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Evolution of a surgical system using deep learning in minimally invasive surgery (Review)

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Abstract. Recently, artificial intelligence (AI) has been applied in various fields due to the development of new learning methods, such as deep learning, and the marked progress in computational processing speed. AI is also being applied in the medical field for medical image recognition and omics analysis of genomes and other data. Recently, AI applications for videos of minimally invasive surgeries have also advanced, and studies on such applications are increasing. In the present review, studies that focused on the following topics were selected: i) Organ and anatomy identification, ii) instrument identification, iii) procedure and surgical phase recognition, iv) surgery-time prediction, v) identification of an appropriate incision line, and vi) surgical education. The development of autonomous surgical robots is also progressing, with the Smart Tissue Autonomous Robot (STAR) and RAVEN systems being the most reported developments. STAR, in particular, is currently being used in laparoscopic imaging to recognize the surgical site from laparoscopic images and is in the process of establishing an automated suturing system, albeit in animal experiments. The present review examined the possibility of fully autonomous surgical robots in the future.

Contents

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1. Introduction

There is no clear definition of artificial intelligence (AI), but it is generally considered to be a computer system with the functions of human intelligence, such as learning, inference, and judgment (1,2). Machine learning refers to the technology by which computers learn large amounts of data and automatically build algorithms and models to perform tasks, such as classification and prediction (1,2). The field of AI has evolved with the development of deep learning. Neural networks are mathematical models that have properties similar to those of brain functions, and deep learning is a machine-learning technique that enhances expression and learning ability by combining neural networks in multiple layers (3,4). Image recognition is an ability developed through deep learning, which is used for face recognition, automated driving, and other tasks (5). The combination of robotics and AI also has numerous benefits in daily life. When a robot is equipped with AI, it functions as a machine that senses its surroundings and determines how to act. AI is also being introduced into the medical field; since it excels in image recognition, previous studies have reported the use of X-ray, CT, ultrasonic, and other images for the diagnosis of diseases through deep learning (6,7). In addition, these studies describe the use of deep learning to diagnose diseases and predict patient prognosis based on information in medical records (6,7).

The use of minimally invasive surgery is now widespread in most surgical fields. Among minimally invasive surgery approaches, indications for robot-assisted surgery systems such as da Vinci have recently been expanded (8).

In recent years, the number of studies on the use of deep learning to analyze surgical videos and apply them to medical care has increased (9,10), and a growing number of studies on the development of autonomous surgical robots have been published (11,12).

The aim of the present review was to examine the possibility of fully autonomous surgical robots in the future. First, studies on the analysis of surgical videos for laparoscopic surgery and robot-assisted surgery using deep learning were described. Subsequently, studies on the development of autonomous surgical robots using AI were presented.

2. Analysis of laparoscopic surgery video using deep learning

One important process in the development of autonomous surgical robots is the recognition of surgical details. A number of studies have used deep learning for laparoscopic surgery and robot-assisted surgery (9,10). Different aspects are described in the following sections: i) Organ and instrument identification, ii) procedure and surgical phase recognition, iii) safe surgical navigation, and iv) surgical education (Table I).

Organ and instrument identification. Previous research has described the identification of organs and anatomical structures in the analysis of laparoscopic images using deep learning. Zadeh *et al* manually annotated the uterus and ovaries on 461 gynecological laparoscopic videos. Mask Regional Convolutional Neuronal Network (Mask R-CNN), a deep-learning method, was used to identify the datasets and automatically segment the uterus, ovaries, and surgical instruments. Segmentation accuracy was examined as the percentage overlap between the segmented area of the manual annotation and that of the Mask R-CNN. The accuracy values were 29.6, 84.5 and 54.5% for the ovary, uterus, and surgical instruments, respectively (10). The segmentation results for the ovaries were not as satisfactory as those for the uterus and instruments. This can be due to the following two main reasons. First, the training dataset contained a lower number of ovary instances because this organ is often hidden by other structures (the fallopian tube or uterus). Second, the ovaries often present with a highly varying appearance across patients (10). There are no other studies on the recognition of ovaries in surgical videos using deep learning. The shape of the uterus also varies across patients; therefore, the shapes of ovaries are not considered to be the only reason for the low rate of correct diagnosis. In addition, it is considered that the rate of correct diagnosis may be improved if the annotation is performed well and the number of ovaries in the training dataset is increased.

