A Review on Deep Learning in Minimally Invasive Surgery

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ABSTRACT In the last five years, deep learning has attracted great interest in computer-assisted systems for Minimally Invasive Surgery. The straightforward accessibility to images in surgical interventions makes deep neural networks enormously powerful for solving classification problems in complex surgical scenarios. The objective of this work is to provide readers a survey on deep learning models applied to minimally invasive surgery, identifying the different architectures used depending on the application, the results achieved until now, and the publicly available surgical datasets that can be used for validating new studies. A total of 85 publications have been extracted from manual research from four databases (IEEE Xplorer, Springer Link, Science Direct, and ACM Digital Library). After analyzing all these studies, they have been classified into four applications: surgical image analysis, surgical task analysis, surgical skill assessment, and automation of surgical tasks. This work provides a technical description of these works and a comparison among them. Finally, promising research directions to advance in this field are identified.

INDEX TERMS Deep learning, convolutional neural network, deep neural network, minimally invasive surgery, laparoscopic surgery, robot-assisted surgery.

I. INTRODUCTION

Minimal invasive surgery (MIS), or laparoscopic surgery, has become the common practice in many surgical interventions with high benefits for patients. However, it introduces new challenges for surgeons such as the lack of direct vision, tactile sensation, and limitation in the motion of the instruments. Robot-assisted surgery (RAS) overcomes several issues of MIS and improves the surgeons’ efficiency with a more accurate and intuitive movement of the instruments. The interest in surgical robots is undisputed if we have a look at the huge economic efforts that the major economies of the world are making to boost this market, which is expected to grow at a compound annual growth rate of 10.7% during the forecast period from 2019 to 2029, reaching a market of $15.43 billion by 2029. Intuitive Surgical is also boosting the research in surgical robotics supporting the scientific community with research platforms of the da Vinci Surgical System, known as da Vinci Research Kit (dVRK), and facilitating cooperation among different research groups.

The efficiency of surgical robots as a tool to improve surgeons’ skills has been widely demonstrated. However, at this moment these systems are not able to provide real assistance to the surgeon. They just limit to replicate the motions performed by the surgeon in a master console into a slave platform. Hence, researchers have addressed their efforts on developing automatic ways of assistance to reduce the surgeons’ workload during the interventions. Being able to perform some autonomous tasks and to take decisions autonomously in real-time requires a deep understanding of the environment in which the system is working. Thus, recognizing what elements are in the scene and inferring what is happening at a particular time during an intervention is vital to advance in intelligent systems for MIS. Explicit modeling approaches for developing visual servoing techniques in a surgical scenario are inefficient given the large variability between people, organs, and tissue. In contrast, machine
learning techniques that learn implicit models directly from raw data appear to be very suitable in these dynamic and complex scenarios [1].

Garrow et al. [2] provided a review of machine learning techniques for surgical phase recognition. In their study, the authors identified Hidden Markov Models (HMM) and artificial neural networks as the most frequent ML models for this application. They also pointed out that neural networks are becoming more popular due to their capability to learn important features from raw data, unlike HMMs, which require manual feature extraction. This is due to the technological advancements in surgery, especially in MIS and RAS, developed in the last decades, which have increased the quantity of data available during an intervention. Thus, deep learning (DL) techniques result very attractive in this area. Furthermore, the surgical scene represents a huge challenge in perception techniques due to the dynamic and complex nature of the human body, which leads to a wide field of new opportunities for investigation. Antebay et al. [3] presented an interesting study of deep learning techniques in laparoscopic surgery. The aim of their review is to familiarize clinicians with this new technique, so they focused their study on the clinical value of the reporting works.

In this work, we present a systematic review of deep learning models applied to minimally invasive surgery from a technical point of view. We analyze the different DL models used in this field and their main applications for surgical computer-assisted systems. The major contributions of this paper are the following:

- It presents a comprehensive review of deep learning publications in minimally invasive surgery. To enable a systematic analysis, the publications are categorized according to their application: surgical image analysis, surgical task analysis, surgical skill assessment, and automation of surgical tasks. This design aims to serve as a reference for researchers looking for studies related to their work.

- It provides a description of the publicly available surgical datasets that researchers can use to validate their DL models. To facilitate future researches of readers, links for downloading these public datasets are also provided.

- For each application, we present a technical comparison of the publications included in this survey. These comparisons offer the readers a classification of the studies with relevant information such as the DL model employed, the type of input data, the surgical procedure analyzed, or the dataset used to validate the models. To facilitate the comparison of the different approaches presented, performance metrics are also reported.

- This work also points out two promising research directions in deep learning for minimally invasive applications.

The rest of the paper is organized as follows. Section II provides an overview of deep learning as well as of the most common models used for minimally invasive surgery applications. Section III describes the review methodology followed to conduct this survey, the criteria used to select the relevant publications, and an analysis of the results. Section IV lists and describes the publicly available datasets of MIS, providing the links for downloading the data. In Section V, the studies included in this survey are described and grouped by the following categories: surgical image analysis, surgical tasks analysis, surgical skill assessment, and automation of surgical tasks. Finally, section VI suggests two promising research directions to advance in this field, and section VII outlines the conclusions.

II. BRIEF OVERVIEW OF DEEP LEARNING

A Deep Neural Network (DNN) is a machine learning technique inspired in the human brain structure that provides computational systems with artificial intelligence. The network receives a set of inputs that undergo successively transformations through processing units, called hidden layers, to learn a high-level representation of the data useful to solve a particular problem. The units in each layer are connected to units in the adjacent layers with a particular weight and bias. The weighted sum of the inputs of each layer is transformed based on an activation function. The output of this function is then fed as input to the subsequent unit in the next layer [4]. The goal of deep learning techniques is to learn or adjust the network parameters (connection weights and bias) to minimize a loss function, which computes the distance between the prediction of the network and the objectives from the training data [5]. This iterative process is represented in Fig. 1. The main difference with earlier generation machine learning techniques is the automation of feature extractors without any manual design. The high advances of DL in the mid-1980s were possible thanks to the advent of the backpropagation learning algorithm, which allows the computation of the contribution of each parameter of the network to the final loss from the outer layers back to the bottom ones. This improvement was complemented by the proliferation of cheaper and powerful processing units and the explosion of big data in the last 10 years.

A. DL MODELS

Convolutional Neural Networks (CNNs) are the most known architectures of DL and they are the most used for image processing applications. Some well-known implementations of CNNs are AlexNet [6], VGGNet [7], GoogleNet [8], or ResNet [9]. A CNN is composed of a series of convolution and pooling layers followed by a fully connected layer. The role of each of these layers of the network is as follows:

- **Convolution Layers**: the convolution operation learns local patterns to extract the high-level features of the input image. Usually, the first convolution layer captures low-level features such as edges or colors, while the outer layers provide a high-level understanding of the images.

- **Pooling Layers**: the goal of these layers is to decrease the dimensionality of the feature maps through a function such as max-pooling or average-pooling.
• **Fully-Connected Layers**: these layers are responsible for the actual classification of the image by learning non-linear combinations of the high-level features extracted in the previous layers.

The designer of the network has to decide the optimal number of layers to achieve a trade-off among a good performance of the model, generalization with new data, and high computational speed to perform real-time inferences. Shallow networks model a few number of parameters and therefore they can perform predictions very fast with more generalization but less accuracy. In this case, the network has not yet modeled all the relevant parameters of the training data. In contrast, very deep networks model a high number of parameters and can provide high accuracy predictions for the training data, but it may lack generalization to new data due to the overfitting of the network, i.e., the network may be learning specific patterns of the training data, but which are not relevant for new data. Another key fact to design good predictive models is to have large amounts of labeled data for training. However, obtaining a sufficient amount of annotated data in specific domains such as surgery is difficult and costly. To alleviate this problem, most networks are pre-trained using labeled data coming from other domains, such as Imagenet [10].

One of the limitations of CNNs is that they cannot handle variable input image sizes. In contrast, Fully Convolutional Neural Networks (FCNNs) have the advantage over CNN of operating on inputs of any size, producing an output with reduced spatial dimensions. This makes them suitable for end-to-end pixel-level semantic labeling, as the spatial configuration of the image is preserved across the layers. However, they lack real-time capabilities and masks usually have holes or do not respect edges. Another limitation of CNNs is that they lack the ability of processing temporal information of data that come in sequences, as video data. To consider the temporal dependencies in the input data, we use Recurrent Neural Networks (RNNs). Unlike feed-forward neural networks, the processing units in an RNN form a cycle. This allows the network to have memory about the previous states and to use that to influence the current output [4]. The main implementation of RNNs is Long Short Term Memory (LSTM) networks. A LSTM consists of blocks of memory cell state through which signal flows while being regulated by input, forget, and output gates [4], which allows to add or remove information to the cell state. The input gate decides which values will be updated, while the forget gate is used to discard information. Finally, the output gate retains the information that is not used in the current time step but can be useful in the future. To take advantage of both networks, many authors propose DL models that combine CNNs with RNNs connected in a serial configuration. These models use a CNN to extract spatial features from the input images, and their output is fed to a RNN to take into account the temporal context of the data.

