An Exhaustive Analysis of AI Applications in Robotic Surgery Focus on the Art Narendra Devarasetty 1*

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Keywords

ABSTRACT

Computer Vision Robotic Surgery Artificial Intelligence While there is a lot of written about AI's great potential, no studies have looked at how well it improves patient safety during robot-assisted surgery (RAS). In accordance with the PRISMA 2020 declaration, a literature search was carried out using PubMed, Web of Science, Scopus, and IEEExplore, Articles published in English between January 1, 2016, and December 31, 2020 that were peer-reviewed were considered. For quality assessment, Amstar 2 was utilized. The Newcastle Ottawa Quality assessment instrument was used to evaluate the risk of bias. The SPIDER tool was used to graphically exhibit the study data in tables. The search parameters were satisfied by 35 articles, which comprised 3436 patients in the study. Among the chosen studies are those pertaining to training (n = 3), tissue retraction (n = 1), urology (n = 12), gynecology (n = 1), and other specialties (n = 1). The detection precision of surgical instruments varies rising from 76.0 percent to 90.6 percent. After a robot-assisted radical prostatectomy (RARP), the average absolute error for predicting urine continence was between 85.9 and 134.7 days. A forecast accuracy of 88.5% was achieved for the duration of stay after RARP. During robotassisted partial nephrectomy (RAPN), the next surgical job was accurately recognized 75.7% of the time. Overall, the quality of the studies that were considered was poor. Due to the restricted size of the datasets, the conclusions are rather constrained. Because methods and datasets are different, it was difficult to compare research that dealt with the same subject. The important tasks of RAS procedures impact patient outcome, but there is no indication that AI can detect them at this time. Immediate action is required to validate AI systems through external means and conduct studies on massive datasets. Surgeons should also be able to understand and use the data to communicate with patients in a way that is understandable to the average person.

Introduction

John McCarthy, now an emeritus professor at Stanford University, first used the term "artificial intelligence" (AI) in 1955 to describe "the science and engineering of making intelligent machine" [1-5]. As shown in dermatology, AI has been applied to other healthcare areas and has even outperformed experienced physicians in some instances [6–18]. Among the many medical subspecialties, surgery is one that produces enormous data collections that can be thoroughly and meticulously examined by AI. Some examples of such datasets are surgical datasets pertaining to pre-operative staging (including patients' clinical, laboratory, and imaging tests), intra-operative datasets (including data from video recordings and kinematic analysis), and patient-reported outcome measures (PROMS), which have been introduced in the last forty years to give an evaluation of the treatment from the patients' point of view.

Artificial intelligence (AI) has evidently many potential uses in the surgical field. These include, but are not limited to, training, simulation, making decisions during surgery, predicting what will happen during surgery, helping surgeons prepare for major operations and re-interventions, tracking their recovery after surgery, handling complications, and even re-validating, credentialing, and re-certifying them.

To enhance interventional healthcare through data collecting and modeling, the term "Surgical Data Science" was recently coined in this context [19–32]. More specifically, digital surgical methods, such as RAS's master-slave manipulators, stand to gain the most from AI development. In 2020, 1.25 million surgeries will be conducted globally employing RAS, with the da Vinci surgical system alone accounting for this number (Intuitive Surgical, Sunnyvale, CA, United States) [33-56]. Thanks to a specialized application programming interface, the da Vinci system may record not only movies but also kinematics (the position and rotation of the surgical instruments on the robotic cart) and event data (e.g., press and release of the camera pedal), all with the company's approval.

Several downsides appear to be preventing the practical deployment of AI technology, despite the considerable buzz surrounding them. As a first point, AI model performance is very data-dependent, meaning it can't be guaranteed regardless of the amount, quality, or diversity of the input data. So, it should come as no surprise that some research shows that old-fashioned statistics can beat AI [57-72]. Second, there is a lack of external validity in some of the published experiments since they only tested their algorithms on their own dataset [73-89]. Thirdly, non-experts, particularly surgeons, sometimes see deep learning algorithms as incomprehensible "black boxes" because of the absence of clear explanations on their operating principles. This poses a problem with the interpretability of these algorithms. So, a lot of seasoned surgeons don't know what to make of them or trust them. From RAS and self-driving vehicles to medical devices, the term "Explainable AI" (xAI) was coined to highlight the need of AI being open and understandable to its end users. With its General Data Protection Regulation (GDPR) on Artificial Intelligence, the European Union sought to resolve the matter of transparency. Transparency of the algorithm and its output is necessary, even if xAI is not yet required by medical device regulatory agencies like the US Food and Drug Administration.

