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Review

Deep learning-based intraoperative guidance system for anatomical identification in laparoscopic surgery: A review

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Abstract: The power of Artificial Intelligence (AI) combined with the surgeons' expertise leads to breakthroughs in surgical care, bringing new hope to patients. Utilizing deep learning-based computer vision techniques in surgical procedures will enhance the healthcare industry. Laparoscopic surgery holds excellent potential for computer vision due to the abundance of real-time laparoscopic recordings captured by digital cameras containing significant unexplored information. Furthermore, with computing power resources becoming increasingly accessible and Machine Learning methods expanding across various industries, the potential for AI in healthcare is vast. There are several objectives of AI's contribution to laparoscopic surgery; one is an image guidance system to identify anatomical structures in real-time. However, few studies are concerned with intraoperative anatomy recognition in laparoscopic surgery. This study provides a comprehensive review of the current state-of-the-art semantic segmentation techniques, which can guide surgeons during laparoscopic procedures by identifying specific anatomical structures for dissection or avoiding hazardous areas. This review aims to enhance research in AI for surgery to guide innovations towards more successful experiments that can be applied in real-world clinical settings. This AI contribution could revolutionize the field of laparoscopic surgery and improve patient outcomes.

Keywords: artificial intelligence; deep learning; computer vision; laparoscopic surgery; semantic segmentation; anatomical structure

1. Introduction

Artificial Intelligence (AI) is a field within computer science that aims to comprehend and construct intelligent entities, frequently displayed as software applications (Russell and Norvig, 2016). Machine learning (ML) is a subfield of AI that encounters challenges with raw data, so it requires data preprocessing and feature extraction to obtain meaningful information, which is time-consuming and requires domain expertise(Jordan and Mitchell, 2015). Deep learning (DL) is a rapidly evolving approach that emerged from ML and enables direct learning from raw data (LeCun et al., 2015). Deep learning has its roots in the 1940s and has experienced three major developmental phases, with the most recent return starting in 2006 (Goodfellow et al., 2016). Sengupta et al. identified several factors contributing to the rise of deep learning in the 21st century. These include the availability of big data with high-quality labels, advancements in optimization algorithms, specialized software platforms for integrating deep learning architectures, and increased parallel computing power

(Sengupta et al., 2020). DL is a cross-disciplinary field that becomes more effective as more data becomes available. Deep learning models can potentially solve problems across various sectors in the modern world (Ahmed et al., 2023). DL models have demonstrated efficacy in various domains, including cybersecurity (Alazab and Tang 2019; Sarker 2021), bioinformatics (Amiri et al., 2024; Cao et al., 2020), robotics (Soori et al., 2023), climate prediction modeling (Lee et al. 2020, Rasp et al., 2018), commercial (Shin and Woo, 2024) industrial (Jauhar et al., 2024), education (Safarov et al., 2023) and healthcare (Rahman et al., 2024).

AI is transforming healthcare, with recent breakthroughs in the surgical field due to the vast advancements of deep learning-based computer vision techniques (Esteva et al., 2019; Taher et al., 2022). Laparoscopic surgery presents a notable potential for applying computer vision techniques, primarily because of the large number of real-time laparoscopic videos recorded by digital cameras containing valuable, underutilized information (Madad Zadeh et al., 2020). Moreover, computational power resources are increasingly accessible, and ML algorithms are experiencing rapid expansion across various sectors (Anteby et al., 2021). According to a statement made in 1978 by Dr. Frank Spencer, a cardiovascular surgeon, the successful execution of surgery predominantly depends on 75% decision-making and 25% manual skill (Spencer, 1978). Deep learning-based computer vision algorithms in laparoscopic surgical videos can aid decision-making (Anteby et al., 2021). The powerful combination of Computer Vision (CV) and Deep Learning (DL) models offers real-time guidance in the operating room, empowering surgeons with valuable insights and analyzing surgical videos to provide post-operative feedback (Guo et al., 2023; Mascagni et al., 2021).

While innovative experiments have been using DL for anatomical navigation in laparoscopic surgery, the research field remains in its early stages. This review investigates recent research on deep learning-based computer vision for anatomical navigation in laparoscopic surgery, aiming to enlighten researchers and enrich the field of AI-based surgery. Developing a real-time intraoperative deep learning model for visual guidance to support the surgeon’s decisions in identifying specific anatomical structures for dissection or avoiding hazardous areas can elevate the field of laparoscopic surgery to new heights.

The research used Google Scholar, PubMedCentral, and Science Direct databases to review articles published in English from 2017 to January 2024. Research keywords are “anatomical navigation in laparoscopic surgery,” “minimally invasive surgery and AI,” “semantic segmentation in laparoscopic surgery,” “image-guided surgery,” and “deep learning-based computer vision and surgery.” There are a total of 31 articles matching these keywords. Of these, 15 studies have been approved for presenting anatomical navigation through semantic segmentation in laparoscopic surgery. Some presented studies also worked on tool segmentation but were not mentioned here. Moreover, studies on DL in robot-assisted surgery are excluded.