Mascagni *et al* (13) developed a deep-learning model to automatically segment the liver and gall bladder in laparoscopic images and evaluate safety criteria for laparoscopic cholecystectomy (LC). Developments in the surgical field method prevent surgical complications. The specific surgical field deployment for safe LC is known as the critical view of safety (CVS). There are three points to consider when developing CVS: i) Fat and fibrous tissue must be removed from Calot's triangle, ii) the neck of the gallbladder must be removed from the gallbladder plate, and iii) ensure that only the cholecystic duct and cholecystic artery are connected to the gallbladder. In this study, 2,854 images from 201 LC videos were annotated and 402 images were segmented. A deep neural network was developed consisting of a segmentation model to highlight the anatomy of the liver sac, and the average accuracy of the classification model to predict the achievement of CVS criteria was 71.9% (13). By increasing the rate of correct diagnosis of this system in the future, the CVS may be determined by this model before proceeding with surgery.

Padovan *et al* used deep learning from laparoscopic surgery videos to construct 3D models that accounted for position and rotation. They confirmed the accuracy by superimposing the constructed data on actual organ images, and the accuracy was >80% in all tests (14). The initial registration of a 3D preoperative CT model to 2D laparoscopic images in an augmented reality system for liver surgery may be useful for surgeons to better identify the internal anatomy. This study aimed to develop a system that automates this process using deep learning instead of the conventional manual method. Specifically, the system automates the construction of a 3D model, the identification of the hepatic limbus in CT images, and the identification of the hepatic limbus in 2D laparoscopic video images (15). Thus, the integration of laparoscopic video and 3D CT may be useful for preoperative simulation in the future.

In the analysis of laparoscopic surgery videos using deep learning, the identification of surgical instruments is equally important to the identification of organs. Therefore, several studies on surgical tool identification have been reported. For example, Namazi *et al* developed an AI model called LapToolNet to detect surgical instruments, such as bipolar, clipper, grasper, hook, irrigator, scissors, and specimen bag, in each frame of a laparoscopic video, all with agreement rates of 80% or higher (16). Several studies have dealt with surgical instrument recognition in this way, but the results are often not very different from those of organ recognition (16,17). In another study, the patterns of instrumentation use were compared among surgeons with different skill levels during laparoscopic gastrectomy for gastric cancer. A total of 33 cases of D2 suprapancreatic lymphadenectomy for gastric cancer were evaluated in this retrospective study. Patterns of surgical device use were compared between surgeons certified under the Endoscopic Surgical Techniques Certification System of the Japanese Society for Endoscopic Surgery and unqualified surgeons. The percentage of time spent using incision forceps and clip appliers was higher among non-technically-certified surgeons than among technically-certified surgeons. For suprapancreatic lymphadenectomy, the percentage of time spent using energy instruments, clip appliers, and grasping tweezers was significantly different between the two groups (17).

One of the key techniques in LC is clipping the cholecystic artery before cutting. For safe clipping, it is important to have full visibility of the clipper while surrounding the artery and biliary duct with the clip applier jaws. Using videos of 300 cholecystectomies, Aspart *et al* developed a deep-learning model that provides real-time feedback on the proper visibility of the clip applier (18). Notably, the study demonstrated the difference in skills between skilled and unskilled surgeons by means of deep learning. Such analysis can be used as an educational tool to improve surgical skills by identifying the so-called 'good surgeries' in the future.

Procedure and surgical phase recognition. Recognition of the surgical technique and stage is important, as is the dissection and identification of surgical instruments. Cheng *et al* used deep learning to recognize and analyze the surgical steps in multiple LC surgical videos. In this study, 163 LC videos sourced from four medical centers were evaluated. The accuracy of the developed model in recognizing the surgical steps was 91% (19). Breaking down the surgical procedure into steps facilitates the acquisition, storage, and organization of intraoperative video data. However, manual data organization is time-consuming; therefore, Kitaguchi *et al* developed a model

Table I. Previous studies on surgical-related artificial intelligence analysis.