There have been relatively few narrative assessments of AI in RAS so far. Unfortunately, we are unaware of any comprehensive evaluations of the burgeoning area of AI in RAS. Reviewing the existing literature on AI in RAS is the main goal of this study, with identifying their strengths, weaknesses, opportunities, and threats serving as secondary outcomes.

Methodology for the Search

Several databases were searched for relevant articles in February 2021, including PubMed, Web of Science, Scopus, and IEEExplore. Results from both randomized and non-randomized trials were considered in the search. Only abstracts from English-language, peer-reviewed publications published within the previous five years in the fields of urology, general surgery, and gynecology were considered. The following search terms were used: (artificial intelligence, deep learning, machine learning), (robot, robotic), (urology, gynecology, general surgery), and (convolutional neural networks, skills assessment, simulation for training, education, image, imaging, video recording). A search was conducted by title or abstract using keywords and Boolean operators. If the information retrieved was inadequate, the authors of the relevant publications were contacted to get more details. Published reviews and the sources cited within them were also included to the search.

Reviews, letters, abstracts, and proceedings from conferences were not included. Neither were papers that had not been peer reviewed. Furthermore, scholarly works published in periodicals that focus on fields other than general surgery, fields of gynecology and urology were not included. Reporting in accordance with AMSTAR 2, our approach to data identification and evaluation agreed with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) 2020 statement and checklist [89-102].

Data Mining

After identifying relevant publications, we reviewed their titles and abstracts to narrow the search. Then, we read the entire texts, extracted data, and checked the references. The studies were examined and retrieved by two independent writers (AM, KG). In every case where there was disagreement, a third reviewer (EG) was contacted, and the outcome was unanimous agreement. The research' designs prevented the use of the PICO framework, which identifies participants, interventions, comparators, and outcomes. Rather, the SPIDER tool—which is based on PICO—was utilized, which stands for sample, phenomena of interest, design, evaluation, and study type [102–112]. By reporting "Yes" for eight criteria, "Partial Yes" for five, and "No" for three, the Amstar 2 instrument demonstrated satisfactory compliance. All three of those "no"s have to do with meta-analyses, which are totally irrelevant to this review.

Analyses

Separate categories were established for the research based on the many applications they pertained to. These categories included motion analysis, urology, other specialties, and other applications. One set was given to each research. A table was made to graphically display the study data for each pair. For each set of studies that met the criteria, the SPIDER tool was used to report the following: dataset with the number of tasks or procedures (Sample), named tasks or procedures (Phenomenon of Interest), design, which includes the application, robotic platform, AI algorithms, and input features; evaluation, which includes the results; research, which includes the studies' strengths and weaknesses. The investigations of each set were thereafter subjected to a separate analysis. Surgical action identification, surgical gesture recognition, surgical gesture segmentation by trajectory or tools, and surgical gesture ma-neuver or phase classification were the outputs of the motion analysis. For urology: categorization of surgical experience level, urine continence, duration of stay, prostate specific antigen (PSA) detection, intra- and post-operative event segmentation, and recognition of surgical job or process. Surgical phase recognition and case length pertain to various fields of expertise. Additionally, for use in retraction of tissues, virtual reality simulator performances, and the Global Evaluative Assessment of Robotic Skills (GEARS) score. Precision, specificity, area under the curve, mean absolute error, and Dice Similarity Coefficient were among the quantitative measures that were gathered and examined. Reports of the same phenomena of interest, designs, and statistical criteria allowed for comparisons across investigations. The research' heterogeneity was investigated by looking at their designs, datasets, artificial intelligence algorithms, input attributes, and assessment criteria. Studies of this sort did not lend themselves to sensitivity analysis or confidence evaluation [113–124].

Discrimination Potential

For the purpose of determining potential bias, the Newcastle-Ottawa quality evaluation scale was utilized. Taking into account the research that were assessed, not all of the Newcastle-Ottawa criteria could be used. Bias was also evaluated according to the way missing data was handled and the sort of financing that was obtained, whether it was public or private. It was determined that the impact measure did not apply after reviewing studies. Nevertheless, the authors thoroughly examined each study, analyzed the data with care, and addressed any concerns regarding methodological quality. The review also addressed any shortcomings.