This study initially provides a concise overview of laparoscopic surgery. Subsequently, it explains the specific types of computer vision models based on deep learning utilized in laparoscopic surgery. It then thoroughly examines anatomical navigation in laparoscopic surgery employing semantic segmentation approaches. The study explores performance metrics commonly used for semantic segmentation and then delves into its limitations. The conclusion represents the suggested future direction of DL and laparoscopic surgery.

2. Related works

This section explains the use of deep-learning-based computer vision for intraoperative anatomical structure navigation in laparoscopic surgery and provides an overview of current experimental studies on this topic.

2.1. Laparoscopic surgery

Laparoscopy, also called Minimally Invasive Surgery (MIS), is a standard surgical procedure where the abdominal cavity is filled with gas to create room. Afterward, small incisions are made in the abdominal wall to introduce ports, allowing access for both a camera and surgical instruments. The surgery is then conducted with guidance from images transmitted to a video monitor (Badgery et al., 2022). Laparoscopic surgery is preferred to open surgery since there is less postoperative pain, rare complications, and fast recovery (Rivas and Díaz-Calderón, 2013; Ziogas and Tsoulfas, 2017). However, it’s important to acknowledge certain disadvantages associated with this approach. In laparoscopic surgery, the workspace is more confined than in open surgery, resulting in a more restricted field of view, which may lead to misinterpretation and further complications (Madani et al., 2022; Tomimaru et al., 2018). The intraoperative stage is more complex due to tissue deformation, visual clarity challenges, and environmental circumstances (Taher et al., 2022). Achieving a safe dissection during surgery through expert intraoperative performance is an ongoing process that involves interpreting the surgical field and making crucial decisions (Madani et al., 2015). Surgical expertise and empirical findings indicate that skilled surgeons can visualize “safe” and “dangerous” dissection areas within challenging and unfamiliar anatomical landscapes (Madani et al., 2017). According to a recent review of human performance flaws in operations, more than 50% of patients who had postoperative problems were shown to be caused by identifiable human mistakes (Kolbinger et al., 2023), accounting for 18.8% of surgical complications are caused by misidentification incidents occurring during surgeries errors because of anatomy misrecognition (Suliburk et al. 2019).

Establishing a real-time deep-learning model during surgery can significantly advance laparoscopic procedures. The model aims to visually guide surgeons, helping them identify specific anatomical structures for dissection or avoid potentially hazardous locations.

2.2. Deep learning-based computer vision in laparoscopic surgery

DL and CV are two subfields of AI that have actively contributed to laparoscopic surgery research for various purposes. Deep learning-based computer vision is the automated analysis of digital images replicating human visual abilities using machine learning techniques, particularly deep learning (Kolbinger et al., 2023). The processes primarily utilizing deep learning approaches in computer vision can be generally categorized into image classification, object detection, semantic segmentation, and instance segmentation (Kitaguchi et al., 2022). In image classification, images are classified according to visual differences and can be applied for real-time automatic phase recognition in surgery (Kitaguchi et al., 2020; Padoy, 2019; Twinanda et al., 2016). Object detection uses boxes around particular objects with labels to identify what is inside the box, such as surgical instrument detection (Yamazaki et al., 2020). Semantic segmentation classifies and labels each pixel in the image into a specific group, which can be helpful in intraoperative guidance (Madani et al., 2022). Instance segmentation is best applied when overlapping objects with different labels need to be identified, such as instrument intersection in surgery (Ross et al., 2021). This review focuses on the semantic segmentation process because it plays a crucial role in providing intraoperative guidance by effectively recognizing anatomical landmarks. It enhances decision-making processes and facilitates more precise dissection, lowering injury chances (Kitaguchi et al., 2022; Madani et al., 2022). Convolutional Neural Networks (CNNs) are widely recognized as the driving force behind the significant advancements in DL, particularly in image recognition tasks. Their introduction has led to remarkable improvements in the accuracy and performance of image recognition algorithms (Soffer et al., 2019). CNN's deep learning architecture is widely employed to autonomously identify and classify components within laparoscopic surgery images and videos. These networks emulate the structure and function of the biological visual cortex, making them a prevalent and practical choice for such tasks (Hashimoto et al., 2018). CNNs are integrated with other algorithms by choosing the most suitable algorithm combination to achieve its objective for performance enhancement (Beyersdorffer et al., 2021; Hashimoto et al., 2018). When the aim is semantic segmentation, essential algorithms commonly utilized include convolutional layers, max-pooling layers, fully connected layers, batch normalization layers, rectified linear units, and a global-pooling layer (Gu et al., 2018; LeCun et al., 1998). Nevertheless, most research efforts in deep learning-based computer vision for laparoscopic surgery have yet to succeed in a tangible clinical phase (Kolbinger et al., 2023; Maier-Hein et al., 2022).

