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Machine Learning in the Optimization of Robotics in the Operative Field

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Abstract

Purpose of review—The increasing use of robotics in urologic surgery facilitates collection of “big data”. Machine learning (ML) enables computers to infer patterns from large datasets. This review aims to highlight recent findings and applications of ML in robotic-assisted urologic surgery.

Recent findings—ML has been used in surgical performance assessment and skill training, surgical candidate selection, and autonomous surgery. Autonomous segmentation and classification of surgical data have been explored, which serves as the stepping-stone for providing real-time surgical assessment and ultimately, improve surgical safety and quality. Predictive ML models have been created to guide appropriate surgical candidate selection, while intraoperative ML algorithms have been designed to provide 3-D augmented reality and real-time surgical margin checks. Reinforcement-learning strategies have been utilized in autonomous robotic surgery, and the combination of expert demonstrations and trial-and-error learning by the robot itself is a promising approach towards autonomy.

Summary—Robot-assisted urologic surgery coupled with machine learning is a burgeoning area of study that demonstrates exciting potential. However, further validation and clinical trials are required to ensure the safety and efficacy of incorporating ML into surgical practice.

Keywords

machine learning; robotic surgery; surgical assessment; surgical training; autonomous surgery

INTRODUCTION

As of 2019, 5,582 da Vinci® robotic surgical systems (Intuitive Surgical Inc., Sunnyvale, CA, USA) have been installed around the world and approximately 1,229,000 robotic-assisted surgeries (RAS) are completed by these systems in a single year [1]. Aside from

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urologic oncology, RAS have been used in urinary tract reconstruction, urolithiasis, and benign prostate hyperplasia [2]. The tremendous amount of data generated from a single RAS offers a unique opportunity to incorporate machine learning (ML) into surgical practice. This review explores ML applications in surgical assessment and training, preoperative treatment strategy, and autonomous robotic surgery, focusing on its advantages over the conventional methods. Finally, we discuss current challenges and future directions of ML in urologic surgery.

MACHINE LEARNING IN SURGICAL ASSESSMENT AND FEEDBACK

Surgical skills assessment has important implications for surgical training, accreditation, and patient outcomes [3]. Historically, skill assessment methodology relied on subjective and laborious evaluations prone to observer biases, making them impractical for timely delivery of surgical feedback. The intersection of ML and instantaneous robotics-derived "big data" is a rapidly evolving field that aims to objectively and efficiently evaluate surgical skill, facilitating timely delivery of meaningful surgical feedback (Table 1).

While ML enables the analysis of large datasets, clinically relevant interpretation remains difficult. Segmentation of surgical procedures at the step, task, and gesture level is one strategy to interpret ML output and reveal clinical meaning. Zia et al. [4] applied ML-based analysis of robot-assisted radical prostatectomy (RARP) to automate segmentation of the 12 RARP surgical steps. Compared to human segmentation, the ML-based model correctly annotated most RARP step boundaries with <200 seconds error. ML has also been used to recognize surgical tasks (i.e., knot tying, suturing, and needle passing) in a simulated lab setting [5,6]. A prime example of ML application for surgical segmentation has been the JHU-ISI Gesture and Skill Assessment Working Set (JIGSAWS), a robotic surgical dataset collected through a collaboration between The Johns Hopkins University (JHU) and Intuitive Surgical, Inc. (Sunnyvale, CA. ISI). The dataset was captured using the da Vinci® surgical system (Intuitive Surgical Inc., Sunnyvale, CA, USA) from eight surgeons with different levels of skill, performing five repetitions of three elementary surgical tasks on a bench-top model: suturing, knot-tying and needle-passing, which are standard components of most surgical skills training curricula. The JIGSAWS dataset consists of three components: instrument kinematic data (Cartesian positions, orientations, velocities, angular velocities and gripper angle describing the motion of the surgeons), video data (stereo video captured from the endoscopic camera), and manual annotations including gesture (atomic surgical activity segment labels) and skill (using modified Objective Structured Assessments of Technical Skills). Khalid et al. [6] developed a ML model using the JIGSAWS video data to classify these surgical tasks and predict expertise and performance scores. ML analysis of surgical video has shown potential in automatically recognizing more basic movements in surgery, even those at the gesture level [7]. Such segmentation will allow for automation of postoperative reports broken down by surgical steps with detailed metrics describing gesture efficacy.