Authors	Year	Procedure	Dataset	No.	Application	Performance score	(Refs.)
Zadeh *et al*	2020	Gynecologic surgery	Mask R-CNN	461 images	Organ identification	Accuracy: 29.6% (ovary) and 84.5% (uterus)	(10)
Mascagni *et al*	2022	Laparoscopic cholecystectomy	CNN	2,854 images	Organ identification	Average accuracy: 71.9%	(13)
Padovan *et al*	2022	Urologic surgery	Segmentation CNN	971 images	Organ identification	IoU: 0.8067 (prostate) and 0.9069 (kidney)	(14)
Koo *et al*	2022	Liver surgery	CNN	133 videos	Organ identification	Precision: 0.70-0.82	(15)
Namazi *et al*	2022	Laparoscopic cholecystectomy	Recurrent CNN	15 videos	Instrument identification	Mean precision: 0.59	(16)
Yamazaki *et al*	2022	Laparoscopic gastrectomy	CNN	19,000 images	Instrument identification	N.A.	(17)
Aspart *et al*	2022	Laparoscopic cholecystectomy	CNN	122,470 images	Instrument identification	AUROC: 0.9107; specificity 66.15%; and sensitivity: 95%	(18)
Cheng *et al*	2022	Laparoscopic cholecystectomy	CNN	156,584 images	Surgical phase recognition	Accuracy: 91%	(19)
Kitaguchi *et al*	2022	Transanal total mesorectal excision	CNN	42 images	Surgical phase recognition	Accuracy: 93.2%	(20)
Kitaguchi *et al*	2020	Laparoscopic sigmoid colon resection	CNN	71 cases	Surgical phase recognition	Accuracy: 91.9%	(21)
Twinanda *et al*	2019	Cholecystectomy and gastric bypass	CNN and LSTM network	290 cases	Surgical time prediction	N.A.	(23)
Bodenstedt *et al*	2019	Laparoscopic interventions of various types	Recurrent CNN	3,800 frames	Surgical time prediction	Overall average error: 37%	(24)
Igaki *et al*	2022	Total mesorectal excision	CNN	600 images	Safe surgical navigation	Dice coefficient: 0.84	(25)
Kumazu *et al*	2021	Robot-assisted gastrectomy	CNN	630 images	Safe surgical navigation	N.A.	(26)
Moglia *et al*	2022	Virtual simulator for robot-assisted surgery	CNN	176 medical students	Surgical education	Accuracy: >80%	(27)
Zheng *et al*	2022	Box trainer for laparoscopic surgery	Long-/short-term memory recurrent neural network	30 medical students	Surgical education	Accuracy: 74.96%	(28)

using deep learning to automatically segment the surgical steps of the transanal total mesorectal excision procedure, achieving an overall accuracy of 93.2% (20). In another study, Kitaguchi *et al* developed a model that uses CNN-based deep learning to recognize the steps and procedures of a laparoscopic sigmoid colon resection based on manually annotated data. The surgical steps were classified into 11 procedures, and the accuracy of their recognition was 91.9% (21). Indocyanine green is sometimes used to investigate blood return after bowel resection and bowel anastomosis in deep endometriosis. In another study, a prediction model of blood return after bowel anastomosis was developed by analyzing images of the bowel after indocyanine green injection using deep learning (22). The course of a surgical procedure is often not predictable, and it is difficult to evaluate the time of the procedure in advance, which renders the scheduling of surgical procedures difficult. Therefore, surgical time prediction is also an important factor in terms of surgical recognition. Fewer studies have been reported on surgical time prediction using AI than others. Twinanda *et al* developed a deep-learning pipeline called RSDNet that automatically predicts the remaining intraoperative surgical time (RSD) using only visual information from laparoscopic images. A key feature of RSDNet is that it can easily accommodate various types of surgeries without relying on manual annotation during training (23).