2.3. Anatomical navigation studies with semantic segmentation

Anatomical structure identification has three main components: binary classification, organ detection, and organ segmentation (Anteby et al., 2021). This section will review recent experiments and studies conducted to identify anatomical structures with organ semantic segmentation for intraoperative guidance to aid surgeons in decision-making. Recognizing anatomical structures poses a significant challenge compared to identifying surgical instruments. Utilizing semantic segmentation for anatomical structures as surgical landmarks may lead to anticipated advancements in this area (Kitaguchi et al., 2022). This review focuses on anatomical navigation using the semantic segmentation technique in laparoscopic surgery. **Table 1** summarizes these studies, showing which laparoscopic procedurehas been tested, the DL model applied, the Dataset name, and the main performance metric, which is either Dice Coefficient (DC) or Intersection over Union (IoU), and in some studies is the F1/Dice score.

Table 1. Summary of anatomical navigation in laparoscopic surgery with semantic segmentation.

Reference	Laparoscopic Procedure	Dataset Name	DL Model	Performance Metrics	
				IoU	**DC**
(Gibson et al., 2017)	Liver resection	Proprietary	F-CNNs (Caffe DL framework)	NA	≥ 0.95
(Scheikl et al., 2020)	LC	EndoVis 2019	U-Net, TernausNet, LinkNet, SegNet, FCN	0.783	NA
(Madad Zadeh et al., 2020)	Laparoscopic hysterectomies	Proprietary (SurgAI)	Mask R-CNN	uterus:0.85 ovaries:0.30	NA
(Kitaguchi et al., 2021)	TaTME	Proprietary	DeepLabv3+	NA	0.77
(Bamba et al., 2021)	Colorectal, hernia, sigmoid resection	Proprietary	IBM Visual Insights	NA	NA
(Mascagni et al., 2022)	LC	Proprietary (CVS)	DeepCVS	0.67	NA
(Igaki et al., 2022)	TME	Proprietary	DeepLabv3+	NA	0.84
(Kitaguchi et al., 2022)	Colorectal resection	LapSig300	DeepLabv3 ResNeSt-269	NA	0.816
(Madani et al., 2022)	LC	Cholec80 M2CAI16- workflow Challenge	CholeNet. GoNoGoNet	> 0.5	0.7
(Silva et al., 2022)	LC	CholecSeg8k	U-Net, U-Net++, DynUNet, UNETR, DeepLabV3+	NA	0.62
(Kojima et al., 2023)	colorectal surgery	Proprietary	DeepLabV3+, Xception	NA	HGN: 0.56 SHP: 0.49
(Laplante et al., 2023)	LC	Proprietary (Prospectively collected)	GoNoGoNet	NA	go zone: 0.58 nogo zone: 0.80
(Kolbinger et al., 2023)	Anterior rectal resections or rectal extirpations	Dresden Surgical Anatomy	DeepLabv3, SegFormer	DeepLabv3 specific: 0.28–0.83 Combined: 0.23–0.77 SegFormer: specific: 0.31–0.85 Combined: 0.26–0.67	NA
(Sengun et al., 2023)	Adrenalectomy	Proprietary	ESFPNet (B2, B3, B4)	0.66	0.77
(Narihiro et al., 2024)	Colorectal surgery	Proprietary	UreterNet FPN, EfficientNetB7	NA	0.716

FCN = Fully Convolutional Network, LC = Laparoscopic Cholecystectomy, IoU = Intersection over Union, DC = Dice Coefficient, TaTME = Transanal Total Mesorectal Excision, TME = Total Mesorectal Excision, CVS = Critical View of Safety, HGNs = HypoGastric Nerves, SHP = Superior Hypogastric Plexus, FPN = Feature Pyramid Networks, NA = Not Available.

