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Artificial Intelligence for Next-Generation Medical Robotics

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Introduction

Since the first use of the word "robot" by a Czechoslovakian author Karel Čapek in a drama as *Rossum's Universal Robots in 1920*, it spread quickly all over the world and became a common term for artificial beings. Robots have been used in surgery since 1978; however, to justify the cost of robotic surgery, a quest for proven advantage over existing surgical techniques remains ongoing. Artificial intelligence (AI) is understood to be near-human intelligence exhibited by a machine for pattern recognition and decision-making. Future systems posing a certain degree of intelligence together with the increased possibility of connectivity will provide the answer for the questions being raised by traditional surgeons. Building these new intelligent robots will be one of the future tasks for humanity.

Artificial Intelligence

Nowadays, vast amounts of data are being generated in every field of medicine, making data analysis an immense task for humans. However, the level of analysis by humans alone of this big data has clearly been surpassed by artificial intelligence (AI) in an age where healthcare is dependent on human precision more than ever. An AI machine displays qualities of human intelligence by using algorithms to perform pattern recognition and decision-making. AI is broadly classified as *general* AI and *narrow* AI where the former describes machines that exhibit and imitate human thought, emotion, and reason (i.e., machines that can pass the Turing test remain elusive for now), whereas the latter is used for technologies that can perform as well or better than humans for specific tasks (like analyzing vast medical data in diverse fields).

AI, by eliminating human error, is expected to significantly reduce the number of misdiagnosis cases, excessive waste of resources, errors in treatment, and workflow inefficiencies and also *increase (not subtract from) the interaction times* between patients and clinicians. It is, therefore, important for surgeons to know about AI and to understand its effect on modern healthcare as they will be increasingly interacting with AI systems within the healthcare environment.

AI currently serves many purposes as a powerful tool in various areas – such as renewable energy systems, economics, weather predictions, manu-

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facturing, and medicine – helping researchers worldwide. Its roots are found in robotics, philosophy, psychology, linguistics, and statistics [1, 2]. The popularity of AI soared with the major advances in computer science, mainly processing power and speed, which enabled the efficient implementation of long developed algorithms within the area. AI can be divided into four main subfields. They are (a) machine learning, (b) natural language processing, (c) artificial neural networks, and (d) computer vision. Although it seems complicated, we will try to explain each field separately and connect them – especially for robotic surgery applications [1–3]. These four subfields are the very foundation of digital surgery.

Machine Learning

Machine learning (ML) is a subfield of AI which can be described as the practice of solving a problem by enabling the machines to learn and make predictions by using a dataset and algorithmically building a statistical model. ML is useful for identifying subtle patterns which are impossible to be seen by humans in large datasets. There are four types of learning algorithms which are termed as follows: *supervised*, *semi-supervised*, *unsupervised*, and *reinforcement* [4].

In *supervised learning*, human-labeled training data are fed into an ML algorithm to teach the computer a function such as recognizing an organ (stomach, duodenum, colon, liver, etc.) in an image. This kind of learning is useful in predicting known results or outcomes, as it focuses on classification.

In *unsupervised learning*, the training dataset consists of unlabeled examples and this unlabeled data is fed into the learning algorithm. Unlike supervised learning, unsupervised learning does not involve a predefined outcome; hence, it is exploratory and used to find naturally occurring undefined patterns or clusters within datasets. The significance of such groups learned through unsupervised learning is evaluated by its performance in subsequent supervised learning tasks (i.e., are these new patterns useful in some way?).

In *semi-supervised learning*, the training dataset contains a small amount of labeled data and a large amount of unlabeled data. It can be viewed as a mix between supervised and unsupervised learning. Training data is clustered similar to unsupervised learning and the labeled training data is used to classify these clusters in a supervised learning fashion. It has been found that unlabeled data can produce significant improvement in learning accuracy when used in conjunction with a small amount of labeled data. Semi-supervised learning is similar to supervised learning in its goals.