Final Product

There were 1358 results found in the database. Following the screening of titles and abstracts, 66 out of 204 reported papers had their entire texts examined. For the purpose of full text analysis, 35 studies were ultimately collected. Outlined here are the articles that were not included. A diagram derived from the PRISMA 2020 document. Of the 35 papers that were a part of the evaluation, 17 dealt with motion analysis, 12 with urology, 1 with gynecology, 1 with multiple specialties, and 4 with other applications. Patients from urology, gynecology, and general surgery were included in one study each, for a total of thirteen trials.

The following acronyms are used in this list: ACA for Aligned Cluster Analysis, CNN for Convolutional Neural Network, COCO for Common Objects in Context, DSC for Dice Similarity Coefficient, FCN for Fully Convolutional Network, GAN for Generative Adversarial Network, GMM for Gaussian Mixture Model, GRU for Gated Recurrent Unit, HACA for Hierarchical Aligned Cluster Analysis, HMM for Hidden Markov Model, JIGSAWS for Johns Hopkins University-Intuitive Surgical Gesture and Skill Assessment Working Set, kNN for k Nearest Neighbors, LR for Logistic Regression, LSTM for Long Short-Term Memory, MICCAI for Medical Image Computing and Computer Assisted Intervention, MIST RNN for Multi-Objective Support Vector Machine, and finally,

A few acronyms: MISTIC-SL, which stands for Minimally Invasive Surgical Training and Innovation Center - Science of Learning, OSATS, which stands for Objective Structured Assessment of Technical Skills, PCA, which stands for Principal Component Analysis, RPN, which stands for Region Proposal Network, SC, which stands for Spectral Clustering, SVM, which stands for Support Vector Regression, TCN, which stands for Temporal Convolutional Network, TSN, which stands for Temporal Segment Network, and so on employing a combination of the da Vinci surgical system and the da Vinci research kit, and a Phantom Omni device that utilizes Raven II. Eight research made use of the JIGSAWS dataset, which stands for Johns Hopkins University - Intuitive Surgical Gesture and Skill Assessment Working Set. JIGSAWS consists of three parts: eight patients take three to three hours to tie knots, suture, and pass needles. Kinematic data and videos are included in it. On the basis of their technical competence, each video was given a score on the OSATS. The 2015 MICCAI EndoVis Challenge dataset was utilized in two papers, while the 2017 MICCAI EndoVis Challenge dataset was used in two more. The Atlas Dione dataset was utilized in two investigations. The dataset comprises 86 movies, or 910 clips, in which ten participants carried out six distinct activities on inanimate models: vesicourethral anastomosis, ball insertion, ring peg transfer, suture pass, suture, knot tie, and suture. The set contains 99 videos that provide annotations of various robotic instruments.

One study used event data (e.g., pressing the camera or clutching the foot pedal) and kinematics, two studies used kinematics and video frames, one study used images and video frames, and four studies used video frames to compute movement (optical flow). The input features to the algorithms also vary. Seven studies used only kinematic data of robotic arms. Dice similarity, accuracy (out of seven), precision (out of four), and sensitivity (out of four) were among the other criteria used to evaluate AI model performance.

It was only feasible to compare research in a small number of instances due to the evident heterogeneity of the methods and datasets. Consequently, when utilizing k-nearest neighbors and support vector machines for surgical skills evaluation on the JIGSAWS dataset, the accuracy ranges from 77.4% to 100%, and when employing fully convolutional networks, it ranges from 92.1% to 100%. All of the research suffer from inadequate datasets due to the minimal number of individuals and tasks used in their recruitment. Despite its use in a number of studies, JIGSAWS has a number of drawbacks. To begin with, it is based on just eight subjects; secondly, it only allows a certain number of attempts per task; for example, 36 for knot tying, 39 for suturing, and 26 for needle passage. The participants' relatively limited RAS experience is a big limitation: two more than 100 hours of RAS experience, four with less than 10 hours, and two with 10 to a hundred hours. Lastly, unlike Atlas Dione, JIGSAWS does not have camera movement or zoom. However, there are only 86 movies total from 10 individuals in Atlas Dione, including two residents, three fellows, and five specialist surgeons. Also, MICCAI EndoVis datasets are on the smaller side; for example, the 2017 edition of the tools segmentation dataset only includes eight RAS operations.

Results were impressive in a number of investigations, with some research reporting scores of 90% or higher. When it came to tool identification, for example, they were even better than state-of-the-art frameworks like YOLO (You Only Look Once) and Faster R-CNN [32].