Table 1 emphasizes the recent studies that show the potential of anatomical segmentation by different deep-learning models to equip surgeons with an accurate guidance system and minimize surgical injuries and complications. Laparoscopic Cholecystectomy (LC) is a common minimally invasive surgical procedure that contributes significantly to computer vision technology advancements (Guo et al., 2023). The main factor is the publicly available datasets for AI-based research. In this review, and as shown in **Table 1**, several studies utilized LC datasets such as CholecSeg8k, Cholec80, M2CAI16-workflow Challenge, and EndoVis 2019. Moreover, Lablante et al. did their experiments with a small dataset by applying the same GoNoGoNet deep learning model from the study by Madani et al. The aim is to validate the model's ability to identify safe and dangerous zones compared to expert surgeons with real-time guidance to reduce injury rates (Laplante et al., 2023; Madani et al., 2022). GoNoGoNet consists of two models: the "Go" model identifies safe zones within the hepatocystic triangle in each frame. In contrast, the "No go" model identifies areas that are not safe and could potentially cause major bile duct injury. The third DL model, "CholeNet," is used to identify gallbladder, liver, and hepatocystic triangle anatomical structures. CholeNet and GoNoGoNet models are constructed using a deep CNN architecture for semantic segmentation, leading to good performance results (Madani et al., 2022). Scheikl et al. present 69 experiments conducted using various combinations of five DL architectures (with their variations) and three loss functions on the LC dataset from the Surgical Workflow and Skill Analysis of the Endoscopic Vision Challenge 2019. The study aims to introduce a context-aware assistance system for surgeons (Scheikl et al., 2020). Mascagni et al. also utilize LC recordings to segment hepatocystic anatomy by 2-stage DeepCVS using DeepLab v3+ with Xception 65 as a backbone to assess the Critical View of Safety (CVS) criteria (Mascagni et al., 2022). Silva et al. applied five DL networks (U-Net, U-Net derivatives, and DeepLabV3+) to segment eight anatomical structures from the CholecSeg8k dataset, aiming to determine the most effective computer-aided system (Silva et al., 2022). CholecSeg8k is a part of the Cholec80 dataset composed of LC procedures.

On the other hand, several studies are presented here, and their datasets are not from LC procedures. Gibson et al. used the "Caffe" deep learning framework, a CNN architecture, for liver segmentation on a laparoscopic liver resection dataset. The study concluded that DL can accurately segment the liver from other structures (Gibson et al., 2017). Madad Zadeh et al. provided a semantic segmentation dataset for gynecology laparoscopic surgical images called "SurgAI." The dataset is classified into three categories: uterus, ovaries, and surgical instruments obtained from Mask Regional Convolutional Neural Network (Mask R-CNN) (Madad Zadeh et al., 2020). Bamba et al. (2021) annotated frames containing the GI tract, blood, vessels, and uterus from different surgery recordings obtained from the surgery department at Tokyo Women's Medical University. The study aims to enhance surgical education by utilizing the IBM Visual Insights framework, which incorporates various types of DL software (Bamba et al. 2021). In their feasibility study, Kitaguchi et al. attempted to minimize the likelihood of Urethral Injuries (UIs) during transanal total mesorectal excision (TaTME) surgery by proposing DeepLabV3+ deep learning model for segmenting the prostate area in real-time (Kitaguchi et al., 2021). Another feasibility study conducted by Kitaguchi et al. on image navigation to identify Inferior Mesenteric Artery (IMA) in laparoscopic colorectal surgeries. They used a subset from the LapSig300 dataset and employed DeepLabV3+ with ResNeSt-269 as a backbone (Kitaguchi et al., 2022). In their feasibility study, Igaki et al. (2022) developed an image-guided navigation system using a DeepLabV3+ deep learning-based semantic segmentation model to locate the areolar tissue in the Total Mesorectal Excision (TME) plane. The dataset for this study was obtained from laparoscopic left-sided colorectal resection videos (Igaki et al., 2022). An experimental pilot study by Kojima et al. aims to protect the autonomic nerves, specifically the hypogastric nerve (HGN) and superior hypogastric plexus (SHP), during colorectal resection using the DeepLabV3+ with Xception deep learning algorithm for semantic segmentation (Kojima et al., 2023). Kolbinger et al. conducted an experimental study to help surgeons accurately identify eleven anatomical structures during laparoscopic colorectal procedures. The study aimed to achieve anatomical recognition near the human expert performance and compared the performance of the DeepLabV3+ and SegFormer deep learning models Moreover, the study provides the publicly available Dresden Surgical Anatomy dataset for machine learning research (Kolbinger et al., 2023). Sengun et al. conducted an experimental study with three efficient stage-wise feature pyramid networks (ESFPNet) to obtain real-time guidance during laparoscopic transabdominal left adrenalectomy by identifying the left adrenal vein (Sengun et al., 2023). Narihiro et al. (2024) performed semantic segmentation on experiments by a CNN model called "UreterNet" to avoid Iatrogenic Ureteral Injury (IUI) depending on laparoscopic colorectal surgery.

The experimental studies discussed here all recommend using CNN architecture for semantic segmentation, utilizing various networks. However, the DeepLabV3+ deep learning model has been used in multiple studies for anatomical image navigation systems. Additionally, some studies have applied multiple DL models to enhance their results.

The best Dice Similarity Coefficient (DSC), or in short, Dice Coefficient (DC) study result is by Gibson et al., which achieved more than 95% in liver segmentation. The high DC result could be due to the liver size and appearance, which can be easily identified and segmented (Gibson et al., 2017). The rest of the studies that computed DC ranged between 0.5 and 0.8; however, there is no direct comparison between these studies because the dataset size, anatomical type, and deep learning algorithms differ. For studies that use Intersection over Union (IoU) as a metric for evaluation, the results obtained are between 0.28 and 0.85.