Reinforcement learning consists of learning algorithms where the machine attempts to accomplish a specified task (playing games, driving, robotics, resource management, or logistics) with the help of a specifically designed reward function. Through its own mistakes and successes, the reinforcement learning algorithm assigns a negative or a positive reward to the agent which learns a policy to perform a task. A policy defines the learning agent's way of behaving at a given time, and it maps the state that the agent is in, to the action the agent should execute in that state. Reinforcement learning is suitable for particular problems in which the decision-making is sequential, and the goal is long term.

Natural Language Processing

Natural language processing (NLP) is the subfield of artificial intelligence where the ability to understand human language is built into a machine [5]. For this purpose, NLP recognizes words and understands semantics and syntax. NLP has been used to identify words and phrases in operative reports and progress notes for surgical patients that predicted anastomotic leak after colorectal surgery. Although the majority of these predictions coincided with simple clinical knowledge (operation type and difficulty), the algorithm was also, quite interestingly, able to adjust predictive weights of phrases that describe patient temperament such as "irritated" or "tired" relative to the post-op day to predict a leak with a sensitivity of 100% and a specificity of 72% [6].

Artificial Neural Networks and Deep Learning

Artificial neural networks (ANNs) are of outstanding importance in many AI applications. ANNs are based on layers of connected nodes (artificial neurons) which model the basic functions of a biological neuron. In this regard, each connection is a pathway to transmit signals to other nodes (neurons) similar to synapses in the brain. *In deep learning, a special structure of neural networks is used that are called deep neural networks (DNNs) with multiple layers between the input and output layers as opposed to simple 1 or 2-layer ANNs, and this complexity in structure enables them to learn more complex and subtle patterns (*Fig. 3.1*). Deep learning's autodidactic quality is what sets it apart from the other subtypes of AI. The neural network is not predesigned, but instead, the number of layers is determined by the data itself with this quality.* A DNN consists of digitized inputs (i.e., speech or image data) which go through multiple layers of connected nodes that detect features progressively and provide an output (i.e., label) in the end. For example, a DNN achieved an unprecedentedly low error rate for automated image classification by analyzing 1.2 million carefully annotated images from over 15 million in the ImageNet database [3, 5, 7].

Computer Vision

Computer vision, also known as machine vision, is an area of science that focuses on how computers gain high-level understanding of images and videos. Image acquisition and interpretation in axial imaging with applications such as image-guided surgery, virtual colonoscopy, and computer-aided diagnosis are all important utilizations of computer vision from a healthcare per-