List of abbreviations: ANN = Artificial Neural Network, APM = Automated Performance Metric, AUC = Area Under the Curve, BMI = Body Mass Index, CNN = Convolutional Neural Network, DICOM = Digital Imaging and Communications in Medicine, DL = Deep Learning, EEG = electro-encephalogram, kNN = k Nearest Neighbors, LND = Lymph Node Dissection, LR = Logistic Regression, LSTM = Long Short Term Memory, MAE = Mean Absolute Error, MRI = Magnetic Resonance Imaging, NASA-TLX = NASA Task Load Index, PCA = Principal Component Analysis, PLACE = Pelvic Lymphadenectomy Assessment and Completion Evaluation, PLND = Pelvic Lymph Node Dissection, PSA = Prostate Specific Antigen, RAPN = Robot Assisted Partial Nephrectomy, RARC = Robot Assisted Radical Cystectomy, RARP = Robot Assisted Radical Prostatectomy, RF =

The field of Urology Utilizes

There was a single multicentric study out of twelve that dealt with urological procedures. With eight out of twelve studies reporting it, robot-assisted radical prostatectomy (RARP) was the most studied surgical procedure. Three studies reported robot-assisted partial nephrectomy (RAPN), while the other two reported robot-assisted radical cystectomy

(RARC). Out of the four RARP studies that focused on PROMS, two dealt with the prediction of urinary continence risk, one with the prediction of duration of stay, and one with the prediction of Prostate Specific Antigen (PSA) recurrence. Prior RARP research on surgical task recognition, surgeon experience, and gesture recognition and categorization during vesicourethral anastomosis execution corroborated these hypotheses. The third study focused on intra-operative image segmentation, the second on surgical event recognition, and the first on post-operative event prediction using PROMS; another study used electroencephalogram (EEG) to categorize the functional brain state of a mentor supervising trainees. The datasets were typically on the smaller side, with RARP ranging from twenty to four hundred operations and RAPN from nine hundred to a thousand. The review's lone RARC research relied on a small dataset consisting of only 20 procedures.

The input characteristics utilized in four experiments were automated performance metrics (APMs). Kinematic data of the robotic arms and events, such pressing and releasing the camera pedal, made up the APMs. A gadget (like dVLogger from Intu-itive Surgical) records and stores them automatically. Between twenty-five and forty-six APMs were found. In all cases, APMs were applied to RARP. Two investigations contained clinicopathological data, and one further integrated video frames [42]. Five of the publications made use of video frames; two of them combined APMs and displacement vectors to model optical flow. One study analyzed pre- and post-operative DICOM images; another analyzed demographic data; a third analyzed clinical data; a fourth analyzed imaging data; and a fifth used electroencephalogram (EEG) features to assess cognitive and functional abilities.

Present Constraints

Firstly, as can be seen in the corresponding tables, our systematic assessment of AI in RAS literature has identified a number of significant inadequacies in the existing literature. The short datasets of the research included in the study are the most common source of this poor judgment, however there are other factors at play as well. Also, not a single study that used this model actually tested it on a dataset from another (external) center. This means we don't have any answers about: (i) how many samples are needed to train AI models for these tasks, and (ii) how well the trained model holds up when tested on other, comparable datasets [56]. The current evaluation also offers a near-to midterm plan based on the authors' estimations of the needs for RAS researchers (engineers, computer scientists, and surgeons).

Lastly, zero of the studies that were considered were prospective. If we want to know where AI models fall short, we need to conduct prospective trials. Since nearly all of the studies (32 out of 35) failed to disclose how they dealt with missing data, it is possible that the results are biased. The fact that seven studies received money from private companies—some of which came from public entities—raises the possibility of bias. The research are not consistent with each other, which weakens the present review. Other RAS specialties, such as cardio-thoracic surgery, head and neck surgery, etc., were also left out of this review, along with grey literature. The number of publications that might have been included in this evaluation would have been small, nevertheless, because these subspecialties account for a relatively small fraction of all surgical procedures performed each year across the world.

Obstacles to be Overcome in the Future

There are yet no AI training guidelines for RAS, according to a recent Delphi study. Machine learning may analyze a wide variety of data sources, including movies, kinematics, and events (such as camera activation), as well as metrics gathered by VR simulators to offer learners an objective evaluation of their skills. Researchers in a recent study used machine learning to estimate how many tries it would take to become skilled using laparoscopic simulator exercises. Two factors need comparable research in RAS. First, rather than focusing on a certain amount of time or number of repetitions of simulated exercises, training should be competency-based and centered on the goal of proficiency. Second, it is useful to be able to anticipate when trainees will acquire surgical skills so that problems may be identified early on. One day, AI may be a game-changer when it comes to providing individualized RAS training that taps on people's natural talents.