While these studies have made important contributions toward automation and analysis of skills assessment, they do not yet provide objective evaluation that might be used for surgeon feedback. Baghdadi et al. [8] described ML analysis of color and texture to recognize anatomical structures during pelvic lymph node dissection and predict dissection quality. The automated skills assessment output from their model compares favorably with manually scored expert ratings of lymph node dissection quality (83.3% accuracy), setting the stage for further evaluation of these training tools.

ML analysis of surgical instrument kinematics offers another avenue for skills assessment [9]. Fard et al. [10] use ML analysis of global movement features (summary data describing raw kinematic tool movements, e.g., path length, speed, tortuosity) during knot tying and suturing tasks to predict surgeon expertise with >90% accuracy within seconds after task completion. Wang and Fey's model [11] predicted surgeon expertise in these surgical task with similar accuracy; however, their model only required 1–3 second windows for data interpretation, making it especially useful for real-time feedback. Hung et al. [12] used ML analysis of raw kinematic data collected during a virtual needle driving exercise to predict virtual simulator scores and general surgical skills (e.g. needle targeting, instrument collision). Ershad et al. [13] combined kinematic surgical motions (i.e. hand and arm tracking) with evaluations of surgeons' movement style (e.g., viscous vs. fluid). In this study, crowdsourced analysis of surgical video was used to create codebooks or ML-based classifier models that assign stylistic behaviors (e.g. fluid vs viscous, relaxed vs. tense) to surgical motion. The combination of these codebooks with kinematic data yielded a 68.5% increase in surgeon expertise classification compared to utilizing only kinematic data. While future work is required to assess the training implications of this automatic and rapid stylistic analysis, the emphasis on interpretable feedback using commonly understood adjectives makes this approach unique.

ML is compatible with diverse datasets, including biometric data (e.g., eye-tracking, electroencephalogram). ML has been used to accurately predict cognitive workload [14] and mentor's trust level of a trainee [15]. Future integration of multimodal input with ML algorithms will allow for robust and multi-faceted skills assessment and training feedback.

Current ML applications in robotic surgery suggest that objective and efficient technical skills evaluation will be available in the near future. The efficiency with which ML can process large data sets makes it uniquely suited to supply interactive feedback, allowing the surgeon to refine skills in real-time. However, further work is required to show how these assessment tools can be incorporated into live surgery.

MACHINE LEARNING ALGORITHMS FACILITATE SURGICAL CANDIDATE SELECTION

With the abundance of information available from electronic health records and medical imaging, ML algorithms can aid in surgical candidate selection by improving diagnosis and disease characterization (Table 2). For example, ML analysis of computerized tomography (CT) images can differentiate small (≤ 4 cm) fat-poor angiomyolipomas from renal cell carcinomas (RCC) with 94% accuracy [16]. Furthermore, low- and high- Fuhrman nuclear grade RCC can be distinguished by ML models with accuracies ranging from 60 to 80% [17,18]. Such information would benefit both surgeons and patients for deciding on the best treatment strategy.

ML algorithms can also inform patient treatment strategies. Auffenberg et al. [19] introduced a web-based platform to accurately predict management decisions (active surveillance, radical prostatectomy, radiation therapy, and androgen deprivation therapy) of newly diagnosed prostate cancer patients by comparing their demographic features and clinicopathologic data to a similar patient cohort in a multicenter clinical registry. This tool can potentially assist both patients and physicians in making appropriate, data-driven decisions regarding surgical management.

Furthermore, ML models can predict postsurgical outcomes, an important variable for surgical candidate selection. Klen et al. [20] introduced a ML model to identify preoperative risk factors for postoperative mortality following radical cystectomy, which achieved an area under the curve (AUC) of 0.73. Identifying high-risk surgical candidates allows physicians to provide appropriate counseling when discussing surgery. While ML models can aid physicians in making medical decisions, further work is needed to validate these models before they can be implemented in a clinical setting.

INTRAOPERATIVE SUPPORT BY MACHINE LEARNING

ML has also been adopted to provide intraoperative support (Table 3).