Bodenstedt *et al* developed a convolutional neural network-based method for continuous prediction of laparoscopic surgery time based on endoscopic images. Various types of laparoscopic images were used, and these methods were evaluated. The results showed an overall average error of 37% and an average half-time error of approximately 28% (24). Recognition of surgical steps provides evidence of the capture of changes in higher-order features, such as surgical procedures, which will lead to the development of surgical navigation systems and autonomous surgical robots in the future.

Surface navigation for safe incisions. One of the most important factors in surgery is making the incision in a safe area, which can be difficult depending on the skill level of the individual surgeon. Thus, several studies on the development of surface navigation systems for safe incisions using AI have been reported.

Igaki *et al* developed an AI-based navigation of the entire mesorectal resection plane in laparoscopic colorectal surgery. A total of 32 videos of laparoscopic left colorectal resections were analyzed using deep learning. The developed model helped identify and highlight the target area, however more images are required to improve the accuracy (25). Kumazu *et al* defined the surgical surface for safe incision as a loose connective tissue fiber (LCTF) and developed a model that automatically segments the LCTF. A surgical video of a robot-assisted gastrectomy was created using U-NET-based deep learning, and the segmentation results were output. The answers to two questions were then obtained from 20 surgeons with regard to the segmentation results including i) is this AI highly sensitive in recognizing LCTF (on a 5-point scale)? and ii) how many frames does the AI misrecognize? The mean value for question 1 was 3.52, and the mean value for question 2 was 0.14. This suggests that AI can be used to recognize difficult anatomical structures and assist surgeons in surgery (26). Regarding this study, it is considered that the present model can be used for gastrectomy as well as other surgeries if developed in the future. However, while LCTF may lead to the recognition of a safe incision line, it may not necessarily lead to the effective navigation of an appropriate incision line, and it is surmised that resolving this issue is a future challenge. In the future, it is important to develop such a navigation system, and it is maintained that the development of such a system will lead to the development of automated surgical robots.

Surgical education. Deep learning has also been applied to the field of surgical education. Moglia *et al* used deep learning to develop a model to predict the proficiency of medical students in a surgical simulator based on their training data. Subsequently, they used the model to predict proficiency from simulator data of untrained medical students with an accuracy rate of >80% (27). Excessive stress experienced by surgeons can negatively affect their surgical procedures, and Zheng *et al* developed a deep-learning model to detect, in real time, the movements of surgical procedures in which surgeons appear to be under stress. In this study, stress-sensitive procedures were identified, which may be integrated into robotic-assisted surgical platforms and used for stress management in the future (28). Future development of such a system may render it possible to use deep learning in surgical education.

3. Autonomous surgical robots

Description of autonomy. Autonomy is defined as being independent and capable of making decisions; however, its definition is ambiguous and without standards, and it is often used inappropriately. For example, the da Vinci system, which is currently used in numerous hospitals, is misnamed a surgical robot, even though it is, narrowly defined, as a high-tech motion repeater manipulator. This designation of the term 'robot' is rather incorrect, but unfortunately, the name has stuck. Therefore, when developing an autonomous surgical system, it is better to define the term 'autonomy' to avoid misnomers (11). Han *et al* and Yang *et al* proposed six frameworks describing the levels of autonomy for medical robots, similar to that for autonomous vehicles. Level 0, which is the no autonomy group, includes surgical robots with motion scaling capabilities that respond to the commands of the surgeon. Level 1, or the robotic assistance group, includes robots that provide some assistance while humans predominantly manage the system. Level 2, which is the task autonomy group, includes robots that autonomously perform a specific task that is started by a human. A feature that differs from that of Level 1 is that the operator controls the system discretely rather than continuously. An example is an automated suturing system in a surgical procedure. The surgeon instructs the robot where to suture, and the robot performs the task autonomously, with the surgeon monitoring and intervening as needed. Level 3, which is the conditional autonomy group, includes robots that can perform system-generated tasks but rely on humans to select among different plans. This surgical robot can perform tasks without close supervision. Level 4, or the high autonomy group, includes robots that can make decisions in surgery, but it is only allowed to do so under the supervision of a qualified physician. Level 5, or the full autonomy group, includes robots that do not require a human at all. This is a 'robotic surgeon' who can perform the entire surgery (12,29). Two additional factors are important for autonomous surgery: Recognition and task. The classification level of recognition is as follows: Level 1, awareness of the environment; Level 2, understanding the current status; and Level 3, prediction of the future status. The classification level of tasks, or Level of Task Complexity (LoTC), is as follows: LoTC 1, simple training tasks that are limited to surgical tasks such as distance considerations; LoTC 2, high training tasks; LoTC 3, simple surgical tasks; LoTC 4, advanced surgical tasks, such as suturing; and LoTC 5, complex surgical tasks, such as stopping sudden bleeding (30). The development of autonomous surgical robots should be aimed at accounting for the abovementioned classification levels.