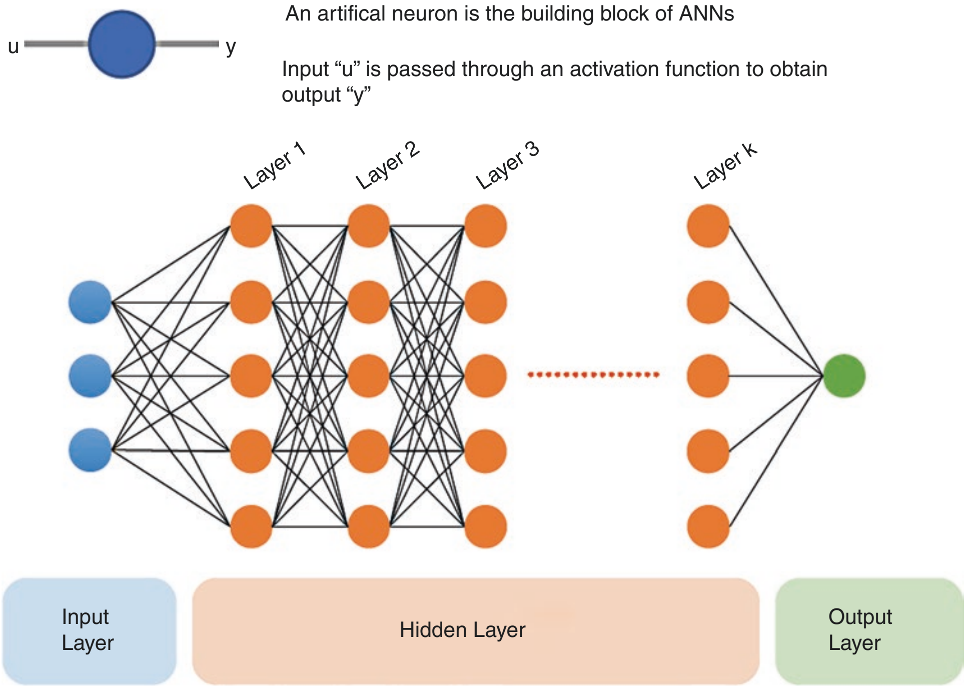

Fig. 3.1 (**a**) Model of a single neuron in machine learning. (**b**) An example of a deep neural network with multiple layers

Fig. 3.2 AI, machine learning, and their use in medicine

spective. Current work in computer vision concentrates on understanding higher-level concepts. In surgery, real-time analysis of a laparoscopic video has yielded 92.8% accuracy in automated identification of the steps of a sleeve gastrectomy and noted missing or unexpected steps [3]. In addition, recent research efforts exist in the field in hopes of "digitizing surgery." This consists of observation of the surgical team and equipment in the operating room and performance of the surgeon with the help of computer vision (real-time, high-resolution, AI-processed imaging of the relevant anatomy of the patient) and integration of a patient's comprehensive preoperative data which includes full medical history, labs, and scans [5].

AI is a powerful tool in medicine and different methods are used from diagnostics to patient care. Figure 3.2 provides a summary of different methods and their respective application areas.

History of Robotic Surgery

The word "robot" was first defined by the Robots Institute of America in 1979 as "*a reprogrammable, multifunctional manipulator designed to move materials, parts, tools, or specialized devices through various programmed motions for the performance of a variety of tasks*" [8]. The first robot used in a real surgery was PUMA (*programmable universal machine for assembly*) developed by Scheinman in 1978 [9]. It was used by Kwoh in 1985 for neurosurgical biopsies and then by urologists in 1988 [10]. It was changed to surgeon-assistant robot for prostatectomy (SARP). This robot could only be used on some *fixed* anatomic targets and was not suitable for operations like gastrointestinal surgery where the surgical targets are dynamic and fluid.

At the Stanford Research Institute, Richard Satava, a military surgeon, developed an operating system for instrument tele-manipulation after the introduction of laparoscopic cholecystectomy. In 1988, Satava and his group started working on a robotic system for laparoscopic surgery. In 1993, AESOP (*automated endoscopic system for optimal positioning*) was developed by Yulin Wang and his company, Computer Motion, Inc., in Goleta, CA, USA. This was the first FDA-approved surgical robot [11]. In 1998, ZEUS, the new robot capable of reproducing the movements of the arms of the surgeon, was developed by DARPA (*Defense Advanced Research Projects Agency*). It was later used in 2001 by Prof. Marescaux to perform transcontinental telesurgery, a landmark achievement [12]. Computer Motion, Inc. was eventually acquired by Intuitive Surgical, Inc., which retired the development of the ZEUS robot, supplanting it with a new system. Intuitive Surgical then developed da Vinci as a master–slave robot, which received CE mark in 1999 and the full FDA approval in 2001. The da Vinci Surgical System is currently the most widely used, which has the models of *S, Si, Xi,* and, more recently, *SP*. This master–slave system overcame the limitations of laparoscopic surgery, its technical improvements including magnified 3D optics, precisely controlled wristed instruments with tremor filtration, and seven degrees of freedom. With the preservation of natural eye–hand–instrument alignment, it made the robotic platform highly suitable for a wide range of surgical procedures. The da Vinci *Xi,* the robotic effectors, have a much slimmer design than previous renditions as well as a longer "arm span," which greatly minimizes instrument clashing and collision. Adjunctive tools and accessories include stapling devices with 6 degrees of freedom (dof) or 6-dof flexible instruments, single site, firefly system, Tilpro system, and double console. Recent advancements on robotic technology also resulted in the development of the VeSPA single-port system. However, the VeSPA system has suboptimal ergonomics with clashing of instruments and provides only 4-dof instruments. The *SP* system designed for single-port access has a single arm that delivers three multi-jointed instruments and a fully wristed 3D HD camera for visualization and control in narrow surgical spaces [10]. Robotics surgery devices such as these are used in many areas in medicine and new applications are emerging with each technological development (Fig. 3.3).