Artificial intelligence (AI) for RAS motion analysis is only starting to take off. Despite being aware of the recent progress in computer vision for motion analysis through deep learning, RAS surgeons have neglected to incorporate a significant shift in clinical practice. This shift is the creation of Observational Clinical Human Reliability Analysis (OCHRA), which is based on the well-established Human Reliability Assessment (HRA) used in high-risk industries like nuclear power, aerospace (including civilian flights), and all hazardous engineering fields. The goal of industrial HRA is to avoid or lessen the likelihood of catastrophic events, and it is completely predictive in nature. In order to avoid or minimize human-machine errors, industrial HRA consists mostly of a probabilistic pre-performance exercise or drill. Thanks to its objective evaluation of the quality of operation execution by fully competent surgeons and residents based on error quantification during the process, OCHRA is currently extensively used for direct manual laparoscopic surgery across surgical specialties. OCHRA has been around for 22 years, but its limited utilization is due to its existing constraints. The current state of OCHRA is labor-intensive since it necessitates the evaluation of unaltered films of operations by a diverse team of specialists in human factors and cognitive engineering in order to discover and classify mistakes according to predetermined criteria. Improvements in AI software and technology (such as GPUs and tensor processing units) will have a profound impact on OCHRA. Our firm belief is that RAS surgeons and researchers can no longer afford to disregard OCHRA.

Computer vision-based force sensing is a relatively new area of study that might launch novel PROMS situations. A recent study mapped the 3D visual-geometric information to the applied force during RAS using long short-term memory and recurrent neural networks. For example, to anticipate bowel anastomosis leaking during RAS, vision-based force sensing might be used to tackle PROMS-related difficulties. Recent proposals have used the model of autonomous vehicles to suggest a six-stage procedure for the development of autonomous RAS, with 0 representing no automation and 5 representing complete automation.

motor vehicles. Among the tele-manipulators and master-slave systems now in use at RAS is the da Vinci surgical system. Using the International Standard Organization's definition, it cannot "perform intended tasks based on current state and sensing without human intervention"; hence, it cannot be considered an autonomous system. A surgical procedure

can be taught to an autonomous robot either by direct programming (explicit learning) or by seeing a film or surgeon carry it out (implicit learning). In a pig model of an experimental anastomotic suturing investigation, the Smart Tissue Autonomous Robot (STAR) outperformed human surgeons, demonstrating an example of explicit learning. Unfortunately, no one has been able to replicate this study and it does have some drawbacks.

Demonstration is a source of implicit learning, also known as imitation learning. It paves the way for robots to learn new skills on their own, which may have medical applications down the road. The surgical job must first be segmented into subtasks, and then recognized and modelled in order to facilitate their execution. A da Vinci surgical system was recently trained to mimic the application of a stitch on an inanimate model using this technique, which it learned from a video of the same exercise in the JIGSAWS dataset.

Problems with Society, Ethics, and the Law

There will be social, ethical, and legal concerns with RAS, as there would be with any AI used in surgery. New information on clinically safe RAS may result from AI, which might lead to changes in the certification and credentialing of RAS surgeons.

There should be regulations in place to ensure the privacy and security of patients' information, including but not limited to electronic health records and intraoperative recordings used to train predictive AI models. Hacking can also occur if the physical hard disks are not adequately safeguarded or if the platforms used to store, retrieve, and share data have Internet connectivity, such as cloud platforms. Past patient injuries due to poor training have given rise to legal disputes in RAS. Policies addressing responsibility owing to malpractice are necessary with the incorporation of AI into RAS. Openness and clarification about AI for RAS should also be part of these policies.

Conclusion

This review highlights a number of issues with previous research on artificial intelligence in RAS, including: small datasets; a lack of external validation; algorithms that did not provide training details; and an absence of explanations written in non-specialist, layman's language. As a result, surgeons view these algorithms as opaque and do not use them. Adopting AI for RAS successfully presents some lofty obstacles in the pursuit of state-of-the-art advancement. In this analysis, we take into account a range of potential needs for RAS AI integration. Among these are autonomous operating robots, computer vision to simplify OCHRA, and future applications on PROMS. Artificial intelligence (AI) may also pave the way for a new category of medical gadgets designed to make RAS safer and more efficient. On a societal, legal, and ethical level, it can have far-reaching consequences. Solutions to these problems and concerns need to come from big, interdisciplinary networking research groups working on AI for RAS in both the academic and business sectors.

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