Several factors may impact the results of performance metrics. These include the size and quality of the dataset, the precise frames annotation of the ground truth, the location of the anatomical part (whether it's under fats or covered with blood), environmental factors in the operating room (such as smoke or blur), the source of the dataset (whether it's from multiple institutions to ensure generalizability and prevent overfitting, or from a single data source), and the DL algorithms applied with different validation techniques.

The following subsections provide detailed information about the study design of the literature presented in **Table 1**. They include details about the dataset annotation methods, the experimental optimization plan, and the evaluation metrics used in these studies and conclude with a discussion of patient privacy.

2.3.1. Data annotation

Table 2. Data annotation information summary.

Reference	Anatomical Structure	Frame/Video No.	Manual Annotation Tool	Annotator(s)
(Gibson et al., 2017)	Liver	2050 frames/13 videos	NA	Clinical research associate in General Surgery
(Scheikl et al., 2020)	Liver, fat, and Gb	210 images/12 videos	Polygon tool	Medical students
(Madad Zadeh et al., 2020)	Uterus, ovaries	461 images	Supervisely online software	1 junior surgeon, 1 expert surgeon
(Kitaguchi et al., 2021)	Prostate area	500 images/17 videos	Microsoft Surface Pen	2 board-certified colorectal surgeons
(Bamba et al., 2021)	GI tract, blood, vessels, uterus	Image: GI tract = 1781, Vessels = 352; blood = 208; uterus= 63	Polygon tool	Field experts
(Mascagni et al., 2022)	Hepatocystic anatomy	2854 images/201 videos	Custom-made annotation software	3 surgeons, have different surgical experiance
(Igaki et al. 2022)	Areolar tissue in the TME	600 images/32 video	NA	One colorectal surgeon
(Kitaguchi et al., 2022)	IMA lymph dissection line	1200 images/60 videos	Microsoft Surface Pen	2 colorectal surgeons
(Madani et al., 2022)	Gb, liver, and hepatocystic triangle	2627 frames/290 video	Think Like A Surgeon	3 acute care and MIS surgeons, fourth high-volume hepatobiliary surgeon for review
(Silva et al., 2022)	AW, Liver, GT, Fat, Gb, CT, Blood, Cystic Duct, Hepatic Vein, Liver Ligament	8080 frames/17 video	Pixel Annotation Tool	NA
(Kojima et al., 2023)	HGN, SHP, and their colorectal branches	HGN:12978frames (245 videos) SHP:5198 frames (44videos)	NA	Junior colorectal surgeon with one board certified colorectal surgeon, two non-medical staff
(Laplante et al., 2023)	hepatocytic triangle, gallbladder, liver	47 frames/25 videos	Think Like A Surgeon	High-volume expert surgeons
(Kolbinger et al., 2023)	Abdominal wall, Colon, IMA, Intestinal veins, Liver, Pancreas, Small intestine, Spleen, Stomach, Ureter, Vesicular glands	13195images (32 videos)	CVAT	3 annotators independently, then fusion by the STAPLE algorithm
(Sengun et al., 2023)	Left adrenal vein	2000 image (40 videos)	CVAT	An endocrine surgeon and a surgeon-in-training, reviewed by 2 senior endocrine surgeons
(Narihiro et al., 2024)	Ureter	14,069 images (304 videos)	NA	10 annotators under 3 board-certified colorectal surgeons

LC = Laparoscopic Cholecystectomy, UI = Urethral injury, TaTME = Transanal Total Mesorectal Excision, TME = Total Mesorectal Excision, CVS = Critical View of Safety, IMA = Inferior Mesenteric Artery, BDI = Bile Duct Injury, AW = Abdominal wall, GT = Gastrointestinal Tract, CT = Connective Tissue, Gb = Gallbladder, HGNs = HypoGastric Nerves, SHP = Superior Hypogastric Plexus, NA = Not Available, CVAT = Computer Vision Annotation Tool.

The first step for the semantic segmentation algorithm applied in medical image segmentation is to prepare the dataset by pixel-wise annotating the targeted anatomical structures. In contrast to medical images like CT and MRI scans, identifying organ areas in intraoperative video is challenging due to unclear surrounding boundaries. Pixel-wise annotation reflects the spatial location and appearance, which requires manual annotation for each frame. Like an expert surgeon, a qualified professional must perform the data annotation. **Table 2** provides a summary of the literature data annotation-related information.