**B. DL FRAMEWORKS AND LIBRARIES**

To facilitate the implementation of DL architectures, there exist several open-source frameworks and libraries that incorporate the complex mathematical functions, training algorithms, and statistical modeling required for developing DL applications. Most of these tools are located on GitHub in the form of repositories. GitHub itself keeps a lot of monitoring information about software development such as the number of stars, watches, or forks. The most popular DL frameworks and libraries, which main characteristics are summarized in Table 1, are listed below:

- **TensorFlow**: It is an end-to-end source platform for machine learning created by Google. It is by far the most popular DL library based on the number of GitHub stars, and it supports both CPU and GPUs. The programming interface includes APIs for Python and C++.
- **Keras**: Keras, also created by Google, is a high-level DL API perfect for beginner users. As low-level motor, Keras uses libraries like TensorFlow, Theano, or CNTK, wrapping them and hiding their complexity for the user. One of the strongest points of this framework is its modularity, which allows an easy combination of neural layers, cost functions, optimizers, initialization schemes, and activation functions.
- **CNTK**: The Microsoft Cognitive Toolkit (CNTK) implements efficient DNNs training for speech, image, handwriting, and text data.
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#### TABLE 1. Popular frameworks and libraries for deep learning [11].

| Tool     | Type       | Creator         | Written in          | API                | GitHub stars | Link                                       |
|----------|------------|-----------------|---------------------|--------------------|--------------|--------------------------------------------|
| TensorFlow | Framework | Google          | Python, C++         | Python             | 13k          | https://github.com/tensorflow/tensorflow   |
| Keras    | Library    | F. Chollet      | Python              | Python             | 50.5k        | https://github.com/keras-team/keras        |
| CNTK     | Framework  | Microsoft       | C++                 | Python, C++, ONNX  | 17k          | https://github.com/microsoft/CNTK         |
| Theano   | Framework  | University of Montreal | C++   | Python             | 8.9k         | https://github.com/Theano/Theano          |
| Caffe2   | Framework  | Facebook        | Python, C++, ONNX   | Python, ONNX       | 45.6k        | https://github.com/facebookarchive/caffe2  |
| PyTorch  | Library    | S. Chintala, G. Chanan | Python |                  |              | https://github.com/pytorch/pytorch         |

- **Theano**: It is a tool written in Python for creating networks using symbolic logic. Theano was started in 2007, but it is no longer under active development.
- **Caffe2**: It is a lightweight, modular and scalable DL framework created by Facebook. It is used at the production level at Facebook while development is done in PyTorch.
- **PyTorch**: It is a Python library for GPU-accelerated DL. It has become popular by allowing complex architectures to be built easily.

### III. REVIEW METHODOLOGY

This section describes the review methodology followed for selecting the publications included in this review. First, the review protocol is described, followed by the selection criteria to discard the non-relevant papers for this survey. Finally, an analysis of the results considering the selected publications is presented.

#### A. REVIEW PROTOCOL

The first step to conduct this review is to search relevant publications in several databases. This search has been carried out in the following databases:

- IEEE Xplorer (https://ieeexplore.ieee.org).
- Springer Link (https://springerlink.com).
- Science Direct (https://sciencedirect.com).
- ACM Digital Library (https://dl.acm.org).

The keywords used during the search were (“Deep Learning” OR “Deep Neural Network”) AND (“Laparoscopic Surgery” OR “Minimally Invasive Surgery” OR “Robotic Surgery” OR “Robot Assisted Surgery”). In each database, the eighth combinations of these keywords were used. The search was restricted to publications in the last five years, i.e., the period between 2015 and 2020. Moreover, in Springer Link the search was limited to the disciplines ‘Computer Science’ and ‘Engineering’, and in Science Direct, only ‘research articles’ type were considered. This first search led to a total of 338 publications, distributed as followed: 104 publications in IEEE Xplorer, 134 in Springer Link, 81 in Science Direct, and 19 in ACM Library.

#### B. SELECTION CRITERIA

From this initial search, abstracts, summaries, reference book entries, tutorials, surveys, and doctoral symposiums were excluded. For the remaining publications, the following inclusion criteria were applied:

- Only technical studies were considered. Thus, medical studies with no technical content were excluded from this survey.
- Selected publications are only related to minimally invasive surgical applications. Thus, papers on the field of medicine related to rehabilitation or out-patient surgery were excluded.
- The type of input data of the papers included in this survey covers laparoscopic images (including simulation environments) of conventional and robotic surgery (using rigid robotic instruments). Thus, non-rigid instruments and studies using X-ray images, computed tomography (CT) scans, or magnetic resonance imaging were excluded from the review.
- After a comprehensive reading of the publications, they have been grouped into four main applications: surgical image analysis, surgical tasks analysis, surgical skill assessment, or automation of surgical tasks. To focus the research, publications out of these categories have been excluded from this survey.

After applying these inclusion and exclusion criteria, a total of 85 publications were considered for exhaustive reading and analysis. As shown in Table 2, most of the papers are from the databases IEEE Xplorer and Springer Link. This table also shows the number of journal and conference papers found in each database.

#### TABLE 2. Number of publications after applying the inclusion criteria from the initial search.

| Database          | Journals | Conferences | Total |
|-------------------|----------|-------------|-------|
| IEEE Xplorer      | 19       | 30          | 49    |
| Springer Link     | 6        | 19          | 25    |
| Science Direct    | 10       | 0           | 10    |
| ACM Digital Library | 0       | 1           | 1     |
| **Total**        | **35**   | **50**      | **85** |

#### C. ANALYSIS OF THE RESULTS

Figure 2 shows the growing interest in DL techniques in the field of minimally invasive surgery in the last years, from 3 publications in 2016 to 24 and 25 in 2019 and 2020, respectively (no publications were found in 2015). From the graph, we can see that the explosion of DL in MIS started in 2017, and it has been growing until the present.

Tables 3 and 4 contain the journals and conferences, respectively, identified as the most relevant according to the number of publications. On the one hand, IEEE Transactions...
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FIGURE 2. Number of publications per year for the last five years.

TABLE 3. Journals identified as pertinent and number of publications.

| Name of the journal                          | Publications |
|---------------------------------------------|--------------|
| IEEE Transactions on Medical Imaging        | 6            |
| IEEE Robotics and Automation Letters        | 5            |
| Medical Image Analysis                      | 3            |
| IEEE Access                                 | 3            |

TABLE 4. Conferences identified as pertinent and number of publications.

| Name of the conference | Publications |
|------------------------|--------------|
| MICCAI                 | 12           |
| ICRA                   | 7            |
| IROS                   | 3            |

FIGURE 3. Number of citations of the publications from 2015 to 2020.

The impact of the research of DL for MIS applications can be measured with the number of citations of the publications, which are represented in Figure 3. Although most of the publications are under 10 cites, it is quite relevant that there are 9 publications with more than 25 and less than 50 cites, 6 with more than 50 and less than 100, and 2 publications with more than 100 citations. These are Twinanda et al. [12] with 246 citations and Shvets et al. [13] with 124.

IV. PUBLICLY AVAILABLE SURGICAL DATASETS

The availability of large datasets is essential to advance in the field of deep learning in order to train neural networks. In the last years, there have been great efforts to develop large public datasets of surgical procedures annotated by experts. Public datasets are important, not only for giving the possibility of developing DL algorithms to researchers that do not have the possibility of acquiring their own data but also for comparing the performance of the different algorithms proposed in the literature.

The Medical Image Computing and Computer Assisted Intervention (MICCAI) society, formed in 2004, hosts annual challenges in their events to promote and facilitate the research, education, and practice of computer vision in medical interventions. These challenges are international competitions that aim the benchmarking of multiple algorithms on publicly released datasets. This facilitates the comparison of the different computer vision solutions developed by researchers all around the world. In 2020, the MICCAI challenge working group elaborated a guideline to standardize the writing and reviewing process of biomedical image analysis challenges and help researchers to interpret and reproduce the results [14]. Yearly accepted challenges datasets are available online on the MICCAI website, and past events challenges can be found on the Grand Challenge website, a platform for end-to-end development of machine learning solutions in biomedical imaging.

