 98.6% sensitivity and 98.2% specificity with 3.4 false positives per scan
Choi W, *et al.*	To develop a radiomics prediction model to improve pulmonary nodule classification in low-dose CT, and to compare the model with the Lung-RADS for early detection of lung cancer	Support vector machine	Improvement of pulmonary nodule classification in low-dose CT	The model achieved an accuracy of 84.6%, which was 12.4% higher than Lung-RADS
Bashir U, *et al.*	To compare the performance of random forest algorithms utilizing CT radiomics and/or semantic features in classifying NSCLC	Random forest	Non-invasive classification of non-small cell lung cancer	Non-invasive classification of NSCLC can be done accurately using random forest classification models based on well-known CT-derived descriptive features

DLAD, deep learning-based automatic detection algorithm; CAD, computer-aided diagnosis; CT, computed tomography; AUROC, area under the receiver operating characteristic; GTFD, Geometric texture features descriptor; Lung-RADS, Lung CT Screening Reporting and Data System of the American College of Radiology; NSCLC, non-small cell lung cancer.

Table 3 Artificial Intelligence studies related to preoperative evaluation in thoracic surgery

Author	Objective	AI algorithm	Application	Main results
Esteva H, *et al.*	Assessment of surgical risk in patients undergoing pulmonary resection	Neural network	Prediction of postoperative outcomes in lung resections	NN can integrate results from multiple data predicting the individual outcome for patients, rather than assigning them to less-precise risk group categories
Santos-Garcia G, *et al.*	To propose an ensemble model of ANNs to predict cardio-respiratory morbidity after pulmonary resection for NSCLC	Artificial neural network	Prediction of cardio-respiratory morbidity after pulmonary resection for NSCLC	In this series an ANN ensemble offered a high performance to predict postoperative cardio-respiratory morbidity
Bolourani S, *et al.*	To identify risk factors for respiratory failure after pulmonary lobectomy	Random forest	Predicting of respiratory failure after pulmonary lobectomy	Two ML-based prediction models were generated and optimized. The first model, with high accuracy and specificity, is suited for performance evaluation, and the second model, with high sensitivity, is suited for clinical decision making
Salati M, *et al.*	To verify if the application of an AI analysis could develop a model able to predict cardiopulmonary complications in patients submitted to lung resection	Extreme gradient boosting	Prediction of cardiopulmonary complications after lung resection	XGBOOST algorithm generated a model able to predict complications with an area under the curve of 0.75
Chang YJ, *et al.*	To construct a prediction model with seven supervised ML algorithms to predict whether patients could be weaned immediately after lung resection surgery	Multiple ML algorithms	Prediction of staged weaning from ventilator after lung resection surgery	The AI model with Naïve Bayes Classifier algorithm had the best testing result and was therefore used to develop an application to evaluate risk based on patients' previous medical data, to assist anesthesiologists, and to predict patient outcomes in pre-anesthetic clinics

ML, machine learning; NN, neural networks; ANNs, artificial neural networks; NSCLC, non-small cell lung cancer; AI, artificial intelligence.

during surgical procedures (51).

Also, the application of AI could prompt the progression of precision surgery and surgical training. ML algorithms have been proposed to accurately assess surgical skills, therefore providing a feedback during learning curves and periodic evaluations (52-54) (*Table 4*).

Albeit its undisputed advantages, robotic surgery is associated with longer procedural times, and substantial costs (55,56), hence an accurate scheduling of surgical procedures is needed. AI algorithms proved to be a valuable tool to properly plan each procedure, improving the prediction of case duration, and the detection of surgeries with high risks of cancellation (57,58).

The problem of surgical room organization has become increasingly important in the last year; the current coronavirus disease pandemic challenged us to face a disruption of healthcare systems, with considerable consequences on surgery waiting lists and scheduling. In this context, it was hypothesized that ML models might have a substantial role in the optimization of operating rooms efficiency, allowing to save costs and maximize resources (59,60).