Emerging Robotic Surgical Systems

The Italian healthcare company Sofar, Milan, Italy (which was later acquired by TransEnterix, *Morrisville, NC, USA*) developed an alternative robotic system, the Telelap ALF-X (currently known as *Senhance*). The design featured a remote surgeon workstation and three cable-actuated robotic arms featuring instruments and a telescope mounted on three separate carts. The device utilizes an open console design with 3D polarized glasses and a monitor with an integrated eye-tracking system which controls camera movements (e.g., the image is zoomed in,

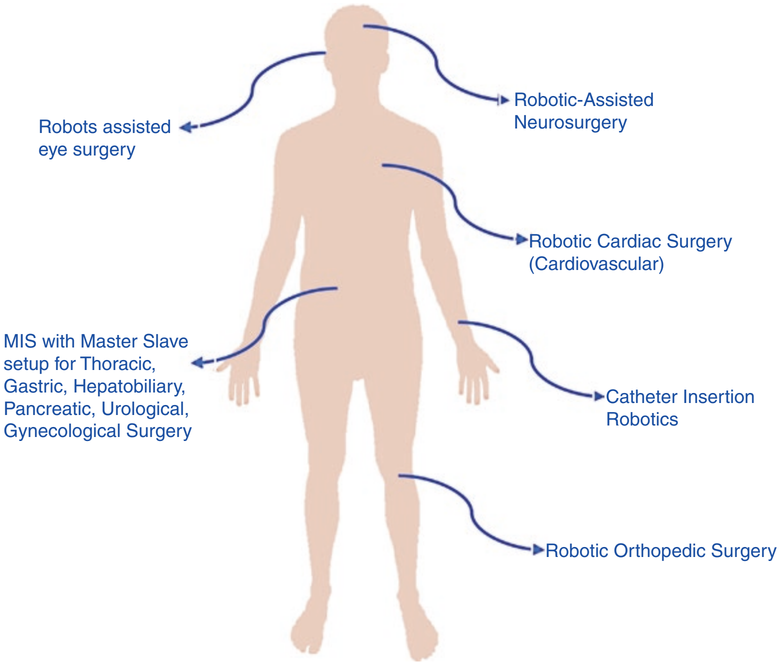

Fig. 3.3 Applications of robotic surgery

when the surgeon's head approaches the screen). Two handles similar to laparoscopic effectors manipulate instruments with 4 dof and 6 dof attached to the robotic arms. Tuebingen Scientific (*Tuebingen, Germany*) developed instruments based on Radius technology. Haptic feedback together with eye tracking is a unique feature of Senhance, when compared to standard da Vinci robots. Haptic feedback is realized by counter-movements of the laparoscopic handle at the console according to force and direction applied at the tip of the instrument [13, 14].

Upcoming Robotic Systems

Robotic surgical systems are evolving to include specific features and improvements of the bedside cart and effector arms (*lightweight, smaller size, mounted on operating table or on separate carts, single arm with a variety of instruments inside*), instruments (*tactile feedback, micro-motors*), console (*open, closed, semi-open*) or without a console, and 3D HD video technology (*polarized glasses, oculars, mirror technology*).