Real-time Surgical Margin Confirmation

Ensuring negative surgical margins (SM) is important to achieve optimal oncological outcomes. Conventionally, intraoperative frozen-section pathology has been used to determine SM status; however, tissue processing can impede operating room efficiency. With the application of ML and advancement in spectroscopy, there is a possibility to provide real-time SM assessment. Haifler et al. [21] showed that ML analysis of short-wave Ramen spectroscopy obtained from a benchtop workstation in the lab setting can differentiate renal cell carcinoma from benign renal tissues with an accuracy, sensitivity, and specificity of 92.5%, 95.8%, and 88.8%, respectively. This process does not require special lighting conditions, supporting the future possibility of real-time SM evaluation while in the operation room [21].

Combination of Machine Learning and Augmented Reality

Augmented reality (AR), which overlays digital content onto the physical world, can be used to superimpose preoperative images onto robotic console during surgery. The combination of ML with AR can further enhance the safety and quality of surgery. Porpiglia et al. [22,23] used magnetic resonance imaging (MRI) to create 3D prostate models, which enable surgeons to visualize cancer features during prostatectomy, especially extracapsular extension (ECE) conditions. After successfully merging the 3D models with the da Vinci ® surgical console view (Intuitive Surgical Inc., Sunnyvale, CA, USA) in live surgeries, they automated this process by developing a computer vision algorithm [24] to anchor the virtual 3D models to the live surgical view of the prostate. Based on these models, metallic clips were placed on regions suspicious for ECE before removal of the neurovascular bundle. Final pathological examination confirmed cancer presence in all clipped spots of pT3 cases with a mean ECE length of 4mm [24]. A comparison between surgical teams with and without 3D AR guidance revealed that the virtual reality model significantly increased ECE identification (47.0% vs 100%, $p = 0.002$) [23]. The authors note that this technique can not only be used in prostate surgery, but potentially also in robotic partial nephrectomy, especially for endophytic or posteriorly located tumors. While further validation is required, 3D AR promises to advance intraoperative navigation and optimize the balance between avoiding positive SM and maximizing functional preservation.

APPLICATION OF MACHINE LEARNING IN AUTONOMOUS SURGERIES

RAS systems provide an excellent platform for ML-guided autonomous surgery [25]. Autonomy of surgical robots ranges from no automation to full automation without the need of human support [26] (Fig 1). In urology, RAS systems are currently at the stage of *surgeon assistance*, as robots provide surgeons with magnified visualization, improved dexterity, and mitigated instrument tremors. Ongoing work is exploring the feasibility of partial automation, in which robots perform repetitive tasks (e.g. camera positioning and tissue retraction), enabling surgeons to concentrate on the critical aspects of a procedure (Table 3). ML can enhance RAS by using computer vision models to perceive surgical environments, and reinforcement-learning methods to learn from a surgeon's physical motions [27]. The unique ability of ML to learn from prior experience enables robots to process novel data, much like how a surgeon deals with different anatomical variances among patients.

Autonomous Camera Positioning

Three sources of data have been utilized by ML algorithms to achieve autonomous camera positioning: instrument kinematics [28], laparoscopic video [29], and surgeon eye-tracking [30].

By using kinematic data from surgical instruments, these algorithms will not be affected by any visual occlusion in the operative field [28]. However, such algorithms require accurate instrument positions, which is not feasible in traditional laparoscopic surgery or when instrument coordinates cannot be obtained by the robotic system. These shortcomings can be overcome by ML analysis of laparoscopic video. Blanco et al. [31] have designed a ML algorithm that can utilize real-time surgical video to automatically orient the laparoscopic camera. They have validated the feasibility of the algorithm in an in-vivo pig experiment. Eye tracking is another technique to achieve camera automation. A new robotic system, the Senhance®, uses an algorithm to center the image at the point of focus of the surgeon. The initial clinical report suggests that the eye tracking feature requires 45–60 minutes of training and a preoperative calibration to the surgeon's eyes before each session [30,32]. After achieving proficiency in camera operation, this system facilitates the visual flow of the procedure [30].

Autonomous Tissue Dissection, Suturing, and Knot Tying

Compared to autonomous camera positioning, other automatic surgical tasks are more difficult to achieve, such as suturing, knot tying, and tissue dissection. A robot must "see", "think", and "act" in order to autonomously complete these tasks [33].