Autonomous (or semi-automatic) surgical robots developed to date. In this section, the autonomous (or semi-autonomous) surgical robots that have been developed thus far are introduced. Despite the increasing adoption of robot-assisted surgery, surgical procedures on soft tissues are still performed completely manually by human surgeons. Shademan *et al* have developed a supervised surgical robot called Smart Tissue Autonomous Robot (STAR), which is a monitored surgical robot that can perform complex surgical procedures that could previously only be performed by humans (31).

The first surgical techniques STAR aimed to perform were anastomosis and suture. These techniques are important because suturing soft organs (such as the intestinal tract, urinary system, and gynecological vaginal segments) is a common surgical procedure that requires repeatability, accuracy, and efficiency and thus supports the development of autonomous surgical robots. Autonomous robotic surgery offers benefits in terms of efficacy, safety, and reproducibility, regardless of the skill and experience of the individual surgeon. In this context, autonomous anastomosis is challenging because it requires complex imaging, navigation, and highly adaptable and precise execution. As reported in 2016, STAR performed intestinal anastomosis in open surgery in pigs. This STAR phase was characterized by the following two points: i) A 3D visual tracking system using near-infrared fluorescence imaging and ii) an automated suture algorithm. Suture consistency, anastomotic leak pressure, number of mistakes, and completion time were compared with those of robot-assisted surgery and manual laparoscopic surgery, and STAR was superior (31). Since then, STAR has undergone a number of improvements. For example, an autonomous 3D path planning system was developed for STAR that utilizes biocompatible near-infrared markings and aims at precise incisions in complex 3D soft tissues. This plan was able to reduce the incision progress error compared to previous autonomous path planning (32). Other improvements include 3D imaging endoscopy and the development of a laparoscopic suture tool to generate a suture planning strategy for automated anastomosis. This tool was 2.9 times more accurate than manual suturing (33). Anastomosis performed by an autonomous robot may improve surgical outcomes by ensuring more accurate suture spacing and suture size than manual anastomosis. However, it is difficult for those robots without features such as continuous tissue detection and 3D path planning, because soft tissues have irregular shapes and unpredictable deformations. Therefore, Kam *et al* developed a new 3D path planning strategy for STAR that allows semi-autonomous robotic anastomosis in deformable tissues. A comparison was performed between STAR using the completed algorithm and a surgeon-completed anastomosis of synthetic vaginal cuff tissue. The results revealed that STAR with the newly developed method achieved 2.6 times better consistency in suture spacing and 2.4 times better consistency in suture bite size than manual performance (34). STAR was also used to create and analyze shared control strategies for human-robot collaboration in surgical scenarios. Specifically, a shared control strategy was developed based on trust, and the accuracy of the developed strategy was analyzed by evaluating the pattern tracking performance, both autonomous and manual. In an experiment with pig fat samples, by combining the advantages of autonomous robot control with complementary human skills, the control strategy improved cutting accuracy by 6.4% while reducing operator work time by 44% compared to manual control (35).

The latest study by STAR describes a novel *in vivo* autonomous robotic laparoscopic surgical technique. The autonomous system developed in this study is characterized by its ability to track tissue position and deformation, interact with humans, and execute complex surgical plans (36). Owing to this improved autonomous strategy, the operator can select among surgical plans generated by this system, and the robot can perform various tasks independently. Furthermore, using the enhanced autonomous strategy, needle placement compensation, suture spacing, completion time, and the rate of intestinal suture failure were compared with those of skilled surgeons and robot-assisted surgical techniques, and the developed STAR outperformed both. Another unique feature reported by this study was the ability to perform subperitoneal surgery (36). However, the issue remains as to whether STAR can also automate incision and hemostasis, as it has only been developed for suturing in the past.