The complete list of the publicly available datasets found during our search is presented in Table 5. This table provides the name of each dataset, the year of publication, the number of videos or images available, the surgical procedure used to collect the data, the type of instruments used (rigid or robotic), and a brief description of the annotations of the dataset. The most common procedures used for collecting data are cholecystectomy, colorectal surgery, and gynecologic surgery. This is because these are easy procedures that are mainly performed using laparoscopy instead of open surgery. Most datasets include video data, but only two incorporate kinematic data, which provides a big amount of useful information for analyzing metrics related to the motion of the tools. Moreover, datasets including kinematic parameters are collected on in-vivo and ex-vivo experiments, but not on real surgeries. This is because kinematic data is straightforward...
to acquire from the dVRK, used in research environments, but not from the commercial versions of the da Vinci, used in real surgeries. Finally, annotations are mainly for tool classification and segmentation, and phase recognition, but there is only one dataset that offers annotations of the complete surgical scene. Next, these surgical datasets are further described:

- **EndoVis sub-Challenges**: these are yearly sub-challenges launched by the MICCAI society under the endoscopic vision challenge. These sub-challenges include rigid and robotic instruments segmentation and tracking as well as surgical workflow analysis for different procedures.
- **M2CAI16**: This event included two sub-challenges: the surgical workflow challenge, and the surgical tool detection challenge. For the first challenge, they introduced eight surgical phases for cholecystectomy procedures. The challenge consists of identifying the phase at a particular time using only visual information. For this challenge, they created the m2cai16-workflow dataset, which has 41 videos (27 for training and 14 for testing) with ground truth annotations of the phases (they defined eight surgical phases) [15], [16]. In the second challenge, the objective is to identify all surgical tools that are present in an image. For this challenge, they created the m2cai16-tool dataset [15], consisting of 15 cholecystectomy videos (10 for training and 5 for testing) with binary annotations of the present tools.
- **Cholec80**: it is a large dataset containing 80 videos, recorded at 25 fps, of cholecystectomy surgeries performed by 13 surgeons at the University Hospital of Strasbourg [12]. The whole dataset is annotated with the surgical phase (at 25fps) and tool presence (at 1 fps). The dataset is divided into two subsets of 40 videos each, for training and testing. In the training subset, 10 videos have also been fully annotated with the bounding boxes of tools. The Cholec80 dataset has been increased with 40 additional annotated with the surgical phases [17]. This dataset, named Cholec120, accumulate over 75h of recordings. Cholec80 has also been used to generate a new dataset for smoke removal applications. This dataset, named ITEC Smoke_Cholec80 Image, contains 100K frames from Cholec80 annotated with classes smoke and non-smoke.
- **JIGSAWS**: the JHU-ISI gesture and skill assessment working set (JIGSAWS) includes data on three elementary surgical tasks (suturing, knot-tying, and needle-passing) performed by eight surgeons on the da Vinci surgical system. Data consists of three components: kinematic data (19 kinematic variables divided into 76-dimensional kinematic data), video data, and manual annotations labels and global rating score tools segmentation

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**TABLE 5. Publicly released datasets.**

| Name           | Year | Data                               | Procedure         | Instruments          | Annotations                          |
|----------------|------|------------------------------------|-------------------|----------------------|--------------------------------------|
| JIGSAWS        | 2014 | 103 videos + kinematic data        | In-vitro experiments | Robotic              | Gestures labels and global rating score tools segmentation |
| EndoVis 2015   | 2015 | Images and videos                  | Colorectal surgery | Rigid and robotic    | Tools segmentation                   |
| M2CAI16        | 2016 | 41 videos                          | Cholecystectomy   | Rigid                | Phases                               |
| Cholec80       | 2016 | 80 videos                          | Cholecystectomy   | Rigid                | Phases and tools                     |
| EndoVis 2017   | 2017 | 8 videos                           | Porcine procedures| Robotic              | Tools segmentation                   |
| ATLASS Dione   | 2017 | 30 videos                          | Colorectal surgery| Rigid                | Phase and tools                      |
| Surgical Actions160 | 2017 | 160 videos                        | In-vitro experiments| Robotic              | Tools, actions, and expertise levels |
| EndoVis 2018   | 2018 | 30 videos                          | Gynecologic surgery| Rigid                | Surgical action                      |
| LapGyn4        | 2018 | 55K images                         | Gynecologic surgery| Rigid                | Scene segmentation                   |
| EndoVis 2019   | 2019 | 30 videos                          | Cholecystectomy   | Rigid                | Phases and tools                     |
| UCI, dVRK      | 2020 | 14 videos + kinematic data         | Ex-vivo experiments| Rigid                | Phases, actions, tools categories, and skills |
| FlapNet        | 2020 | 62 minutes video                   | Lobectomy         | Robotic              | Tools segmentation                   |
| LapSig300      | 2020 | 300 videos                         | Colorectal surgery| Rigid                | Tissue flap and tools                |

\(^1\) Robotic Instrument Segmentation and tracking sub-challenge.
\(^2\) m2cai16-workflow dataset.
\(^3\) m2cai16-tool dataset.
\(^4\) m2cai16-tool-location dataset.
\(^5\) Robotic Instrument Segmentation sub-challenge.
\(^6\) Surgical Workflow Analysis in the SensorOR sub-challenge.
\(^7\) Robotic Scene Segmentation sub-challenge.
\(^8\) Surgical Workflow Analysis in the SensorOR sub-challenge.
\(^9\) Surgical Workflow and Skill Analysis sub-challenge.
\(^10\) Robust Medical Instrument Segmentation (ROBUST-MIS) sub-challenge.

4https://ai.stanford.edu/theeung/tooldetection.html
5http://camma.u-strasbg.fr/m2cai2016/index.php/program-challenge/
6http://ftp.itec.aau.at/datasets/Smoke_cholec80/
7http://cirl.csrl.jhu.edu/jigsaws
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V. DEEP LEARNING APPLICATIONS IN MINIMALLY INVASIVE SURGERY

In the latest years, DL techniques are having a huge impact on minimally invasive surgery research. On the one hand, deep learning was devised to manage complex data such as raw images. In MIS, images are a straightforward source, which is always available in any intervention. On the other hand, the number of publicly available datasets greatly facilitates to advance in this field even for researchers that do not have access to clinicians. Moreover, robot-assisted surgery augments the possibilities of DL techniques with large kinematic data of the instruments and the surgeons’ gestures. As shown in Figure 4, the main applications of DL models in the field of minimally invasive surgery are: surgical image analysis, surgical tasks analysis, surgical skill assessment, and automation of surgical tasks. These tasks provide computer-assisted surgical systems information for understanding the surgical scenario, and therefore, they are the basis for developing autonomous systems able to make decisions, to collaborate with surgeons during the interventions, or to provide useful feedback to surgeons during trainee or on-line surgery. This section describes the studies included in this survey, classified into the previous categories.

A. SURGICAL IMAGE ANALYSIS

Analyzing the surgical image is essential for understanding the surgical scenario, and therefore, for being able to reason and take-decisions about it. The methods for objects recognition in an image can be divided into the following, depending on the expected output of the model:
• **Classification**: Given an input image, the network outputs a class or label mask (Figure 5(a)). This mask may be binary, in case the aim of the network is to detect the presence of an object, or it can be a multi-class classification problem, in which there are several masks, one for each type of object. For example, an image can be labeled as “Grasper” or “Scissors”, if we are performing instruments classification.

• **Detection**: These algorithms are used to locate the objects in the image and to represent them with bounding boxes (Figure 5(b)). The bounding boxes are always rectangular, so this method cannot detect shapes or edges.

• **Segmentation**: In segmentation tasks, the image is marked with pixel-wise masks for each object in the image. It can be divided into binary segmentation, every pixel in an image is labeled as an instrument or background, as in Figure 5(c), or multi-class segmentation, in which different colors represent different object categories.

Technical characteristics of the publications included in this survey for surgical image analysis are shown in Table 6. These studies are ordered by the particular application, and the following information is given: the year of the publication, the type of tool (rigid or robotic), the application of the study, the DL model used, the surgical procedure of the input data, the dataset used in the study, and the metric that evaluates the performance of the model. The type of input data is not included in this table because all these studies, except [20] that combines images with kinematic data, uses only image data to train the networks.

Surgical instrument recognition is the most studied application in surgical image analysis, as instruments represent the interaction mechanism between the surgeon and the surgical scenario. Moreover, the type of surgical instrument used at a given time provides key information of what is happening in the surgery. Thus, being able to recognize surgical instruments in the scene is vital for context-aware surgical systems. Recognition of anatomical structures is also an important task in a surgical scenario and has many applications for understanding the surgical scene as well as for computer-assisted diagnosis systems. Recognition of other surgical material, such as the suturing thread, provides useful information for the automation of surgical tasks. Recognition of the suture thread is a challenging task, as it is high deformable and suffers from frequent occlusion. Hu et al. [27] proposed a multi-stage framework for suture segmentation based on predicting directly the curvilinear structural information of the thread, instead of modeling the task. Similarly, Lu et al. [28] addressed the problem of suture thread segmentation. They proposed a DL model for accurately detect the suture’s tip. Then, they used a numerical method to segment and compute the 3D coordinates of the thread. They achieved good results in in-vitro experiments. Next, the rest of the studies included in the surgical image analysis category are further described.