The first step is to "see" – vision recognition. One advantage of ML is it can process optical signals that the human eye and brain are not capable of processing. Samiei et al. [34] adopted a computer vision model to process data collected by a molecular chemical imaging endoscope, a novel technique which combines molecular spectroscopy and digital imaging in real-time. The system successfully identified anatomical structures such as the ureter, lymph node, blood vessels, and nerve bundles versus tissue background, with an AUC ≥ 0.90 in live porcine models. This technique has the potential to supplement a surgeon's conventional view, avoid iatrogenic injury and shed light on a new method that can facilitate autonomous surgery design.

The second step is to "think" – task planning. Osa et al. [35] designed an algorithm which can plan instrument trajectories based on human demonstrations in dissection, suturing, and knot-tying tasks. They validated its ability to fulfill predefined tasks under dynamic conditions in a lab setting. Baek et al. [36] utilized the reinforcement-learning model to effectively avoid instrument - tissue collisions during automatic trajectory planning phase.

The final step is to "act" – task execution. Delicate and pliable human tissue requires complex models to employ appropriate force, especially during tissue retractions. Thananjeyan et al. [37] adopted a deep reinforcement learning model, namely trust region policy optimization (TRPO), to control the retraction tension during dissection process. The new model outperformed conventional models (i.e., fixed and analytic approach) in simulated cutting tasks. Another group [38] further developed this algorithm by allowing a multipoint retraction, rather than single-point, and improved both accuracy and reliability. On the other hand, Alambeigi et al. [39] focused on tissue retraction during cryoablation of kidney masses. By using a vision-based optimization framework, they successfully manipulated the tissue to predefined cryoablation-needle insertion locations in an *ex vivo* lamb kidney. Their algorithm can estimate tissue deformation in real-time, thus is useful when handling tissues with unknown physical properties. Despite tremendous improvement in modeling and programming technology in recent years, these retraction models are limited to computer simulation or controlled lab settings. While further testing on animal models is required, these prototypes may inspire even more powerful algorithms capable of being incorporated into the live surgical setting.

Training Machine Learning Models

Much like training a surgeon, the process of training a ML model is important for its surgical performance. Reinforcement learning is the most frequently applied ML strategy in autonomous surgery. These algorithms can learn through expert demonstration, through trial-and-error, or through a hybrid approach [27]. Shin et al. [40] found that ML models with expert surgical demonstration learned faster than models that are purely data-driven, highlighting the importance of expert experience in guiding the model's learning process. Another study from Pedram et al. [41] combined these two methods together, and found that with a careful initial selection of simple and intuitive features instructed by surgeons, the mixed ML algorithm can be trained successfully in multiple tissue dynamic circumstances. This method may serve as an efficient model to balance the time of a surgeon training the algorithm and the best learning effect of it.

Current Products and Future Directions

A number of studies have attempted to combine all aforementioned aspects to produce a final product. In 2016, Shademan et al. developed an anastomosis robot (STAR) system to automatically perform end-to-end intestinal anastomosis with the help of a human retraction assistant in the open surgical setting [42]. The team updated STAR in recent years by adopting a new 3D imaging endoscope and a suturing planning strategy. It outperformed manual suturing on the consistency of suture bite and number of suture repositioning [43].

CHALLENGES AND LIMITATIONS

Despite the promise of ML, there are formidable obstacles and limitations. One of the overriding problems involves data availability. In order to train ML models, large-scale and high-quality surgical data must be manually collected in the clinical setting, a task which is rarely completed outside of research settings currently. Another challenge involves the security of high-volume surgical data. Safety protocols must be designed to process sensitive patient information without violating patient privacy regulations. Finally, closes collaboration between surgeons and engineers is required. The best ML strategy for autonomous surgery now is learning from both expert demonstrations and trial-and-error. Thus, only by intimate interdisciplinary collaboration, such a learning method can be realized [44].

CONCLUSIONS

The intersection of ML and robotics-derived "big data" is a rapidly evolving area of study, harboring the potential to optimize surgical safety and quality. Multiple studies have utilized ML models to provide objective and efficient surgical assessment, with the ultimate goal of providing timely and meaningful surgical feedback intraoperatively to prevent adverse events. Predictive ML models have been used to guide surgical patient selection. Finally, ML empowers surgical robots to learn procedures autonomously through expert demonstrations, trial-and-error, or a hybrid of these two approaches. With the rapid development of computer science and surgical techniques, the narrative of applying ML in the surgical field has just begun.