Another reported autonomous surgical robot is the RAVEN-II system. The features of the RAVEN-II system are as follows: i) Provides software and hardware to support research and development of surgical robots; ii) provides advanced robotics such as computer vision, motion planning, and machine learning; iii) establishes a software environment compatible with functions; and iv) provides a hardware platform that allows for solid evaluation of experiments (37). Using the RAVEN-II system, a prototype medical robotic system designed to autonomously detect and remove residual brain tumors after the majority of the tumor has been removed by conventional surgery has been developed. The scenario assumes that the majority of the brain tumor has been removed, and then the cavity, the size of a ping-pong ball is exposed. The system is equipped with a multimodal scanning fiber endoscope, a suction machine for blood removal, and multiple robotic arms with devices for brain tissue resection. The automated surgical procedure is performed in six subtasks: i) Medical image acquisition, which involves scanning of the surgical cavity after tumor removal; ii) medical image processing, which involves 3D construction of the aforementioned surgical cavity and recognition of the residual tumor; iii) ablation plan creation; iv) selection of the plan by the surgeon; v) performance of the plan by the robot; and vi) verification of the ablation results (38).

Another experimental system is the da Vinci Research Kit (dVRK). The dVRK is a joint industry-academia effort to repurpose the obsolete da Vinci system (Intuitive Surgical, Inc.) as a research platform to promote surgical robotics research (https://research.intusurg.com/index.php/Main_Page). This is important to facilitate the entry of new research groups into the field of surgical robotics. For example, in the master tool manipulator of the dVRK, hysteresis forces from the electrical cables of the robotic joints often prevent accurate parameter estimation in gravity-compensation models due