1) **CLASSIFICATION AND DETECTION OF SURGICAL INSTRUMENTS**

In laparoscopic videos, each image usually contains more than one instrument at once, thus multi-label classification is more interesting than binary classification. In this type of algorithms, each instance can belong to more than one class. Wang et al. [25] presented a multi-class classification method combining two CNN models, VGGNet and GoogLeNet, to produce the final result. Each network is trained separately, and the prediction of each of them is averaged to compute the final classification. However, temporal context is important to distinguish surgical tools, to overcome the problem of the high similarity to one another. Mishra et al. [29] propose to incorporate spatio-temporal information into the tools classification problem using a deep LSTM network. In the first stage, a CNN is trained to detect tool presence in individual frames. Then, the features learned by the CNN are used to learn a temporal model using a LSTM network, providing a higher accuracy of classification. Similarly, Al-Hajj et al. [30] propose monitoring tool usage during surgery using convolutional and recurrent neural networks. The proposed framework consists of several CNNs that extract visual features of the videos and RNNs for analyzing the temporal sequence throughout the entire surgery, based on
TABLE 6. Comparison of the surgical image analysis publications using DL architectures.

| Ref. | Year | Tools Application | DL model | Procedure | Dataset | Results |
|------|------|------------------|----------|-----------|---------|---------|
| [23] | 2017 | Rigid Instruments classification | VGGNet+GoogLeNet | Cholecystectomy | m2cai16-tool | 63.8% (mAP) |
| [12] | 2017 | Rigid Instruments classification | EndoNet | Cholecystectomy | m2cai16-tool | 81% (mAP) |
| [29] | 2017 | Rigid Instruments classification | ResNet50+LSTM | Cholecystectomy | m2cai16-tool | 88.7% (mAP) |
| [30] | 2018 | Rigid Instruments classification | CNN+RNN | Cholecystectomy | Cholec10 | 97.9% (mAP) |
| [31] | 2019 | Rigid Instruments classification | 3D DenseNet+GCN | Cholecystectomy | m2cai16-tool | 90.2% (mAP) |
| [32] | 2017 | Robotic Instruments classification | U-Net | Colorectal surgery | EndoVis 2015 | 99.9% (mAP) |
| [33] | 2020 | Robotic Instruments classification | VGG-50+LSTM | Cholecystectomy | Cholec10 | 89.1% (acc) |
| [19] | 2017 | Robotic Instruments detection | RPN + Fast R-CNN | In-vitro experiments | Atlas Dione | 90% (mAP) |
| [34] | 2018 | Robotic Instruments detection | FCNN | Colorectal surgery | EndoVis 2015 | 83.7% (AP) |
| [35] | 2018 | Robotic Instruments detection | VGG16 | Cholecystectomy | m2cai16-tool | 81.8% (mAP) |
| [36] | 2019 | Robotic Instruments detection | 3D FCNN | Colorectal surgery | EndoVis 2015 | 85.1% (dice) |
| [37] | 2019 | Robotic Instruments detection | CNN+STC | In-vivo experiments | NPA | 93.2% (AP) |
| [38] | 2020 | Robotic Instruments detection | Hourglass+VGG-16 | In-vitro experiments | Atlas Dione | 91.6% (mAP) |
| [39] | 2020 | Robotic Instruments detection | VGG16 | In-vitro experiments | Atlas Dione | 90.01% (mAP) |
| [40] | 2017 | Robotic Binary segmentation (instruments) | ResNet-50 | Colorectal surgery | EndoVis 2015 | 88.9% (dice) |
| [41] | 2017 | Robotic Binary segmentation (instruments) | ToolNet | Colorectal surgery | EndoVis 2015 | 81% (mAP) |
| [42] | 2018 | Robotic Binary segmentation (instruments) | ResNet+LSTM | Colorectal surgery | EndoVis 2015 | 92.6% (mAP) |
| [13] | 2018 | Robotic Binary segmentation (instruments) | TernausNet-16 | Porcine procedures | EndoVis 2017 | 90.1% (dice) |
| [43] | 2020 | Robotic Binary segmentation (instruments) | ResNet-18 | Porcine procedures | EndoVis 2017 | 86.6% (dice) |
| [26] | 2019 | Robotic Binary segmentation (instruments) | CNN | Porcine procedures | EndoVis 2017 | 96.4% (dice) |
| [44] | 2019 | Robotic Binary segmentation (instruments) | U-NetPlus | Porcine procedures | EndoVis 2017 | 76% (dice) |
| [45] | 2020 | Robotic Multi-class segmentation (instruments) | MobileNetV2 | Porcine procedures | EndoVis 2017 | 46.07% (dice) |
| [46] | 2020 | Robotic Binary segmentation (instruments) | ResNet-18+LSTM | Porcine procedures | EndoVis 2017 | 91% (dice) |
| [47] | 2020 | Robotic Binary segmentation (instruments) | VGG16 | Porcine procedures | EndoVis 2017 | 81.15% (dice) |
| [48] | 2019 | Robotic Multi-class segmentation (instruments) | ResNet-10 | Various surgeries | NPA | 81.4% (mAP) |
| [49] | 2019 | Robotic Binary segmentation (instruments) | LinkNet-152 | Phantom and porcine tissue | NPA | 88.9% (dice) |
| [50] | 2020 | Robotic Binary segmentation (instruments) | Ternaus-11 | Cholecystectomy | Cholec10 | 93% (AP) |
| [51] | 2017 | Robotic Multi-class segmentation (instruments) | ResNet-101+RNN | Cholecystectomy | m2cai15-tool | 93.3% (mAP) |
| [20] | 2020 | Robotic Binary segmentation (instruments) | FCNN | Ex-vivo experiments | UCL 4VRK | 95.16% (IoU) |
| [27] | 2018 | Robotic Suture thread detection | U-Net | In-vitro experiments | NPA | 1.33 (p-e) |
| [28] | 2019 | Robotic Suture thread segmentation | GoogleNet+LSTM | Artificial tissue | NPA | 99.63% (acc) |
| [52] | 2018 | NA Classification of anatomical structures | GoogLeNet | Porcine tissue | NPA | 97.93% (acc) |
| [53] | 2019 | NA Liver segmentation | U-Net | Gynecologic surgeries | NPA | 78.1% (acc) |
| [54] | 2020 | NA Liver detection | VGG16 | Liver surgery | NPA | 90.32% (dice) |
| [55] | 2019 | NA Nerve and dura mater detection | YoLoV3 | Liver surgery | NPA | 85.9% (acc) |
| [56] | 2019 | NA Surgical scenario segmentation | Xception | Spinal endoscopy | NPA | 95.12% (AP) |
| [57] | 2019 | NA Polyp detection | VGG16 | Sleeve gastrectomy | EndoVis 2015 | 98.44% (dice) |

* When more than one result is presented in the study, the one with the best performance is reported in this table.

** AP = average precision; mAP = mean average precision; p-e = pixels-error; NPA = not publicly available; NA = not applicable.

Sarikaya et al. [19] presented in 2017 the first approach that incorporates DNNs for tools detection and localization in robot-assisted surgery. They applied a Region Proposal Network (RPN) jointly with a modulodal convolutional network for localization and a Fast R-CNN for object detection. In this work, they also introduced the ATLAS Dione dataset, the first public set of data of robot-assisted surgery videos with tool annotations. In [34] and [35], the authors focused on articulation detection for robotic instruments. They model each tool as a set of joints and connections between joints (Figure 6). Then, they used a Fully Convolutional Neural Network (FCNN) to detect the joint pairs, which output is used to

the outputs of the CNNs. With this approach, they augmented the model performance to around 98%. The temporal dimension is also considered in [31]. In this work, the authors use a Graph Convolutional Network (GCN) to learn better features by considering the relationship between continuous video frames. Kurman et al. [32] proposed a modified U-Net architecture for semantic segmentation, with a high performance score. However, this study only considers three different tools versus the seventh classes of the previous works. The code of this work is available at GitHub.13

13https://github.com/aimi-lab/instrument-pose
2) SEGMENTATION OF SURGICAL INSTRUMENTS

Binary segmentation of surgical instruments is studied in Laiana et al. [40], who proposed a novel method for real-time instrument tracking that takes advantage of the interdependency between localization and segmentation by carrying out these two tasks simultaneously in a unified CNN. For the same task, Garcia-Peraza-Herrera et al. [41] proposed a lightweight architecture, called ToolNet, which feature one order of magnitude fewer parameters than the state-of-the-art, requiring less memory and allowing for real-time inference. They encoded the multi-scale constraint inside the network architecture to improve the performance of the CNN. Milletari et al. [42] proposed an encoder-decoder architecture in which the encoder is a very deep network based on residual learning, and the decoding is implemented using LSTM cells. This model achieves an accuracy of over 92% both for binary and multi-class segmentation. The code of this work is available at GitHub.\(^\text{14}\)