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KEY POINTS

- The intersection of machine learning (ML) and robotics-derived "big data" is a rapidly evolving field.
- ML has the potential to provide objective, efficient, and scalable surgical assessment.
- ML can accurately make preoperative diagnoses and surgical risk assessments to optimize surgical candidate selection.
- ML allows robots to learn surgical procedures autonomously through either expert demonstration, trial-and-error, or both.
- Future applications of ML require secure and robust surgical data acquisition with close collaboration between surgeons and engineers.

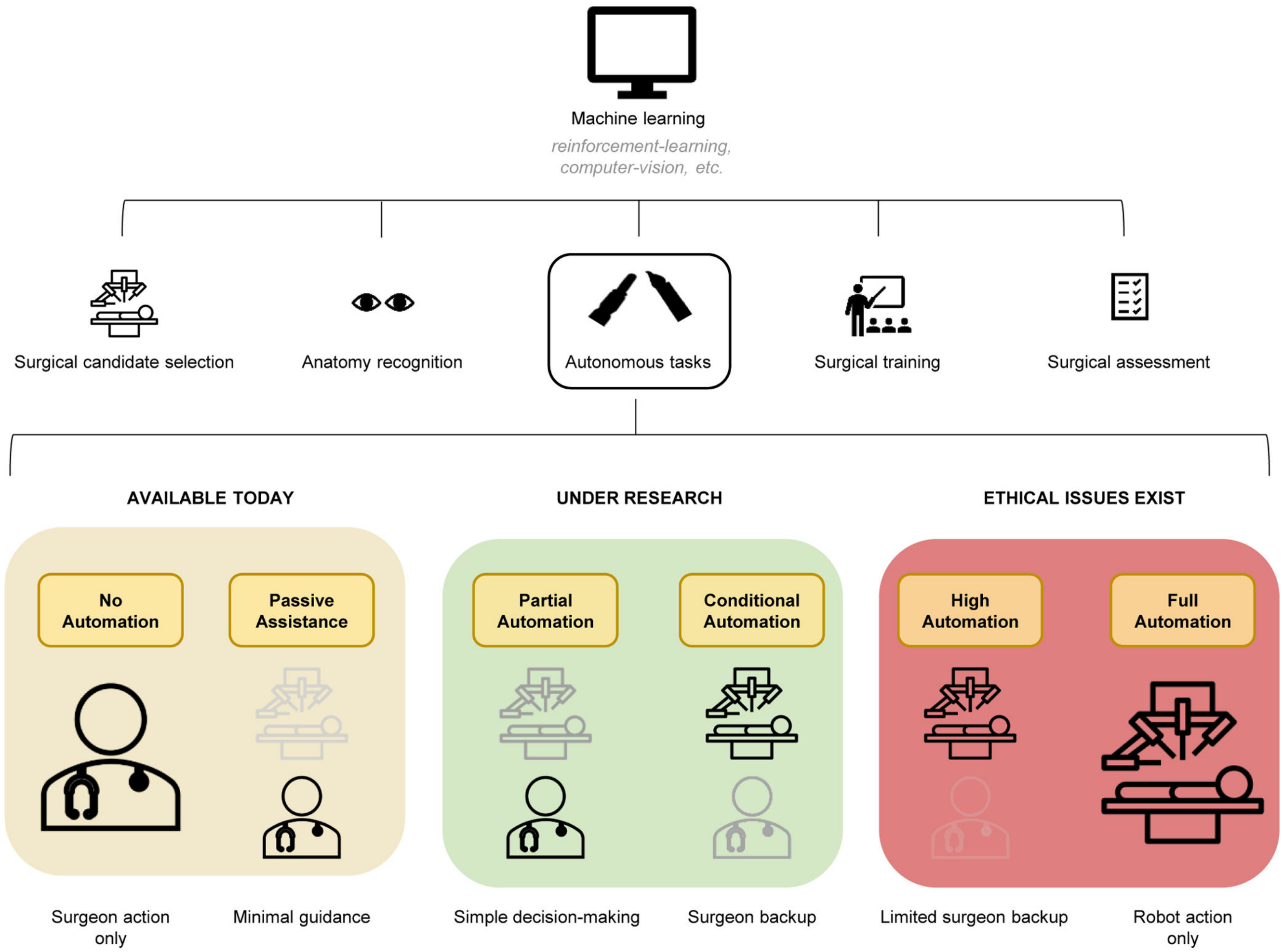

Figure 1.
Applications of machine learning in urologic surgery

Table 1.