Pathology

Histopathological diagnosis remains a crucial step for the optimal therapeutic planning and prognosis prediction. The high variability among pathologists prompted to evaluate the application of AI to computational pathology. In 2016, Yu *et al.* successfully used ML methods for the prognostic prediction of lung adenocarcinoma and squamous cell carcinoma (SCC) patients (61). Comparable results were obtained by Coudray *et al.*, who trained a CNN to distinguish between adenocarcinoma and SCC and to predict mutations from NSCLC histopathology (62). Neural networks algorithms were similarly employed to distinguish histologic patterns of lung adenocarcinoma (63,64), and, more recently, to successfully differentiating

Table 4 Artificial Intelligence studies related to surgical performance

Author	Objective	AI algorithm	Application	Main results
Dai Y, *et al.*	To develop and validate a novel grasper-integrated system with biaxial shear sensing and haptic feedback to warn the operator prior to anticipated suture breakage	Biaxial haptic feedback system	Improvement of outcomes related to knot tying tasks in robotic surgery	This system may improve outcomes related to knot tying tasks in robotic surgery and reduce instances of suture failure while not degrading the quality of knots produced
Shademan A, *et al.*	To demonstrate *in vivo* supervised autonomous soft tissue surgery in an open surgical setting, enabled by a near-infrared fluorescent imaging system and an autonomous suturing algorithm	Smart Tissue Autonomous Robot	Feasibility of supervised autonomous robotic soft tissue surgery	The outcome of supervised autonomous procedures is superior to surgery performed by expert surgeons
Cho Y, *et al.*	To enhance the accuracy of gesture recognition for contactless interfaces	Support vector machine classifier and Naïve Bayes classifier	Enhancement of the accuracy of gesture recognition	Overall accuracy of the five gestures was 99.58%±0.06%, and 98.74%±3.64% on a personal basis using SVM and Naïve Bayes classifiers
Wang Z, *et al.*	To propose an analytical deep learning framework for skill assessment in surgical training	Convolutional neural network	Objective skill evaluation in robot-assisted surgery	The proposed learning model achieved competitive accuracies of 92.5%, 95.4%, and 91.3%, in the standard training tasks: suturing, needle-passing, and knot-tying
Fard *et al.*	To build a classification framework to automatically evaluate the performance of surgeons with different levels of expertise	Multiple ML algorithms	Automated robot-assisted surgical skill evaluation	The proposed framework can classify surgeons' expertise as novice or expert with an accuracy of 82.3% for knot tying and 89.9% for a suturing task
Ershad M, *et al.*	To propose a sparse coding framework for automatic stylistic behavior recognition in short time intervals using only position data from the hands, wrist, elbow, and shoulder	Support vector machine	Evaluation of technical skills in robotic surgery	The proposed dictionary learning method can assess stylistic behavior performance in near real time using user joint position data with improved accuracy

SVM, support vector machine.

between lung carcinoma and non-neoplastic lesion (65) (*Table 5*).

Finally, some studied investigated the application of AI on CT scan and PET/CT to provide a pathological classification of lung carcinoma (66,67).

Prognosis

Some researchers recently explored the application of AI models and radiomics to predict therapy response and outcomes in lung malignancies (68,69).

Moreover, machine learning approaches provide encouraging results to predict the risk of recurrence of lung and esophageal adenocarcinoma (70,71).

Limits, legal and ethical issues

Despite the encouraging results of AI implementation in all fields of patient-care settings, before it can be applied to daily practice, several issues remain to be addressed.