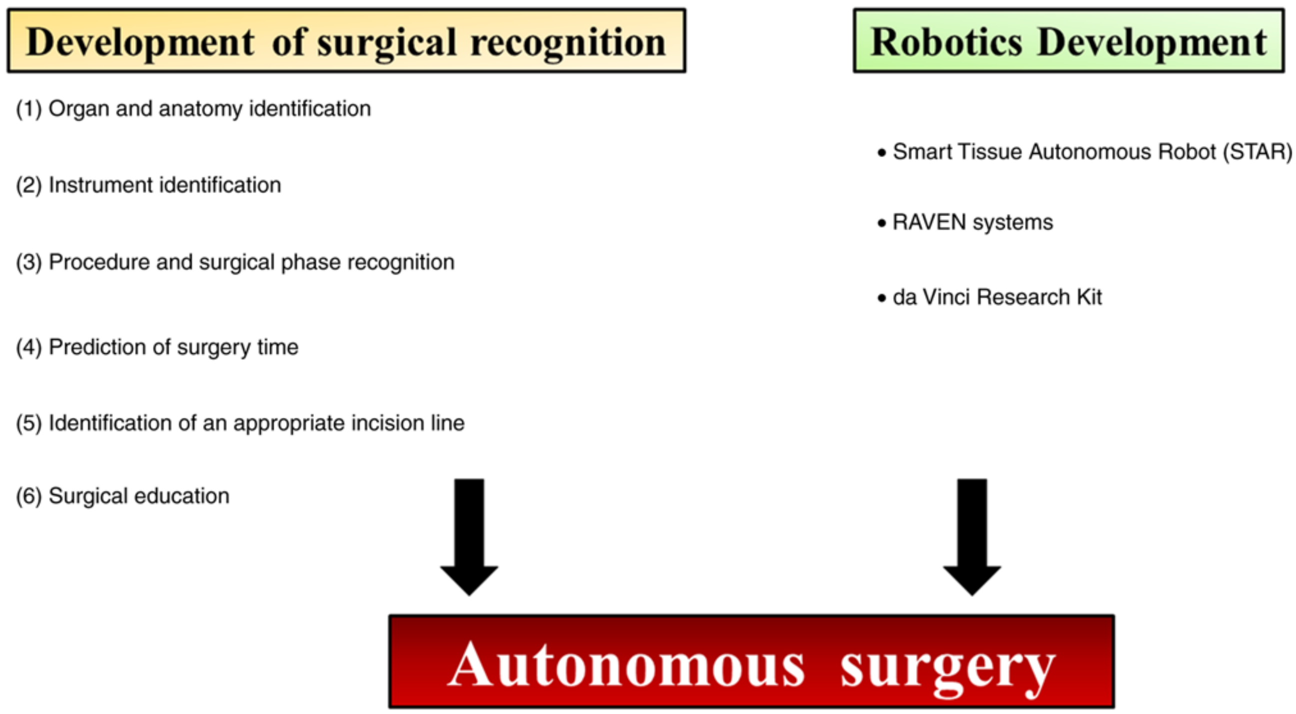

Figure 1. Overview of autonomous surgical-system development.

to the magnitude of gravity and identification. Therefore, a strategy to classify these two hybrid forces and evaluate them in individual learning-based algorithms has been proposed. A specially designed Elastic Hysteresis Neural Network model was employed to capture the external hysteresis. The gravity compensation method developed in this study for the master tool manipulator of the dVRK exhibits improvement over the previous one (39).

Ethics. Although it will still require a long time before the development of a fully autonomous surgical system, the development of a hybrid system may be realized in the near future. Therefore, it is necessary to discuss ethical issues related to autonomous surgical systems (27).

One of the most controversial ethical issues to be discussed is responsibility. In a three-part sequence of operations, including input, internal state (deep learning algorithm), and output, full transparency is not ensured. This is especially true for the algorithm, owing to the 'black box' design inherent in deep-learning systems and the non-disclosure of source code for reasons of copyright law and protection of trade secrets (12,27). This prevents physicians and patients from trusting robots. Another concern is responsibility for the system used. Is it the developer or the physician using the system who is responsible? For example, who can be held responsible for surgical complications caused by an autonomous surgical robot? Who is guilty and who should be punished if an anomaly occurs, such as loss of communication during an aggravated teleoperation? One proposed solution regarding liability is that, as in the case of autonomous vehicles, the surgeon stays in the same room as the surgical robot, which can be controlled by the physician at any time. Another option is to use a limited system that does not give full autonomy but assists the surgeon in routine surgery (12,27). Discussion of ethical and other regulations should be completed by the time an autonomous surgical robot is developed that is safe and has more consistent performance than a human surgeon.

4. Conclusion

Although the clinical applications of fully autonomous surgical robots may yet take some time, partially autonomous surgical robots may see practical applications in the not-too-distant future. For this purpose, it is necessary to advance surgical recognition and robotics through deep learning using surgical videos (Fig. 1). In this review, various studies on the recognition of surgical videos, including organ recognition, surgical instrument recognition, and surgical education were investigated. Among these tasks, it is considered that identifying the resection site is the most important. However, it is inferred that the accuracy of the currently reported AI models is still far from that required for clinical application. Strictly speaking, the ultimate goal is for physicians to be able to perform surgery safely according to navigation assistance provided by the AI model. To improve diagnostic accuracy, it is necessary to use public databases of moving images and develop programs. Furthermore, in this review, autonomous surgical robots were described. The STAR system is the most widely reported, and the development of automatic suturing and anastomosis systems is progressing with further innovations. In the future, it will be necessary to develop applications for other surgical techniques, such as incisions. For the time being, it is necessary to develop semi-automatic systems that can perform simple tasks and systems with a human surgeon on standby, who can intervene in case of an emergency. To ultimately develop an autonomous surgical robot, it is necessary to integrate the navigation system with the surgical robot as aforementioned. Particularly, it is necessary to develop a deep-learning model that can feed back the results recognized by the navigation system to the surgical technique.

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Authors' contributions

KS, ST, YT, AT, YM, MM, TI, OWH, and YO contributed to literature research, as well as manuscript writing and review. KS, ST, YT, and AT designed the figure and table. KS, MM, TI, OWH, and YO conceptualized and supervised the study. Data authentication is not applicable. All authors read and approved the final manuscript.

Ethics approval and consent to participate

Not applicable.

Patient consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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