Machine learning in surgical skills assessment

Author	Application	Machine Learning Algorithms/Models	Samples	Training Input	Performance
Zia et al. 2019 [4]	Produce automated post-op efficiency reports broken down by individual in step levels	CNN-LSTM	100 prostatectomies	Image and systems data	Jaccard Index for RP-Net-V2 (VGG19) .81+/− 0.06, median difference between human rater and ML algorithm < 200 seconds for most steps
Funke et al. 2019 [5]	Assess surgical skill from a dataset using raw video data	Deep learning (3D ConvNet)	103 video clips (JIGSAW)	Videos	Skills classification accuracy of suturing (100%), needle passing (96.4%), and knot tying (95.0%)
Khalid et al. 2020 [6]	Accurately detect surgical actions and performance level	Neural networks	103 video clips (JIGSAW)	Videos	Precision 91% and recall 94% in detecting surgical actions; precision 77% and recall 78% in predicting surgical expertise
Hung et al. 2020 [7]	Predict virtual simulator score and general surgical skills from virtual exercises	GRU, RNN, LSTM	360 simulated sutures from 11 participants	Raw kinematics in simulated exercises	Simulation score predicted with mean error 29%; needle mistargeting predicted with accuracy 76%
Baghdadi et al, 2019 [8]	Automate assessment of pelvic lymph node dissection	Computer vision	20 PLND videos	Videos	Accuracy 83.3% compared to expert ratings
Fard et al. 2018 [10]	Predict surgeon experience based on global movement features from knot tying and suturing tasks	k-NN, LR, SVM	103 video clips (JIGSAW)	Global Kinematics	Classification of surgeon expertise with accuracy of Knot tying (82.3%) and suturing (89.9%)
Wang et al. 2018 [11]	Accurate and real-time task identification for objective skill assessment	CNN	103 video clips (JIGSAW)	Motion Kinematics	Gesture identification accuracy of suturing (92.5%), needle passing (95.4%), and knot tying (91.3%)
Hung et al. 2020 [12]	Recognize and distinguish suturing gestures during UVA	Deep learning computer vision: LSTM, GRU, RNN	426 videos	Videos	Identified forehand over vs. under with accuracy 90.3%; left vs. right instrument with accuracy 92.5%
Ershad et al. 2019 [13]	Predict surgeon motion styles during surgery (e.g. fluid vs viscous; smooth vs rough; relaxed vs tense)	SVM PCA Sparse coding	14 surgeons of various expertise performed 2 tasks	Raw kinematic data of hand, wrist, and shoulder	Classification success rate ranging from 71.0% to 98.5% of various stylistic behaviors
Wu et al. 2019 [14]	Assess surgeon mental workload	Naïve Bayes algorithm	8 trainees, 15 simulation sessions with 12 exercises each session	Eye tracking metrics and demographic features	Accuracy 84.7% in predicting high vs. low workload states.
Shafiei et al. 2018 [15]	Evaluate trust between trainee and trainer during robotic surgery	SVM with KTA and KTS criteria	1 mentor, 3 trainees, 87 UVA and 83 LND operations	EEG waveforms	During simple tasks, functional brain features are sufficient to classify trainee trust; in complex tasks, adding cognitive features improves accuracy.

CNN, convolutional neural networks; GRU, gated recurrent unit; JIGSAW, The Johns Hopkins University and Intuitive Surgical Gesture and Skill Assessment Working Set, collecting from 8 surgeons performing 4–5 trials of various surgical tasks; k-NN, k-nearest neighbors; KTA, kernel-target alignment; KTS, kernel class separability; LND, lymph node dissection; LR, logistic regression; LSTM, long short term memory; PCA, principle component analysis; RNN, recurrent neural network; SVM, support vector machine classifier; UVA, urethrovesical anastomosis.

Table 2.