2.3.2. Semantic segmentation optimization methods

Developing a deep learning model for semantic segmentation of anatomical parts in MIS requires optimization methods to guarantee the best applicable results. However, as of the date of this literature, no study has met the clinical criteria to be applied inside the operating room. Optimizing experiments begins with the dataset; when the data size is small, some studies use augmentation to increase the size and consider different angles and situations that the frame may encounter. Also, to increase the training size of the data and evaluate the performance, most studies followed the N-fold cross-validation, where N= dataset partition number. Usually, N-1 partitions were used for the training set, and the last part was used for the validation set. This is done N times where, in each iteration, the validation set will change. The partitions should be per-case level to avoid data from the training set appearing in the validation set (Madani et al., 2022). Experimental design summary of the literature is shown in **Table 3**.

Table 3. Experimental design summary.

Reference	Data			DL Design	
	Augmentation	N-fold cross-validation	Pretrained	DL architecture	Hyperparameters
(Gibson et al., 2017)	N	13-fold cross-validation	N	Fully-CNN: Convolutional feature layer, Four deep residual learning units Three segmentation units Fusion layer	Logistic loss Learning rate weight decay momentum
(Scheikl et al., 2020)	Y	N	Y	U-Net TernausNet/VGG encoder FCN/up sampling sizes LinkNet/ResNet encoder SegNet	Adam Optimizer learning rate loss functions: Soft-Jaccard (SJ) Generalized Dice (GD) Cross Entropy (CE)
(Madad Zadeh et al., 2020)	N	N	Y	Mask R-CNN from Facebook AI Research	Transfer learning (update NN weights)
(Kitaguchi et al., 2021)	Y	5-fold cross-validation	Y	DeepLab v3 plus	NA
(Bamba et al., 2021)	N	N	N	IBM Visual Insights: GoogLeNet, Faster R-CNN, Tiny YOLO V2, YOLO V3, Detectron, SSD SSN	5e-4 Weight decay 0.9 Momentum 1e-3 Learning rate 4000 max iterations
(Mascagni et al., 2022)	N	5-fold cross-validation	Y	Two stages of DeepCVS Deeplab v3+ 6-layer classification network	NA

Table 3. (*Continued*).

Reference	Data			DL Design	
	Augmentation	**N-fold cross-validation**	**Pretrained**	**DL architecture**	**Hyperparameters**
(Igaki et al. 2022)	N	N	Y	DeepLabv3plus.	NA
(Kitaguchi et al., 2022)	N	5-fold cross-validation	Y	DeepLabv3+ ResNeSt-269 network backbone	Y
(Madani et al., 2022)	N	10-fold cross-validation	N	GoNoGoNet/CholeNet PSPNet: CNN; ResNet50 Pyramid pooling module (multi-scale)	NA
(Silva et al., 2022)	Y	N	N	DeepLabV3+ U-Net, U- Net++ DynUNet UNETR (transformers and CNN)	Average Dice loss Adam optimizer. 1e-4 learning rate 500 epochs
(Kojima et al., 2023)	N	5-fold cross-validation	Y	DeepLabV3+ Xception	Y
(Laplante et al., 2023)	N	10-fold cross-validation	N	GoNoGoNet	NA
(Kolbinger et al., 2023)	Y	4-fold cross-validation	Y	DeepLabv3/SegFormer Structure-specific model (individual encoders/decoders) Combined model (common encoder/individual decoders)	Cross-entropy loss AdamW optimizer 1e-4 learning rate 100 epochs
(Sengun et al., 2023)	N	N	Y	ESFPNet: (B2, B3, B4) sizes MiT encoder ESFP decoder	Binary Cross Entropy AdamW optimization, 1e-4 learning rate, 200 epochs
(Narihiro et al., 2024)	N	N	N	UreterNet: FPN(CNN) EfficientNetB7 (backbone)	Y

N = No, Y = Yes, NA = Not Available, PSPNet = Pyramid Scene Parsing Network, SSD = Single Shot Detector, SSN = Structured Segment Network, MiT = Mix Transformer, FPN = Feature Pyramid Network.

2.3.3. Results evaluation metrics

The main performance metric that reflects the semantic segmentation performance of deep learning algorithms in identifying anatomical structures is the Dice Similarity Coefficient (DSC) or Intersection over Union (IoU), as presented in all literature. However, other performance metrics are also adopted in some studies to demonstrate the efficient segmentation capability of deep learning algorithms. The F1 score with dice represents the spatial correlation between ground truth annotation and model prediction; however, three studies adopted the F1 score. Precision, recall, sensitivity, and specificity are commonly reported in various studies, along with Positive Predictive Value (PPV) and Negative Prediction Values (NPV). Frame Per Second (FPS) measures the model inference time per frame to evaluate if it is a near real-time performance. If the frame rate exceeds 20 frames per second, it operates in real-time, as in the DeepLabv3 FPS result (Kolbinger et al., 2023).

Table 4 presents the evaluation metrics computed in the literature. Section 3 will provide a thorough explanation of these evaluation metrics.

Table 4. Presence of evaluation metrics in literature.

