Automated Stand-alone Surgical Safety Evaluation for Laparoscopic Cholecystectomy (LC) using Convolutional Neural Network and Constrained Local Models (CNN-CLM)

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***Abstract*—In this golden age of rapid development surgeons realized that AI could contribute to healthcare in all aspects, especially in surgery. The aim of the study will incorporate the use of Convolutional Neural Network and Constrained Local Models (CNN-CLM) which can make improvement for the assessment of Laparoscopic Cholecystectomy (LC) surgery not only bring opportunities for surgery but also bring challenges on the way forward by using the edge cutting technology. The problem with the current method of surgery is the lack of safety and specific complications and problems associated with safety in each laparoscopic cholecystectomy procedure. When CLM is utilize into CNN models, it is effective at predicting time series tasks like identifying the sequence of events in the Laparoscopic Cholecystectomy (LC). This study will contribute to show the effectiveness of CNN-CLM approach on laparoscopic cholecystectomy, which will frequently focus on surgical computer vision analysis of surgical safety and related applications. The method of study is deep learning based CNN-CLM to better detect nominal safety as well as unsafe practices around the critical view of safety and AI-based grading scale. The general design flow of AI-recognition of surgical safety is firstly collecting safety surgical videos for frame segmenting and phase according to the image context by surgeon reviewer by CNN-CLM. For this advance research, the dataset is splatted into three main parts where 70% of which is used for training, 15% of which is used for testing and the rest for the cross validation, to achieve the accuracy up to 98.79% of this specific research. For result part, different metrics of CNN-CLM to evaluate the performance of the proposed model of safety in surgery. The study uses one of the top three performing methods CNN-CLM for the evaluation yields and anatomical structures in laparoscopic cholecystectomy surgery.**

Keywords*—Artificial Intelligence; Surgical Safety; Laparoscopic Cholecystectomy; Convolutional Neural Network, Constrained Local Models; Laparoscopic Cholecystectomy

I. Introduction

The issue is the automation of safety evaluation, which imitates structured technique and predicts more specific ways to prevent accidental clipping, is a source of concern in the surgeries. The solution is the CNN-CLM that model allows for straightforward partial supervision during training and technology-based explain ability in the networks and outputs that result. In today's operating rooms, automated assessment of surgical safety has become increasingly important, since the surgical safety would directly affect the patient safety and the high-stress working conditions of clinicians reviewed in [1, 2]. Recognition of the surgical phase has been gradually becoming an essential basis for monitoring the surgery process, scheduling surgeons, predicting upcoming events, alerting and suggesting modifications, etc. according to [3]. In addition, automatic segmentation of the surgical video can also help to facilitate the surgeon skill evaluation and improve the efficiency of documenting surgical reports. Previous studies have relied on signals of surgical tools to carry out the cholecystectomy procedure phase recognition in laparoscopic surgery stated in [4, 5, 6]. However, the information about tool usage relies heavily on manual annotation or additional built-in sensors according to [4]. Recognizing surgical phase solely based on visual information is a promising direction, yet a quite challenging task. The main challenges lie in the high scene variability and lack safety within the surgery videos due to the blood occlusion and camera motion. As [7] have utilized a convolutional neural network (CNN) and Constrained Local Models (CLM) consisting of 9 layers to learn features from visual information of the frames, and achieved state-of-the-art performance according to [8, 9]. With the times, the surgical management and assessment for safety for Laparoscopic Cholecystectomy (LC) needs to be improved, and might be overcome with the help of new emerging technology, artificial intelligence (AI) described by [10]. The Laparoscopic cholecystectomy technique is the surgical operation performed by placing minimally invasive instruments in the abdominal cavity. Therefore, laparoscopic surgery has the advantages of short operation time, less injury, less pain, less visceral interference, low probability of abdominal infection, and less incidence of complications such as postoperative intestinal adhesions according to [11, 12]. Today, laparoscopic cholecystectomy surgery is widely used in surgical procedures. For most patients with gallbladder stones, laparoscopic cholecystectomy is a well-established procedure. However, there are still many complications after laparoscopic surgery, which are often caused by technical mistakes such as improper operation of surgical instruments by doctors stated by [13, 14].

The state-of-the-art solution validated by using as computer-based automation is now commonly used in surgery. Laparoscopic cholecystectomy is a well-established procedure for most patients with gallbladder stones according to [15]. AI can be defined as utilizing computer programs to simulate independent and intelligent behavior comparable to a human. AI behaves with varying levels of autonomy. According to the definition, three-dimensional (3D) reconstruction, virtual reality (VR), augmented reality (AR), and mixed reality (MR) all could independently and automatically carry out construction or projection of surgical images and models based on medical imaging without artificial assistance were classified as general AI technology according to [16, 17]. Relatively, there are narrow AI techniques that cover various subfields. Machine learning (ML) focuses on how computers learn independently without additional programming. It comprises algorithms known as artificial neural network (ANN) that draws inspiration from the biology of the human brain and could be used for prediction after lots of training and validation. The ANN composed of many internal neural layers is also named deep learning (DL) explained by [18]. Convolutional neural network (CNN) is one of DL architecture designed to recognize images by analyzing various features in the image, like shape or edges. Constrained Local Models (CLM) RNN) is more suitable for temporal learning of shape and local patches context stated by [19]. The statement of problem is how the modularity and generality of AI-augmented model has been advantageous for representing complex relationships and inter-dependency between objects in a laparoscopic cholecystectomy and how the CNN-CLM approach of automated surgical safety on mitigation systems for surgical safety laparoscopic cholecystectomy and help in implementation of safety measure for prevention of accidental clipping according to [20].