The EndoVis 2017 sub-challenge Robotic Instrument Segmentation proposed segmentation tasks: binary segmentation, segmentation of different parts of the instruments, and multi-class segmentation for recognizing different surgical instruments (Figure 7). A comparison of different approaches used in this challenge is shown in Table 6. The lower performance in multi-class segmentation in all the studies may be due to the relatively small dataset size. There are 7 instruments classes, and several of them appear just few times in the training set. Shvets et al. [13] evaluated 4 different DL architectures for instruments segmentation: a modification of U-Net, two modifications of TernausNet and a modification of LinkNet. They achieved the best performance using modified TernausNet architectures for binary and multi-class classification, although in terms of computational efficiency, LinkNet-34 is the fastest model due to the lighter encoder. Their solution is publicly available at GitHub.\(^\text{15}\)

Pakhomov and Navab [43] used a FCNN built upon a ResNet-18 for the same task, getting better performance results. This lightweight deep residual network allows real-time segmentation with a seed of up to 125 fps on high-resolution images. The code of this work is available at \(^\text{16}\). A similar approach is presented in [26], but using auxiliary supervised deep adversarial learning, which allows outperforms previous works in inference speed.

In [44], the authors propose a modified U-Net architecture, named U-NetPlus, for surgical tool segmentation that uses a pre-trained model as the encoder with batch-normalization. In the decoder part, they substitute the deconvolution layer with an upsampling layer that uses nearest-neighbor interpolation, followed by two convolution layers. In [45], robotic instruments segmentation is addressed using an encoder-decoder architecture. The lightweight architecture MobileNetV2 is used as the encoder, and a custom lightweight attention decoder is used to recover the location details. Similar speed but with a better segmentation performance is achieved by Islam et al. [46] using ResNet-18 network with LSTM.

Lee et al. [49] present a weakly supervised framework for surgical tools tracking and segmentation based on a hybrid sensor system that integrates electromagnetic tracking with processing of visual data. This way, it is possible to generate semantic labelling of surgical tools without the need of manual annotations. Another method for instruments segmentation that does not require labeled data is proposed in [50]. In this work, the authors merge supervised learning using simulated images (automatically labeled) and unsupervised learning using real images in a joint learning scheme. Similarly, Lui et al. [47] propose an unsupervised framework for instruments segmentation based on generating anchors to provide initial training supervision, and augmenting the supervision by a semantic diffusion loss. For the anchor generation, they encode the knowledge about surgical instruments into hand-designed cues and generate pseudo labels for training. Then, a semantic diffusion loss is proposed to resolve the ambiguity in the generated anchors exploiting the temporal correlation in the surgical videos.

Previous works use surgical images as the input source for the deep learning models. Surgical robots allow an easy access to an additional key information of the motion of

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\(^{14}\)http://github.com/faustomilletari/CFCM-2D

\(^{15}\)https://github.com/ternaus/robot-surgery-segmentation

\(^{16}\)https://github.com/warmspringwinds/pytorch-segmentation-detection
surgical instruments: the kinematic data of the surgical system. Kinematic data include the 3D position and velocity of the instruments, the rotation and also force and torques. Thus, combining kinematic data with laparoscopic images could improve the performance of the models for instruments recognition, and could deal with the problem of large annotated data. This approach is addressed by Colleoni et al. [20] using a FCNN model. The model inputs images recorded with a dVRK and segmentation masks produced using a simulator, which shares the same kinematic values with the real robot. For this work, they generated the UCL dVRK dataset, which contains annotated images with both segmentation ground truth and kinematic information.

3) SEGMENTATION OF ANATOMICAL STRUCTURES
Segmentation of surgical instruments has grabbed the attention of many researchers in the field of machine learning applied to surgical procedures. However, laparoscopy is a complex scenario that involves many other objects which recognition is essential for a deep analysis and understanding of a surgical scene, such as other surgical material as the suture thread or anatomical structures. Liver segmentation is a another particularly challenging task as this organ suffers many deformations during a surgery, and it is usually overlapped by other organs. Nazir et al. [54] proposed a method to search a part of the liver view from its respective full view at runtime. The idea is to construct an image pyramid using different sizes from a full view input image for scale-invariance. Liver segmentation has also been studied by Fu et al. [53]. In this work, they study the effect of adding more labelled or unlabelled data for improving segmentation tasks, particularizing in liver segmentation. They concluded that although adding more labelled data improves the segmentation, using more unlabelled data in a semi-supervised learning can achieve a comparable level of segmentation accuracy.

Cui et al. [55] particularized the surgical image recognition problem to nerve and dura mater in spinal endoscopy videos using a YOLOv3 architecture. They collected videos from 15 patients, and three senior surgeons labelled the images. Hwang et al. [57] addressed the segmentation of colonoscopic images for automatic detection of polyps using a cascaded structure of encoder-decoders.

Finally, Kadkhodamohammadi et al. [56] created a custom laparoscopic sleeve gastrectomy dataset labeled with surgical instruments and the anatomical structures present in the scene. For segmentation, they propose an AE framework with the Xception architecture as the encoder and a simple feature aggregation decoder.

B. SURGICAL TASKS ANALYSIS
Surgical tasks analysis is an important task in the field of minimally invasive surgery due to its many potential applications, ranging from development of context-aware systems, automatic indexing of surgical video databases, autonomous robotic applications, etc. Within this field, surgical phases recognition has been the most studied task, as it allows a computer-assisted system to follow the workflow of a procedure. This tasks consists on dividing a procedure into a set of phases, and training the system to identify what phase corresponds to a given image. The main limitation of this task is that to be effective it requires a general consensus about the surgical procedure. Thus, it has been widely studied for cholecystectomy and gynecologic surgeries, but it has a poor generalization to other procedures.

Others authors analysis the surgical tasks in a deeper level by analyzing surgical gestures instead of phases. In this case, a particular task such as suturing is divided into a set of gestures. This is a more challenging problem as gestures are more similar to one another compared to overall phases. Until now, gestures segmentation has been analyzed only for the suturing task. Most attempts have been addressed on in-vitro environments with quite good results, and only one work [71] perform it in a live suturing.

Trajectory segmentation is another approach to deeply analysis the motion of the surgical instruments. It consists on splitting trajectories into sub-trajectories. This task can facilitate learning from demonstration, skill assessment, phase recognition, etc. To perform trajectory segmentation, authors leverage the kinematics information provided by surgical robots, which merged with video data provide better accuracy results. Finally, surgery time estimation is another important task that may be useful for optimizing clinical resources or to predict instruments usage for context-aware assistance.
TABLE 7. Comparison of the surgical tasks analysis publications using DL models.