Several modifications of master–slave systems have been developed and the implementation of the console is one design aspect which separates these systems (discussed below). Intuitive Surgical and Avateramedical have chosen to design their robotic systems with a *closed console,* with in-line 3D video technology. An advantage of this is that polarized glasses are not needed, but an important disadvantage is that closed consoles are generally associated with loss of brightness at the periphery of the field of view. An *open console* system may provide better communication with the team at bedside and the flexibility to integrate future technologies such as ultra-HD (4K) video or full HD 3D screens.

Avatera

Avateramedical (*Jena, Germany*), in collaboration with Force Dimension (*Nyon, Switzerland*) and with Tuebingen Scientific (*Tuebingen, Germany*), has been developing Avatera which, as previously mentioned, was designed with a closed console configuration with an integrated seat using microscope-like technology with two adjustable oculars for in-line 3D image with full-HD resolution. Four robotic arms are mounted on a single cart and 6 degrees of freedom (dof) instruments with a diameter of 5mm are used. The system has no force feedback and only been used in preclinical experimentation [15].

Medicaroid

In 2016, Medicaroid (*Kobe, Japan*) started a corporation in Silicon Valley to prime the US market for medical robots made in Japan with the R&D and manufacturing expertise of Sysmex and Kawasaki Heavy Industries. The device features three robotic arms attached to the operating table; a semi-closed console with ocular-like in-line technology, which still requires polarized glasses; and a telescope with 3D HD technology. However, the system has no force feedback. Clinical launch is expected in 2020 [16].

Medtronic

In 2013, Covidien (Dublin, Ireland, later in 2015 Medtronic) acquired the license for versatile system by MiroSurge (German Aerospace Centre, Oberpfaffenhofen, Germany) and included further developments including instruments in their two research and development centers in the USA and announced the robot in 2019. The system comprises three to four modular robotic arms, an open console with an autofocusing monitor, 3D HD telescope and 3D glasses, fingertip-controlled handles, clutch mechanism, and foot switches to activate bipolar energy. The robotic arms are composed of seven joints with serial kinematics, comparable to human arms, and the instruments are driven by micro-motors optionally providing tactile feedback via potentiometers [17].

Raven

The Raven Project (Universities of Santa Cruz, Berkeley, Davis) has an open-source system that would allow two surgeons to operate on a single patient simultaneously. The prototype system included two portable surgical robotic arms, each offering 7 dof, and a portable surgical console. Raven III offers four robotic arms and (optionally) two cameras. Raven III is one of the most advanced surgical robotic research platforms, focused on battlefield and underwater remote surgery [18].

Revo-I

In collaboration with Yonsei University and multiple Korean academic and industry groups, Meerecompany (Hwasong, Korea) designed the Revo-I platform which features an open console, two handles, and foot controller for clutch mode and cautery. The four-arm system mounted on a single cart uses a 3D HD stereoscope and 6-dof instruments with a diameter of 8mm. In 2016, the first results of animal studies were published in collaboration with Samsung and approval for human trials in South Korea has been received [19].

SPORT™

After the unsuccessful introduction of the Amadeus RSS, Titan Medical focused on the SPORT™ Surgical System as a platform for robotic laparo-endoscopic single-site surgery (LESS). SPORT™ has an open console with 3D HD vision controlling, a 3D flexible telescope with fiber-optic-based illumination, and two flexible instruments on a single robotic boom. Its main application is expected to be LESS cholecystectomy. Recently, robotic single-port partial nephrectomy was performed in animal models requiring additional trocars for retraction. The FDA approval for the system is currently pending [20].

Da Vinci *SP*

The da Vinci *Xi* system also allows the use of the robotic single-port *SP* 1098 platform including a 3D HD flexible telescope and three flexible instruments. This system has a master console and slave patient cart with a single arm. Once introduced into the abdominal cavity (or, alternatively, through a natural orifice), the flexible instruments, with a snake-style wrist, can separate to achieve triangulation [10, 14].

Verb Surgical

Verb Surgical was formed in 2015 as an independent start-up company, backed by Google and Johnson & Johnson to harness the unique capabilities of both companies [21]. It is detailed elsewhere in this textbook.