Reference	F1score	DC	IoU	PPV	NPV	FPS	Precision	Recall	Specificity	Sensitivity
(Gibson et al., 2017)		√		√	√					
(Scheikl et al., 2020)			√			√				
(Madad Zadeh et al., 2020)			√				√	√		
(Kitaguchi et al., 2021)		√				√				
(Bamba et al., 2021)			√				√	√		
(Mascagni et al., 2022)			√				√	√	√	√
(Igaki et al. 2022)		√								
(Kitaguchi et al., 2022)		√				√				
(Madani et al., 2022)	√	√	√	√	√	√			√	√
(Silva et al., 2022)		√	√				√	√		
(Kojima et al., 2023)		√					√	√		
(Laplante et al., 2023)	√	√	√	√	√				√	√
(Kolbinger et al., 2023)	√		√			√	√	√	√	
(Sengun et al., 2023)		√	√	√						√
(Narihiro et al., 2024)		√				√	√	√		

2.3.4. Ethical considerations

All the studies mentioned in this literature followed a protocol reviewed and approved by the research ethics board responsible for study registration. Additionally, all studies obtained informed consent from all participants, and all the mentioned datasets were anonymized.

3. Evaluation metrics in semantic segmentation

Anatomical structures' semantic segmentation model

s often measure performance using the following metrics: DSC, IoU, F1 score, PPV, NPV, recall, precision, specificity, and sensitivity, as presented in **Table 4**. However, it's important to note that specificity and accuracy can be misleading in scenarios with small anatomical structures due to a potential bias toward the true negative class imbalance (Müller et al., 2022). Other research also emphasizes Frames Per Second (FPS), which indicates the frequency of model intervention within each frame measured in milliseconds (ms) (Kolbinger et al., 2023). This metric assesses whether the system operates in near real-time performance or experiences delays. However, the DSC is the predominant measure utilized in most scientific articles on MIS for evaluating the accuracy of semantic segmentation (Liu et al., 2021).

The DSC is defined as follows:

$$DSC=\frac{2\times|A\cap B|}{|A|+|B|} \quad (1)$$

where A is the manual annotation of an expert surgeon, and B is the DL prediction of anatomical area o, The degree of overlap between A and B directly correlates with the level of success of DL, which is quantified by a number ranging from 0 to 1. The ideal correlation coefficient is 1, indicating a perfect match, whereas 0 means no overlap (Kitaguchi et al., 2022; Liu et al., 2021).

Figure 1 depicts the DSC assessment using images from experiments implemented by the YOLOv8x-seg deep learning model to segment the left ureter**.** Subfigure (a) displays the manual annotation performed by a colorectal surgeon, denoted as (A). while subfigure (b) displays the predicted value by the DL model, denoted as (B). Subfigure (c) represents the intersection of (A) and (B), and this is denoted as (A ∩ B). Subfigure (d) presents the mathematical formula of the DSC metric with A, B, and (A ∩ B) parameters and their visual representation in the case of left ureter segmentation. **Figure 1** is a modified version of the figure originally shown in (Kitaguchi et al., 2022).