| Ref. | Year | Method | Procedure | DL model | Input data | Dataset | Results |
|------|------|--------|-----------|----------|------------|---------|---------|
| [58] | 2016 | Phases recognition | Gynecology | AlexNet | Images | NPA | 48.67% (acc) |
| [52] | 2018 | Phases recognition | Gynecology | GoogleNet | Images | NPA | 59% (acc) |
| [59] | 2018 | Phases recognition | Gynecology | GoogleNet | Images | NPA | 79.6% (AP) |
| [12] | 2017 | Phases recognition | Cholecystectomy | EndoNet | Images | Cholec80 | 92% (acc) |
|       |      | Phases recognition | Cholecystectomy | VGG-50+LSTM | Images | EndoVis 2015 | 86% (acc) |
| [33] | 2020 | Phases recognition | Cholecystectomy | ResNet+LSTM | Images | Cholec80 | 89.2% (acc) |
| [60] | 2018 | Phases recognition | Cholecystectomy | ResNet50+LSTM | Images | NPA | 93% |
| [61] | 2020 | Phases recognition | Cholecystectomy | ResNet50+LSTM | Images | NPA | 85.8% (acc) |
| [62] | 2018 | Phases recognition | Cholecystectomy | GAN+LSTM | Images | m2cai16-workflow | 92.7% (acc) |
| [63] | 2018 | Phases recognition | Cholecystectomy | ResNet50+LSTM | Images | Cholec80 | 89.4% (acc) |
| [24] | 2020 | Phases recognition | Colorectal surgery | Xception | Images | LapSig300 | 81% (acc) |
| [64] | 2018 | Phases recognition | Prostatectomy | InceptionV3 | Images+kineamtic data+events | NPA | 80.9% (AP) |
| [65] | 2019 | Phases boundaries detection | Cholecystectomy | LSTM | Images | Cholec80 | 48% (MAE) |
| [66] | 2020 | Surgery type recognition | 9 types of surgeries | VGG16+LSTM | Images | NPA | 75% (acc) |
| [67] | 2019 | Similar frames detection | Cholecystectomy | ResNet50 | Images | Cholec80 | 99.1% (acc) |
| [68] | 2019 | Gestures segmentation | In-vitro experiments | 3D CNN | Images | JIGSAWS | 84.3% (acc) |
| [69] | 2020 | Gestures segmentation | In-vitro experiments | Deep RL | Images | JIGSAWS | 81.7% (acc) |
| [70] | 2020 | Gestures segmentation | In-vitro experiments | VGG16 | Images+kineamtic data | JIGSAWS | 86.3% (acc) |
| [71] | 2020 | Gestures identification | Live suturing tasks | AlexNet+LSTM | Images | NPA | 89.4% (acc) |
| [72] | 2020 | Gestures segmentation | Gynecology | Shallow CNN | Images | LapGyn4 | 99.2% (acc) |
| [73] | 2020 | Fine-grained activities | Cholecystectomy | ResNet-18 | Images | Cholec80 | 24.8% (acc) |
| [74] | 2019 | Objects state detection | In-vitro experiments | VGG16 | Images | NPA | 89% (IoU) |
| [75] | 2016 | Trajectory segmentation | In-vitro experiments | AlexNet+VGGNet | Images+kineamtic data | JIGSAWS | 0.806 (NMI) |
| [76] | 2018 | Trajectory segmentation | In-vitro experiments | Dense CNN | Images+kineamtic data | JIGSAWS | 70.6% (mAP) |
| [77] | 2018 | Trajectory segmentation | In-vitro experiments | Stacked AE | Images+kineamtic data | JIGSAWS | 79.1% (mAP) |
| [78] | 2019 | Trajectory segmentation | In-vitro experiments | RNN | kinematic data | JIGSAWS | 71% (acc) |
| [79] | 2017 | Trajectory segmentation | In-vitro experiments | VGG16+LSTM | Images+kineamtic data | JIGSAWS | 71% |
| [17] | 2017 | Surgery time prediction | Cholecystectomy | ResNet-152 | Images | Cholec120 | 460 s (MAE) |
| [80] | 2019 | Surgery time prediction | Cholecystectomy | ResNet-152+LSTM | Images | Cholec120 | 460 s (MAE) |
| [81] | 2020 | Anticipating instruments usage | Cholecystectomy | | Images | Cholec80 | |

* When more than one result is presented in the study, the one with the best performance is reported in this table.
** NR = not reported; AP = average precision; mAP = mean average precision. NMI = normalized mutual information; MAE = mean absolute error (in seconds); NPA = not publicly available.

Technical characteristics of the works included in this survey performing analysis of surgical tasks using DL models are shown in Table 7. Next, these works are further described.

1) SURGICAL PHASES RECOGNITION

Petscharnig and Schöffmann [58] explored the single-frame model for semantic surgery shot classification in gynecologic surgery videos manually annotated with 14 semantic classes. In [52], the authors extended the previous work with anatomical structure annotations and with more images, improving the performance with respect to the previous work. In later studies [59], they investigated the impact of early and late fusion of temporal information in surgical phases classification. Early fusion refers to extracting motion information from two consecutive video frames, and fuses it to the RGB image. With this approach, they outperforms previous work by more than 10%.

Twiananda et al. [12] presented a novel CNN architecture, called EndoNet, that performs phase recognition and tool presence detection in a multi-task manner using only visual information. EndoNet is an extension of the AlexNet architecture, in which the last layer is connected to a fully-connected layer which performs tool detection. The output of this layer is then concatenated with the output of the AlexNet to extract visual features from the images. Then, these features are used to estimate the current phase using Support Vector Machine and Hierarchical Hidden Markov Models. The authors validated this approach with the Cholec80 dataset, and they demonstrated the generalization of the results with the EndoVis workflow challenge at MICCAI 2015. Jin et al. [33] also exploit the relatedness between tools detection and phase recognition using a multi-task deep learning network. The proposal is an end-to-end architectures with two branches: a CNN module for tools detection and a RNN for phase recognition. They designed a correlation loss to model the relatedness between these two tasks and to minimize the divergence of the predictions of the two branches. The source code is available at 17.

17https://github.com/YuemingJin/MTRCNet-CL
Another custom framework is presented in [60]. This network, called SV-RCNet, merges visual and temporal information in an end-to-end architecture using a ResNet-50 architecture to extract visual features and a LSTM network to model the temporal information of sequential frames. They demonstrated the effectiveness of the spatio-temporal joint learning versus separate training. They performed experiments on two surgical datasets, m2cai16-workflow and Cholec80. Segmentation of cholecystectomy is also addressed in [61] using a ResNet550 with a high accuracy. However, in this work they use a dataset annotated with only 4 phases, two of them out-of-the-body (preparation and trocar placement), which simplifies the problem compared with m2cai16-workflow and Cholec80 datasets.

The previous supervised methods require large amount of annotated data. Chen et al. [62] proposed a semi-supervised method based on a spatio-temporal CNN. First, they use a Generative Adversarial Network (GAN) to extract spatial features from the images. Then, they use a LSTM network to distinguish frames based on their temporal context. Finally, they use a semi-supervised learning method to integrate the spatial and temporal information to fine-tune the network. Funke et al. [63] proposed a self-supervised method that uses a ResNet-50 CNN initialized with the general database ImageNet and fine-tuned with unlabelled videos of laparoscopic surgery using temporal coherence. They achieved better results compared to non-pretrained networks. Their work is available at GitLab. A self-supervised method is also proposed by Chittajallu et al. [67], but applied to extraction of video content descriptors to find similar segments in laparoscopic videos. In the medical domain, recordings of surgical procedures are commonly used off-line for teaching inexperienced surgeons or to check and learn from errors that occurred during the interventions. But manual checking of particular events is very cumbersome and time-consuming. Thus, these authors propose to train a ResNet50 model to extract semantic image descriptors to facilitate the searching in large databases.

Previous works can successfully perform surgical phases classification at a frame level. However, they are not able to explicitly determine the transition time (frame) between two consecutive phases. Namazi et al. [65] proposed a deep learning method to detect the transition time of different phases by learning the beginning and ends frames of each phase. Kannan et al. [66] address the problem of video classification for the early recognition of the type of surgery using a CNN + LSTM architecture. The CNN captures spatial information within the video frames, while the LSTM captures temporal information related to the evolution of the surgery. As the aim of this work is early recognition, during the training, the CNN is fed with samples of the complete video, emphasizing the initial frames with higher weights. They introduce a novel framework with a teacher LSTM model to predict future events, which improves the early recognition performance.

They used the Laparo425 dataset, consisting of 425 videos of 9 types of laparoscopic surgeries performed at the University Hospital of Strasbourg/INU. They obtained an accuracy of 75% after 10 minutes of the surgery.

2) GESTURES SEGMENTATION

Gao et al. [69] address the problem of gesture recognition in surgical videos as a path searching problem, proposing a framework based on Deep Reinforcement Learning (RL) and tree search, taking advantage of predictions of future frames to make decisions on the current time step. Funke et al. [68] addressed the same problem with better results, but proposing a 3D CNN to learn spatio-temporal features from consecutive video frames. They demonstrated the superiority of this approach compared to 2D CNNs on JIGSAWS dataset. Source code of this work can be accessed at GitHub. Khatibi and Dezyani [72] evaluated a shallow CNN for performing surgical action recognition from single frames and multiple frames. The designed CNN can be trained faster because it requires to tune fewer parameters. They achieved the best performance using multiple frames for training the network (the first, the middle and the last video frames of each surgical frames). The main limitation of this work is that they do not consider video frames without surgical instruments in the scene.

The same problem is addressed by Qin et al. [70], but using multiple input data to train the DL model. For the JIGSAWS dataset, they augmented the accuracy score incorporating the kinematic data to the recognition. They also created a dataset, called RIOUS, that incorporates system events as an additional source to train the model. The system events include camera and instruments follow, surgeon head in/out of the console, master clutch for the hand controller, and two ultrasound probe events. They demonstrated the better performance when fusing multiple data compared to using only video data, kinematic data or video + kinematics. Luongo et al. [71] studied the problem of gestures identification (identifying when a gesture is happening) and gestures segmentation (identifying what gesture is happening) on live suturing clips. This work achieved an accuracy over 63% identifying 5 different gestures on live suturing.

In an attempt to deeply analyze the surgical actions, Nwoye et al. [73] presented a method for fine-grained surgical actions recognition based on modeling each phase as action triplets \(<instrument, verb, target>\) representing the tool activity. They annotated 40 videos from the Cholec80 dataset with 6 instruments, 8 verbs, and 19 target classes. To recognize the instruments-tissue interactions they used a multitask deep learning network with three branches (instrument, verb, and target). The performance score of this work is low, but it outperforms previous models addressing actions recognition. This shows the challenging nature of fine-grained action recognition. Peng et al. [74] proposed a method to detect the state of an object, defined as the
location of the object and the interaction among objects. First, the object state is modeled as a semantic object, which contains the target object class and the interaction with other objects. Then, a DL method is applied to locate and detect these semantic objects in the image. This methodology can be applied to surgical training simulators and to other context-aware computer-assisted systems.