EndoMaster

Developed in Singapore originally for endoscopic resection of gastrointestinal polyps and tumors, EndoMaster has been used for natural orifice transluminal endoscopic surgery (NOTES) as well as transoral robotic surgery. This system has been designed with robotic arms (a grasper and a probe for monopolar diathermy) that are incorporated into the end of a flexible endoscope. It consists of a master telesurgical workstation and a slave manipulator (endoscope with robotic arms). Thus far, EndoMaster has only been used for preclinical trials on cadavers and animal models [22].

Computer Technology Drives Progress in Robotics

Innovation in robotic surgery will continue to parallel advancements in technology; especially with the considerable progress in computer science and AI. Novel distinct features, such as haptic gloves, cellular image guidance, or even autonomy might be the next step in the evolution of next-generation devices. Shademan et al. have described in vivo supervised autonomous soft tissue surgery in an open surgical setting, enabled by a plenoptic 3D and near-infrared fluorescent imaging system that supports an autonomous suturing algorithm. A computer program generates a plan to complete complex surgical tasks on deformable soft tissue, such as suturing an intestinal anastomosis based on expert human surgical practices [23]. Despite dynamic scene changes and tissue movement during surgery, they were able to show that the outcome of supervised autonomous procedures was superior to surgery performed by expert surgeons and robot-assisted techniques. The Smart Tissue Autonomous Robot (STAR) results show the potential for autonomous robots to improve efficacy, consistency, functional outcome, and accessibility of surgical techniques. By 2020, robotic surgery, once a simple master–slave device, is poised to merge fundamental concepts in AI as it evolves into digital surgery [24].

Autonomous Robotic Surgery

What Is Autonomy?

Physical, mental, technical variables dictate the performance of the surgeon and these factors affect the outcome. Surgical robots have the advantage of tremor cancellation, scalable motion, insusceptibility to fatigue, and greater range of axial movement which should, in turn, positively impact the quality of surgical care rendered.

Autonomy is defined as "an ability to perform intended tasks based on current state and sensing without human intervention." Although da Vinci is a master–slave robot and completely dependent on human control, to some extent, it has a variable degree of autonomy, since there is "built-in" tremor resistance and scalable motion. If equipped with cognitive capabilities, surgical robots could accomplish more supervised tasks and thus provide a greater level of assistance to the surgeon. Partially autonomous robots such as TSolution-One (Think Surgical, Fremont, CA), Mazor X (Mazor Robotics, Caesarea, Israel), and CyberKnife (Accuracy, Sunnyvale, CA) are currently in clinical use.

A robot is not a *single* device; rather it is a system with three components, *sensors, end effectors, and control architecture*, that process data and perform actions. During the procedure, there is continuous interaction between the robot, the surgeon, and the patient. A learning system is augmented with a process that allows a surgeon to watch the robot and provide feedback based on the behavior of the robot.

Combining AI (*machine learning, natural language processing, artificial neural networks, and computer vision*) with surgical robots may reduce technical and human errors, operative time, and rates of complications and improve the outcome as an ultimate end point. The robots can be taught specific procedures. There are certain methods proposed to "teach" the robots either by directly programming it (*explicit learning*) or by having the robot observe a surgeon or video directly (*implicit learning*); in this case, the robot may even be trained in simulation or virtual reality.

Prior knowledge (*collected data*) is of key importance in machine learning, and in surgery, prior knowledge is typically obtained from an experienced surgeon. *The skills, in this case, are collected from robotic surgery videos and from the data provided by the robot's sensory apparatus during similar procedures that were performed by a skilled surgeon.* A surgical activity dataset by Johns Hopkins University and Intuitive Surgical Inc. consisting of motion and video data is available for researchers interested in this problem [24, 25]. However, having access to all this data and video content is not enough for a robot to perform surgery autonomously. The learning model would also need a large database of explicit knowledge on how to accomplish a specific task in surgery. This sort of database would (and should) depend on the inputs from the surgical community, based on the international surgical consensus for each type of operation. In any case, it is highly unlikely that either implicit or explicit learning alone would be sufficient for automation in robotic surgery. However, a merger of both techniques with constant reinforcement and adjustment by human surgical experts could achieve acceptable levels of autonomy in surgical robotics.