Machine learning application in the preoperative evaluation of surgical candidates

Author	Application	Machine Learning Algorithms/Models	Samples	Training Input	Performance
Feng et al. 2018 [16]	Noninvasive method of differentiating small AMLwvf from RCC	SVM-RFE + SMOTE	58 patients (17 AMLwvf & 41 RCC)	CT texture features	Achieved accuracy 93.9%, sensitivity 87.8%, specificity 100%, and AUC 0.955
Kocak et al. 2018 [17]	Noninvasive method of predicting nuclear grade of ccRCC	ANN ± SMOTE	81 unenhanced CT images	CT texture features	Accuracy 81.5% of ANN alone and 70.5% of ANN with SMOTE
Lin et al. 2019 [18]	Noninvasive method of predicting nuclear grade of cc RCC	CatBoost	231 patients with proven ccRCC lesions	CT texture features	Three-phase CT image model achieved highest diagnostic performance with AUC 0.87, PPV 91%, and NPV 59%.
Auffenberg et al. 2018 [19]	Predict treatment decision in patients newly diagnosed with prostate cancer	Random Forest	Derivation cohort: 5,016 patients; Validation cohort: 2,527 patients	Patient clinicopathologic factors, demographics, and treatments	Accurately predicted prostate treatment cancer treatment with AUC 0.81
Klen et al. 2018 [20]	Postoperative risk prediction tool using preoperative data to identify high-risk surgical candidates	Logistic regression with lasso approach	1,099 radical cystectomy patients	Baseline clinical variables and patient outcome	AUC 0.73; identified 4 significant patient risk factors for surgery

AMLwvf, angiomyolipoma without visible fat; ANN, automated neural network; AUC, area under the curve; ccRCC, clear cell renal cell carcinoma; NPV, negative predictive value; PPV, positive predictive value; RCC, renal cell carcinoma; SMOTE, synthetic minority oversampling technique; SVM, support vector machine classifier.

Table 3.

Machine learning application in intraoperative robotic surgery support and autonomous surgeries

Author	Application	Machine Learning Algorithms/Models	Sample	Training Input	Performance
Haifler et al. 2018 [21]	Differentiate renal cell carcinoma from benign renal tissues	Sparse multinomial logistic regression	93 spectra from six ccRCC and six normal renal parenchyma tissue samples	Spectrum	Classifier accuracy 92.5% with sensitivity 95.8%, specificity 88.8%, and AUC 0.94.
Porpiglia et al. 2020 [22]	Identify precise tumor location and suspicious ECE locations by superimposing virtual 3D prostate model onto real-time RARP video	Computer vision	10 RARP videos with suspicious ECE	Videos	Successfully superimposed virtual 3D models on surgical video to identify ECE location in 100% of the cases.
Blanco et al. 2018 [31]	Autonomous laparoscopic camera positioning	Reinforcement learning	5 users performing 20 trials each	Videos	Algorithm provided the best camera behavior for each user after a short training period of only 15 trials.
Saimiei et al. 2019 [34]	Human tissue recognition to avoid iatrogenic injury	Machine learning	3 surgeries on porcine models	Videos	Distinguished ureter, lymph node, blood vessels, and nerve bundles from tissue background with AUC ≥ 0.90.
Baek et al. 2018 [36]	Collision avoidance path planning during autonomous robotic surgery	Reinforcement learning	N/A	Simulation data	Algorithm improved with each training time, as evidenced by increasing score of q learning function.
Thananjeyan et al. 2017 [37]	Plan trajectory of instruments in real-time	Deep reinforcement learning	Training: 10,000 simulation trials Validation: 17 different curved contours in simulation and 4 in physical experiments	Simulation data	Learning to tension with deep reinforcement learning achieves performance improvement of 43.30% from non-tensioned baseline.
Nguyen et al. 2019 [38]	Plan trajectory of instruments in real-time	Deep reinforcement learning	17 open and closed curved contours in simulation	Simulation data	Proposed method is superior to existing state-of-art method in both performance and robustness.
Alambeigi et al. 2018 [39]	Estimate deformation behavior of tissue during real-time manipulation	Vision-based optimization framework	2D silicon phantom and 3D ex vivo lamb kidney	Simulation data	Successful real-time estimation of the deformation behavior of deformable tissues while manipulating them to the desired insertion locations.

AUC, area under the curve; ccRCC, clear cell renal cell carcinoma; ECE, extracapsular extension; N/A, not available; RARP, robotic-assisted radical prostatectomy.