The widespread application of AI has opened new debates about legislative issues and the protection of privacy. This aspect has become even more evident in the world of healthcare, where progress has to deal with the protection of personal and extremely sensitive information. For this reason, some scientific societies have developed specific guidelines on the subject (72,73). Nevertheless, the technology at the moment is spread so fast that the legislative paths are not always able to keep its rapidity. An example is the General Data Protection Regulation 2018 by

Table 5 Artificial Intelligence studies related to lung pathology

Reference	Objective	AI algorithm	Application	Main results
Yu KH, *et al.*	To improve the prognostic prediction of lung adenocarcinoma and squamous cell carcinoma patients through objective features distilled from histopathology images	Elastic net-Cox proportional hazards model	Prediction of the prognosis of lung cancer by automated pathology image features and thereby contribution to precision oncology	Automatically derived image features can predict the prognosis of lung cancer patients
Coudray N, *et al.*	To train a deep convolutional neural network on whole-slide images obtained from The Cancer Genome Atlas to accurately and automatically classify them	Deep convolutional neural network	Detection of cancer subtype or gene mutations and mutation prediction from non-small cell lung cancer histopathology	Deep-learning models can assist pathologists in the detection of cancer subtype or gene mutations
Wei JW, *et al.*	To propose a deep learning model that automatically classifies the histologic patterns of lung adenocarcinoma on surgical resection slides	Deep neural network	Improvement of classification of lung adenocarcinoma patterns	All evaluation metrics for the model and the three pathologists were within 95% confidence intervals of agreement
Gertych A, *et al.*	To a pipeline equipped with a CNN to distinguish four growth patterns of pulmonary adenocarcinoma (acinar, micropapillary, solid, and cribriform) and separate tumor regions from non-tumor	Convolutional neural network	To assist pathologists in improving classification of lung adenocarcinoma patterns by automatically pre-screening and highlighting cancerous regions prior to review	The overall accuracy of distinguishing the tissue classes was 89.24%
Kanavatl F, *et al.*	To train a CNN, using transfer learning and weakly-supervised learning, to predict carcinoma in Whole Slide Images	Convolutional neural network	Development of software suites that could be adopted in routine pathological practices and potentially help reduce the burden on pathologists	Highly promising results for differentiating between lung carcinoma and non-neoplastic lesion

CNN, Convolutional Neural Network.

the European Union. (EU-GDPR), which despite having been drawn up to meet new requirements, not explicitly insert the term “artificial intelligence” in the text (74). Furthermore, by not specifically addressing the subject of AI, often the indications provided are sometimes too stringent to allow adequate progress of these technologies and escape strategies are needed to be able to continue developing them (75). If on the one hand AI in medicine is offering many promises, on the other hand the rights of citizens must always be able to be considered; it is a very delicate balance between progress and privacy (76). A specific regulation of AI in healthcare will probably be necessary. Furthermore, a legislative expert should be also included in each multidisciplinary research group dealing with this topic in order to be in line with current legislation.

The efficacy, validation, and improvement of ML algorithms depend on the amount and supply of high-quality data (4). Data need to be available in a standard format and accurately labeled to be shared across centers, thus raising concerns about data protection, informed consent, and cybersecurity (77,78). Furthermore, data used for ML training models can be easily biased, hence the publication of consensus guidelines to assess the validation of AI-based technologies is needed (79). Still, the different geographic distribution of AI implementation remains a major ethical concern; a mindful effort should be made to ensure that all population can receive equal access to the benefits provided by ML models (11).

Finally, due to the huge influence that the implementation of AI algorithms can exert on clinical practice, a primary focus should be the involvement of physicians and researchers, who need to be adequately educated on these technologies, their proper use, and limitations (80). Recently, several prestigious Universities and Scientific Societies are offering specialized courses regarding the use of Big Data, AI and ML in healthcare. It will be essential that healthcare professionals reach a certain degree of digital literacy that will enable them to interface with these new technologies and to extrapolate the maximum use for their patients (81). This will allow for parallel growth and prevent the physician from succumbing to this technological revolution.

Conclusions

Technologies are becoming more and more present in health-care settings. In the perioperative medicine, ML algorithms implementation could prompt a multidisciplinary approach, particularly in preoperative assessment, risk stratification, and postoperative outcomes. AI along with the last innovations of the Health-Technology Assessment (HTA) and Telemedicine, will be the cornerstone of the future of perioperative medicine. Several applications in thoracic surgery have been described, both clinical, organizational, and educational. However, further validation studies are needed to understand the real impact of AI in this specific surgical context.

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Footnote

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