Machine Learning in Autonomous Robotic Surgery

Future surgical robots will have the ability to virtually see, think, and act without active human intervention. Certain surgical tasks (suturing, cauterizing a leak in gastric bypass, clamping a certain area, etc.) could be autonomously performed with varying levels of human supervision. Of course, this would only be considered when an automated robotic system has repeatedly demonstrated its ability to achieve an acceptable level of performance in executing the necessary surgical tasks.

Three parameters define the task of an autonomous surgical robot: complexity of the surgical task, environmental difficulty (properties of the surgical site), and human independence. Versatile autonomous surgical devices will require extensive R&D and integration of control algorithms, robotics, computer vision, and smart sensor technology – in addition to extensive trial periods with surgeon-led vetting. Careful study is needed due to the highly deformable nature of soft tissue environments, the presence of hollow organs that are susceptible to rupture, and the delicacy of tissues.

There are certain autonomous systems that have been able to execute confined surgical tasks based on an exemplary dataset (provided by human input). For suture knot-tying tasks on a laparoscopic telesurgical workstation [26], faster and smoother trajectory executions were achieved (compared to a human) via *trajectory smoothing* of surgeon-provided motion examples. The parameters of a controller function were iteratively updated based on the error of a target trajectory (which is derived from the provided examples) to achieve faster trajectories [27]. The EndoPAR system (Technical University of Munich, Germany), a ceiling-mounted experimental surgical platform, was able to execute knot-tying tasks autonomously using recurrent neural networks (RNNs) using a database of 25 expert trajectories [25]. RNNs are a class of artificial neural networks that allows previous outputs to be used as inputs (feedback connections) while having hidden states. In other words, such a machine remembers from the past, and its decisions are influenced by what it has learnt in the past – so the same input could produce a different output depending on previous inputs in the series (sequential memory). This means that RNNs can (in principle) approximate any dynamic system and can be used to implement sequence to sequence mappings that require memory such as the set of trajectories involved in suture knot-tying [28]. The da Vinci Research Kit (DVRK) is used as a platform to apply learning by observation techniques with the aim of automating multilateral subtasks, such as debridement and pattern cutting. This approach involved segmenting motion examples by a human demonstrator into *structural gestures* such as grasping, retraction, penetration, and cutting, which is then used to define a finite state machine (FSM). An FSM is a mathematical model for any system that has a limited number of conditional states it can exist in for any point in time. In a study by Murali et al., 96% repeatability for 50 trials were achieved for the debridement task of 3D Viscoelastic Tissue phantoms and a repeatability of 70% for 20 trials of pattern cutting of 2D Orthotropic Tissue phantoms [29].

A novel endovascular surgery (ES) robot (currently experimental only) was recently used to test a convolutional neural network (CNN)-based framework to navigate the ES robot based on surgeons' skills. The CNN-based method shows capability of adapting to different situations while achieving a similar success rate in average operating time compared to known standards. Compared to manual operation, robotic operation was observed to demonstrate similar operating trajectory and maintained a similar level of operating force [30]. Finally, STAR (mentioned previously) was used for performing supervised autonomous robot-assisted surgery in various soft tissue surgical tasks such as ex vivo linear suturing of a longitudinal cut along a length of suspended intestine, ex vivo end-to-end anastomosis, and in vivo end-to-end anastomosis of porcine small intestine [31].