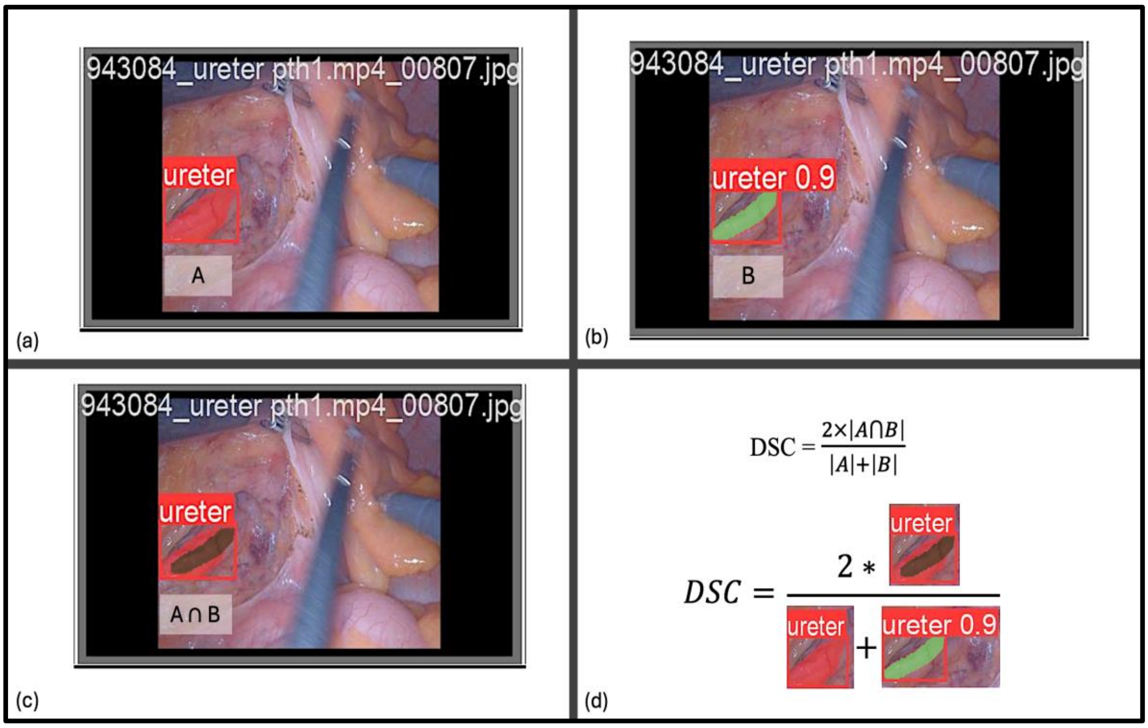

Figure 1. DSC illustrated example from left ureter segmentation.

IoU is also employed in many experimental studies in semantic segmentation but with a stricter overlap assessment. For minimally invasive surgery, like laparoscopic surgery, the boundaries of anatomical structure images are not well-defined, making DSC more practical than IoU (Kitaguchi et al., 2022). In terms of the confusion matrix, intersection over union is calculated as follows:

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN}} \quad (2)$$

where TP = True Positive, FP = False Positive, FN = False Negative (Müller et al.

2022). Kolbinger et al. (2022) and Madani et al. (2022) utilized F1/Dice spatial correlation index score to measure the accuracy of object segmentation. Dice coefficient score is computed in terms of confusion matrix, as shown:

$$\text{Dice (DSC)} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{3}$$

Dice score is computed for each sample (image) to present the overlap between groud truth and model prediction in semantic segmentation (Igaki et al., 2022; Kitaguchi et al., 2022; Quero et al., 2022). F1 score represents the overall performance of a model by the precision and recall metrics combinations (Quero et al., 2022). The F1/Dice score considers the size of the object and its positional accuracy (Carass et al., 2020). However, it is important to assume that the value of fine anatomical structures will be underestimated compared to surgeon vision. This small error can have a significant impact on the denominator of the formula, which includes both False Positive (FP) and False Negative (FN) values (Eelbode et al., 2020), as shown:

$$\frac{\text{F1}}{\text{Dice}} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP} + \text{FN})} \tag{4}$$

Other evaluation metrics mentioned in **Table 4** are calculated as follows (Müller et al. 2022; Narihiro et al. 2024):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{8}$$

4. Challenges of using DL in laparoscopic surgery

In laparoscopic surgery, computer vision research has primarily focused on preclinical phases. Until now, no AI model using intraoperative surgical imaging data has been implemented in operating rooms (Kolbinger et al. 2023; Maier-Hein et al., 2022). Several factors are hindering the advancement of AI’s role in MIS. A key barrier is the need for a centralized infrastructure for data storage, annotation, model development, and deployment. The limited availability of high-quality annotated images and video datasets hinders AI’s progress in MIS. Many studies have used datasets from a single institution, which limits generalizability. The insufficient collaboration between scientific researchers and surgeons limits the possibility of developing AI solutions that may successfully meet unfulfilled patient demands in the field of surgery. The small size and fatty tissue coverage of vessels and nerves pose a significant challenge to surgeons and AI regarding anatomical factors. The growing adoption of AI in surgery presents various technological, ethical, therapeutic, and business-related obstacles. To facilitate the rapid and secure growth of AI implementation in the field of surgery, it is imperative to ensure that surgeons possess comprehensive fundamental AI principles and their potential applications across various stages of surgical patient care.

5. Conclusion

This review explores recent advancements in deep learning-based computer vision for anatomical navigation in laparoscopic surgery, seeking to inform researchers and advance the field of AI-assisted surgery. A real-time intraoperative deep learning model for visual guidance could significantly enhance laparoscopic surgery by aiding surgeons in identifying specific anatomical structures and avoiding potential hazards.

Postoperative issues were caused by identifiable human errors, contributing to mistakes due to misrecognition of anatomy. Nevertheless, it is crucial to recognize specific drawbacks linked to laparoscopic surgery, which involves a limited workspace resulting in a narrower field of view, which could lead to misunderstandings and risky decisions. Developing a real-time intraoperative deep learning model to provide visual guidance, aiding surgeons in identifying specific anatomical structures for dissection or avoiding risky areas, has the potential to advance the field of laparoscopic surgery significantly.

For future perspectives, it is advisable to prepare the data for preprocessing and annotation by expert surgeons from all surgery departments to enhance the research on this topic. A standardized data pipeline facilitating international collaboration and centralized model deployment through a cloud-based environment is crucial for advancing AI in surgery, especially in complex laparoscopic procedures. Also, the DL models should be practiced in the operating room in a simulated way to address the possible risks and potential obstacles.

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