3) TRAJECTORY SEGMENTATION
Murali et al. [75] presented an algorithm called Transition State Clustering with Deep Learning (TSC-DL) for surgical tasks segmentation, which is an unsupervised method that merges video and kinematic data. The key of this work is that they use pre-trained CNNs (AlexNet and VGGNet) for extracting relevant features from videos, and then they create an augmented state-space with the visual features and the kinematic data. Their results reveal that using both kinematic and visual information results in better performance over just using kinematics. The code of this work is available at GitHub.\(^2^0\) Kinematic data is also used for the task of instruments trajectory segmentation. Zhao et al. [76] presented an unsupervised network for tools trajectory segmentation based on laparoscopic image and kinematic data. This work is based on a structure of dense connection, in which the first half of the network, the dense block, is an encoder that performs feature extraction, the transition layer performs the trajectory segmentation, and the up-sampling layer is used for image reconstruction. A similar approach is presented in [77], but using a compact stacking convolutional auto-encoder model and wavelet transform based filtering. Marban et al. [79] propose a method to estimate the position and velocity of the instruments in 3D from monocular videos using a regression model based on CNN + LSTM.

In contrast to previous works that merges video and kinematic data, Itzkovich et al. [78] proposed a DL model for trajectory segmentation which relies only on kinematic data, in order to use their model in online segmentation in the future. In this work, they deal with the problem of the lack of generalization of the models trained with the JIGSAWS dataset to real surgery. They demonstrated the poor generalization to rotation of the data when trained on a small and not sufficiently diversified dataset. Thus, they augmented the original dataset generating new data by rotating the images about different axes and rotation angles.

4) SURGERY TIME PREDICTION
Aksamentov et al. [17] proposed a deep learning pipeline with a CNN and a LSTM network to estimate the remaining duration of a surgical procedure. They connected the visual features coming from a ResNet network, pre-trained on the ImageNet dataset, to the LSTM network to extract phase information. Then, they used regression to estimate the remaining time of the surgery. Twinanda et al. [80] proposed to eliminate the need for manual annotations for the training process by training the CNN to perform progress estimation instead of surgical phase recognition, i.e., predicting how long the surgery has progressed with respect to its expected duration. At training time, the CNN architecture is fed with the video frames along with their progress label, which is automatically generated. They demonstrated the generalization of their approach using two datasets: Cholec80 and Bypass170, which contains 170 bypass videos performed by 28 surgeons.

Rivoir et al. [81] addressed the problem of the anticipation of surgical instruments by predicting the remaining time until the occurrence of sparse events rather than dense action segments. This way, only annotations related to instrument occurrence are required. The code of this work has been shared at GitLab.\(^2^1\)

C. SURGICAL SKILL ASSESSMENT
A major task in medical training is the assessment of surgical skills to grade the trainees’ performance and to monitor their development during the training process. This evaluation is usually performed manually by experts, which is not only very time-consuming but also subjective and lacks consistency and reliability. To solve these problems, many authors have addressed the task of automatic skill assessment through descriptive analysis of the instruments motion, which requires high manual feature engineering, or using predictive modeling such as Hidden Markov Models, achieving high accuracy ranging from 94.4 to 100\% [90], [91]. However, these methods require large amount of time and computational effort for tuning and modeling the parameters. In contrast, deep learning models can process raw data and can perform feature self-learning to discover abstract representations during the training process. Table 8 shows the technical characteristics of the studies performing surgical skill assessment using DL models included in this survey.

Most of the works found in the literature performing surgical skill assessment segmentation using DL models divide the levels of expertise into three categories: novice (N), intermediate (I), and expert (E). Thus, given a task performance, the DL algorithms are trained to provide the probability of the input data to belong to one of these classes. This is the case of the work developed by Fawaz et al. [82]. They designed a one dimensional CNN dedicated to surgical skill classification, and achieved very competitive results with 100\% accuracy on the suturing and needle-passing tasks of the JIGSAWS dataset. Their source code is publicly available.\(^2^2\) A similar approach is presented in [83], which model is able to reliably interpret skills within a 1-3 second window, without needing an observation of the entire training trial. Wang and Fey [84] proposed a multi-output model, SATR-DL, for online trainee skill analysis and task recognition, achieving accuracies of 96\% and 100\% for these two tasks.

\(^2^0\)https://github.com/BerkeleyAutomation/tsc-dl
\(^2^1\)https://gitlab.com/nct_tso_public/ins_ant
\(^2^2\)https://germain-forestier.info/src/miccai2018/
TABLE 8. Comparison of the surgical skill assessment publications using DL models.

| Ref. | Year | Method | DL model | Input data | Dataset | Results |
|------|------|--------|----------|------------|---------|---------|
| [82] | 2018 | Level of expertise | CNN | Kinematic data | JIGSAWS | 100% (acc) |
| [83] | 2018 | Level of expertise | CNN | Kinematic data | JIGSAWS | 95.4% (acc) |
| [84] | 2018 | Level of expertise | SATR-DL | Kinematic data | JIGSAWS | 96% (acc) |
| [85] | 2019 | Level of expertise | 3D ConvNet | Images | JIGSAWS | 95% (acc) |
| [86] | 2019 | Level of expertise | CNN+LSTM | Kinematic data | JIGSAWS | 98.4% (acc) |
| [87] | 2020 | Level of expertise | CNN | Kinematic data | JIGSAWS | 99.1% (acc) |
| [88] | 2020 | Detecting similar levels of expertise | SN | Kinematic data | NPA | 83.4% (acc) |
| [89] | 2019 | Pairwise ranking | LSTM | Kinematic data | JIGSAWS | 75.1% (acc) |
| [115] | 2018 | Performance score (GOALS) | R-CNN (VGG16) | Images | m2cai16-tool-location | **When more than one result is presented in the study, the one with the best performance is reported in this table.**

**acc = accuracy.**

Other studies perform the task of automatic skill assessment using only video data. Funke et al. [85] used a 3D ConvNet achieving an accuracy of 95% on the JIGSAWS dataset. The source code of this work is available at GitLab.23 Nguyen et al. [86] extended automatic skill assessment to open surgery procedures, using inertial measurement units to get the participants’ hands motion. They achieved an accuracy of 98.2% on in-vitro experiments. They also perform experiments in the well-known robotic surgery dataset JIGSAWS to demonstrate the generalization of their approach, with competitive results. Zhang et al. [87] proposed an automatic microsurgical skill assessment for robot-assisted microsurgery based on cross-domain transfer learning. The pre-trained model is obtained via the JIGSAWS dataset and then transferred for microsurgical skill assessment. The idea is to transfer the knowledge gained from JIGSAWS to accelerate learning in the new domain.

The previous works have demonstrated to be able to separate between experts, intermediate, and novices surgeons. However, it still remains to be shown if deep learning techniques are able to distinguish trainees with similar expertise from one another. In this way, Getty et al. [88] propose a Spiking Neural Network (SNN) to detect surgeons of similar level using only kinematic data. The purpose of this approach is to be able to offer adaptive assistance during surgery and training. Similarly, Oğul et al. [89] address the problem of surgical skill assessment as a pairwise ranking task in which two input actions are compared to identify the better surgical performance.

Other works addressing surgical skill assessment are based on analyzing the motion of the tools to extract key metrics for analyzing the performance of the surgeon. This allows, not only to classify the performance into a level of expertise, but to provide a performance score to a given demonstration, which is very useful objectively evaluate trainees. Jin et al. [15] developed an approach leveraging region-based convolutional neural networks (R-CNN) to perform spatial detection of tools, and then they used this information to analyze the movement of the tools. This way, they are able to extract tool usage patterns, movement range, and economy of motion metrics to analyze surgical skills. In this work, they use a modified version of the GOALS assessment rubric to provide a performance score.

D. AUTOMATION OF SURGICAL TASKS

In the last decades, much progress has been made in the automation of complete surgical tasks or the semi-automation of particular parts so robotic systems can collaborate with surgeons with specific maneuvers. A classification of the publications using DL models for surgical tasks automation is shown in Table 9.