Although systems that can perform autonomous surgical tasks exist, considerable work will be required to bring fully autonomous surgical robots into fruition. The existing systems are only used in experimental setups on inanimate or animal models. However, the advances and improvements enabled by the power of machine learning cannot be neglected. The automation operations, with the aid of ML, will decrease the time of surgery, enhance the performance, and reduce miscommunication. As mentioned above, ML approaches have the potential to learn a model of surgical skills of experienced surgeons, provided by data points collected in the operating room. Such data could also be used for quantitatively evaluating surgical skills of trainees and to improve existing trainers by accurately modeling the interaction amongst surgeons, patients, and robots [32]. It is apparent that the future of surgery and surgeons will be shaped by these improvements.

Limitations of Artificial Intelligence

Although AI and ML have the potential to revolutionize the way surgery is taught and practiced, it is not a panacea that can solve all problems in surgery. In some cases, traditional analytical methods outperformed AI/ML. Thus, the addition of ML does not always improve results [33].

ML and other AI analyses are highly data driven and the outputs are naturally limited by the types and accuracy of available data. Hence, the patterns AI can recognize, or the predictions it can make, *are susceptible to the systematic biases in clinical data collection.* Furthermore, despite advances in causal inference, AI cannot yet determine causal relationships in data at a level necessary for clinical implementation nor can it provide an automated clinical interpretation of its analyses as of yet. Instead of a single surgeon's error resulting in single patient's harm, in the era of digital surgery and AI, the potential exists for a machine algorithm to result in iatrogenic harm affecting multiple surgical patients. The possibility of such an inadvertent outcome must be carefully considered before AI/ML systems are deployed in operation theaters. Specifically, systematic debugging, audit, extensive simulation, and validation, along with prospective scrutiny, are required when an AI algorithm is introduced into clinical and surgical practice.

As Professor Stephen Hawking has warned, the creation of powerful AI will be *"either the best, or the worst thing, ever to happen to humanity"*. Hawking had praised the creation of an academic institute dedicated to researching the future of intelligence as "crucial to the future of our civilization and our species" [34].

What Surgeons Should Do?

What does the future hold for surgeons as machine learning and deep learning technologies advance? Data will become increasingly voluminous, and to properly interpret such vast datasets, AI and ML will be integral. Where engineers can provide automated, computational solutions to data analytics problems that would otherwise be too costly or time-consuming for manual methods, surgeons have the clinical insight that can guide data scientists and engineers to answer the *right* questions with the *right* data.

Technology-based advancements have the potential to empower every surgeon with the ability to improve the quality of global surgical care. Given that research has indicated that high-quality surgical techniques and skill sets correlate positively with patient outcomes, AI could help *pool this surgical experience* – similar to efforts in genomics and biobanks – to *standardize* decision-making, thus creating a global consensus in operating theaters worldwide. Surgeons can prove to be essential to data scientists by imparting their understanding of the relevance and importance of the relationship between seemingly simple topics, such as anatomy and physiology, to more complex phenomena, such as a disease pathophysiology, operative course, or postoperative complications. AI needs to be held accountable for its predictions and recommendations in medicine; hence, it is up to the surgeons and engineers to push for transparent and interpretable algorithms to ensure that more professionals have an in-depth understanding of its implications. Next-generation surgical robots will be integral in augmenting a surgeon's skills effectively to achieve accuracy and high precision during complex procedures [35]. The next level of surgery that will be achieved by surgical robotics will likely evolve to include AI and ML [36].

At the beginning of the twentieth century, robotics, machine learning, artificial intelligence, surgical robots, and telesurgery were the stuff of science fiction. Yet today, they are all proven reality. We believe everything will change much faster in the twenty-first century as compared to the twentieth century. Although robots will become an indispensable part of routine life, in the field of medicine, surgical robots with artificial intelligence will evolve to have at least some autonomy and ML-/AI-based decision analysis in the near future. Fully autonomous surgical robots probably remain far from reach. However, in the coming decade, the use of machine learning, deep learning, big data analysis, and computer vision, will translate into (appropriately equipped) surgical robots capable of learning every step of an operation – a harbinger for the age of digital surgery.

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