Reinforcement learning (RL) is a popular control method in uncertain scenarios and when dealing with complex dynamics systems. The recent fusion between RL and DNNs opened a new field, known as Deep Reinforcement Learning (Deep RL), that leverages new opportunities to control non-linear systems. In the RAS domain, Thananjeyan et al. [92] employed Deep RL techniques to develop a tensioning planner for pattern cutting tasks. The input of the planner is a desired cutting contour, and then the planner selects a tensioning point and the sequence of tensioning actions as the surgical scissor follows a pre-planned trajectory. The optimal tensioning policy is learned using Deep RL, trying to minimize the error from the cutting trajectory to the marked contour. For this, they modeled the tensioning problem as a Markov Decision Process, where the actions are the movements of the tensioning arm, and the state space is a tuple consisting of the time index of the trajectory, the displacement vector from the original pinch point, and the location fiducial points of the cutting sheet. They implemented this approach using a dVRK in both simulated and physical scenarios. In later works, this method is improved with a multiple pinch point Deep RL algorithm that exhibits better results [93], [94].

Another task that has been the focus of automation is autonomous surgical debridement. Seita et al. [95] propose the use of DNNs to automate the debridement task using a dVRK. First, the robot collects data to train a DNN by automatically exploring trajectories in the workspace with random targets. The DNN inputs are the tool position relative to the camera frame and rotations relative to the base frame, and the output is the tool position relative to the base frame. In the second phase, the robot moves to target locations, and a human directly corrects the positions to generate a small amount of high-quality data. Similarly, Attanasio et al. [21]...
propose a method to remove tissue from the surgical area autonomously to expose the underlying anatomical structures. First, a CNN (U-Net) is used to detect candidate tissue to be retracted, and then a planning algorithm based on experts interviews is used to perform the retracting task. They perform a set of experiments on the dVRK and release a specific dataset, named FlapNet, dedicated to retraction.

Mikada et al. [96] propose a human cooperative control for suturing in which a human operator inserts the needle with an instrument and a robot automatically pulls it out with another instrument. This method uses two CNNs, one to detect the needle, and another one to estimate its state. For autonomous robotic palpation tasks, Xio et al. [97] proposed a CNN + LSTM architecture to detect tumorous areas and to estimate the depth of the inclusion.

Force estimation based on visual data is also a problem that has been addressed using DL strategies. Aviles et al. [98] proposed using deep-neuro-fuzzy strategies for the force estimation task, which is a fusion between fuzzy systems and deep neural networks. On the one hand, the Fuzzy theory enables handling uncertainties of the visual information and allows to increase the accuracy of the DL model. Adding Fuzzy resulted in a reduction of the absolute error form 2mm to as little as 0.1025. In [99], the authors proposed a solution based on visual geometric information, using a learning system to find the nonlinear relationship between tissue deformation from the images and geometric data provided by the robot. The proposed solution starts with extracting the geometry of motion of the heart’s surface by minimizing an energy functional to recover its 3D deformable structure. Then, an LSTM-RNN architecture is used to learn the relationship between the extracted visual-geometric information and the applied force, and to find accurate mapping between the two. They achieved a root-mean square error of 0.02N. Advancing in this work, Marban et al. [100] proposed a semi-supervised learning approach consisting of an encoder network serially connected with an LSTM network. First, unlabelled video sequences are used to train the encoder network to extract visual features from the images. Then, these feature vectors are used to train the LSTM network. In [101], these authors investigated different input data to the network, and concluded that force estimation is better when both video and tools data is processed.

In [102], the authors proposed a force estimation based on visual cues to infer tissue deformation, using a Temporal Convolutional Network (TCN). The input of the network are RGB and depth images collected using a Kinetic2 camera. Then, a spatial block encodes 2D and 3D features, and temporal block models force changes over time. They achieved an absolute error of 0.814N in an ex-vivo experiment using the da Vinci Surgical System.

VI. OPPORTUNITIES

Despite the complexities of minimally invasive scenarios, significant progress has been made in computer-assisted systems thanks to the advances in machine learning techniques, especially in deep learning approaches in the last years. Based on our review, we point out two promising research directions to augment the capabilities of current surgical systems and to develop new tools to benefit medical personnel and patients: the development of autonomous surgical systems and intelligent surgical training systems.

A. DEVELOPMENT OF AUTONOMOUS SURGICAL SYSTEMS

The scientific community has made huge advances in the line of extracting semantic information from surgical images to provide context-awareness in real complex scenarios. To date, recognition of surgical instruments and segmentation of some surgical tasks has been successfully addressed. Segmentation of some specific organs, such as the liver, and surgical material such as the suture thread have also been focused of study. However, there is still much to do to provide computer systems a real understanding of the surgical scene. This is the idea of the European project Smart Autonomous Robotic Assistant Surgeon, which aims to go a step further developing a cognitive robotic system able to autonomously understand the present and future surgical situation to autonomously collaborate with the main surgeon supplying the functions of the assistant [103]. To achieve this goal, recognition of the complete surgical scene, including anatomical structures, and segmentation of fine-grained gestures are essential tasks that must be addressed.

Surgical scene understanding is essential to apply current strategies for performing autonomous surgical tasks to real dynamic scenarios with a priori unknown conditions and to perform tasks on-line in collaboration with humans.
during a real surgical intervention. Deciding when the system should take a particular action is also vital for computer-assisted tools such as virtual reality or haptic guidance systems. Recently, Islam et al. [104] proposed an enhanced graph neural network to perform spatial reasoning to infer the tool-tissue interaction graph structure in a surgical scene. Based on the scene segmentation of the MICCAI Challenge 2018 dataset, they generated a graph-based tissue-tool interaction dataset with new annotations. Moccia et al. [105] propose to use instrument segmentation to develop shared control techniques based on virtual fixtures to avoid instruments collision during surgery.

B. INTELLIGENT SURGICAL TRAINING SYSTEMS

Current methods for objective and autonomous surgical skill assessment have demonstrated to be effective to quantitative and qualitative assess a surgical performance. Thanks to these advances, commercial virtual reality training systems used for novice surgeons to get skilled in laparoscopy (either traditional or robotic) usually provide a performance report to the user with the overall score of the task. However, these systems lack the ability to assist a trainee during the performance of the exercises, which would allow to online teach the user how to perform a task or how to improve his/her performance. In this sense, there is a research opportunity in the field of surgical training systems to study approaches for autonomously coaching novices during their training process. This would reduce the long learning curve, especially in robot-assisted surgery, and would facilitate self-sufficiency of the trainees, which could make a difference in surgical training, taking into account the scarce availability of expert surgeons for teaching purposes.

Some authors are proposing new methods that go in this line. Fawaz et al. [82] use the class activation map technique to visualize which parts of a performance contribute the most to a certain skill level classification, which could serve to guide novices surgeons to improve their skills. Similarly, Zia and Essa [106] propose a method for generating task highlights to give surgeons more direct feedback about their performance. Tan et al. [107] presented a robot-assisted laparoscopy training system for improving surgeons’ skills based on experts’ demonstration and reinforcement learning. This approach combines the latent patterns from experts’ trajectories and objective-constrained trajectories generated by the RL agent. Engelhardt et al. [108] propose the use of conditional adversarial networks to provide a more realistic visual appearance to phantoms used for surgical training.

VII. CONCLUSION

Many scientific fields have been transformed in the latest years thanks to the advances in deep learning algorithms, including predicting movie ratings, decision to approve loan applications, time taken by car delivery, diagnostic of diseases, discovery of new drugs, prediction of natural disasters, etc. This has been possible thanks to the proliferation of cheaper and powerful processing units and the explosion of big data. Thus, in the latest years the research community has made a huge effort on publishing large annotated data of minimally invasive surgery interventions, which has boosted great advances in this area.

This work presents a rigorous systematic literature review of DL methods in the field of minimally invasive surgery. This survey has been conducted with a total of 85 publications from the last five years. After a comprehensive reading of each of them, we have classified these works into four applications: surgical image analysis, surgical task analysis, surgical skill assessment, and automation of surgical tasks. The most studied application in surgical image analysis is instruments recognition. This task can be classified into instruments classification, instruments detection and instruments segmentation. In the literature we can find many works proposing deep learning architectures that exhibit high instruments recognition performance. In addition to instruments, recognition of anatomical structures and other surgical material such as the suture thread or the needle, have also attracted the interest of researchers. Surgical task analysis is another important task in the field of minimally invasive surgery. The most studied application is surgical phases recognition for cholecystectomy and gynecologic surgeries, although there are also studies that offer a deeper analysis of the task performing gesture and trajectory segmentation. On the other hand, surgical skill assessment applications allows to classify a surgical performance into different levels of expertise, generally novice surgeons, intermediate and experts. Most of these works use kinematic data to train the networks. Finally, automation of surgical tasks has also been addressed using deep algorithms, such as deep reinforcement learning. This algorithm has been used for developing an automatic tensioning planner for pattern cutting tasks. Force estimation in robot-assisted surgery has also been addressed using deep learning architectures.

Based on the review presented in this work, we point out two promising research directions: the development of autonomous surgical systems and of intelligent surgical training systems. We believe that these research lines are key to augment the capabilities of current surgical systems and to develop new tools that will benefit medical personnel and patients.

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