The effectiveness of laparoscopic cholecystectomy surgery should be further enhanced, and surgical safety should be ensured according to [21]. Realizing AI is a promising tool, and we tried to determine the role it plays in Cholecystectomy surgical procedures assistance, particularly laparoscopic surgery. The images and surgical videos are the common clinical data associated closely with laparoscopic surgery according to [22]. Here, we focus on the AI-related display for surgical assistance in cholecystectomy surgery by reviewing AI's integration with CNN-CLM and anticipating its combination with automated surgical depiction for the safety evaluation described by [23, 24]. Laparoscopic cholecystectomy, the surgical field has been initially explored for identifying the surgical phases from videos with safety study models and has high accuracy. Safety study models generally include a visual model, CNN, and a temporal model, CLM, of which CNN is used for object feature detection in images (surgical content), and CLM is used to identify the frame sequence (surgical step sequence); the combination of the two can work better for automatic assessment of surgical phase and safety in the videos mentioned in [25, 26].

A. *Problem Formulation - Structured Surgical Analysis*

In this paper, we define the problem of computational surgical safety analysis that infer the state of the surgery in terms of a set of artificial intelligence (AI) concepts that pertain to the surgery with the specific approach of CNN-CLM at each time frame of laparoscopic cholecystectomy (LC). In our case, CNN-CLM are individual frames from the surgical video obtained by the laparoscope according to [27]. Concepts can include visible objects, or latent, higher-level notions deduced from the surgery safety. Inferring their latent state can be expressed as a set of emitted outputs about each concept - for example, the visibility of a region in a specific tool safety, or the understanding that a particular temporal phase / operative step of the surgery is taking place at that time. When surgeons reason about surgical procedures safety, they frequently utilize their conceptual understanding with the help of technology about how these various aspects relate to one another according to [28]. Understanding surgical workflow from a minimally invasive video can be formulated as two complementary processes:

i. Is there lack of safety procedure by hands on practices by surgeons?

ii. How the modularity and generality of AI-augmented model has been advantageous for representing complex relationships and inter-dependency between objects in a laparoscopic cholecystectomy.

iii. How the CNN-CLM approach of automated surgical safety on laparoscopic cholecystectomy help in implementation of safety measure for prevention of accidental clipping.

iv. Inferring on surgical decision support and risk mitigation systems for surgical safety in laparoscopic cholecystectomy.

v. There are also specific complications and problems associated with safety in each laparoscopic cholecystectomy procedure.

In this work, the concern is the automation of safety evaluation that mimics structured technique and prediction of more specific prevention of accidental clipping. The model lends itself to straightforward partial supervision in training and explainability by using technology in the resulting networks and their outputs. Our approach leverages a knowledge CNN-CLM structure, suitable for learning, making inferences and predicting different concepts in surgical safety video streams as well as other types of temporal data and generalizable across surgical procedures, hence resulting in tremendous clinical impact in laparoscopic cholecystectomy according to [29]. Less pain and early discharge associated with early beginning to work, made laparoscopic cholecystectomy not only a convenient and acceptable method, but the preferred and desired for both the patient and his surgeon by the help of technology. This paper is novel as this method with concerned approach has not been used before in many researches and makes use of this method to learn about and predict surgical safety and protection during cholecystectomy, and it uses multiple graphs to explain the various operative concepts in the data for safety implementation.

B. *Contributions*

We present a novel knowledge AI-based CNN-CLM approach for temporal automated surgical safety data analysis and evaluation. This paper also leverages this approach towards learning and prediction of surgical safety and protection during the cholecystectomy and reason about the different operative notions contained in the data for the safety implementation through multiple graphs.

We demonstrate results on several important surgical problems in laparoscopic cholecystectomy understanding, including a novel dataset for the problems investigated. Specifically, we show how CNN-CLM approach allows us to better detect nominal safety as well as unsafe practices around the critical view of safety and AI-based grading scale.

Moreover, we provide an outlook into future possibilities for AI augmented surgical decision support and risk mitigation systems for surgical safety in through multiple surgeries. The paper demonstrates effectiveness of CNN-CLM approach on laparoscopic cholecystectomy, which has been frequently focused on in surgical computer vision analysis of surgical safety and related applications.

C. Background

Adequate education and training in laparoscopic cholecystectomy (LC) surgery are essential to minimize the complications and adequate safety for the surgery. It is quite well known that the development and progress of laparoscopic cholecystectomy interventions is closely related to the invention of new surgical instruments and evolvement of new techniques for safety, and what seems today to be impossible or unacceptable laparoscopically may prove to be simple and practical with the help of AI in the future according to [30, 31]. On the other hand, some laparoscopic procedures on which studies are undertaken now may be abandoned in the future because of inefficacy or increased risk and rate of complications when compared to the classical open version of the same operation according to [32]. This procedure became the treatment of choice for patients with symptomatic gall stones in many different parts of the world. Although performed under general anesthesia, most patients are discharged within twenty-four hours after the procedure. Instead of the large laparotomy incision, four small incisions are made in the abdominal wall.

In recent years, the accessibility of CNN and CLM and the rise of DL potentially enable machines to understand clinical data, particularly surgical safety and videos. At present, video-based surgical AI researches show relatively high accuracy in instruments safety, anatomical structures for safety, and surgical phase recognition in other surgical fields like cataract surgery, gynecological surgery, and laparoscopic surgery (Table 1), showing the potency of AI and corresponding techniques in the videos analysis of laparoscopic cholecystectomy surgery and other surgeries according to [33]. The conceptual surgical notions in place to relativize operational risk as well as the required reasoning about complex anatomical structures and thorough consideration of potential consequences and complications resulting from surgical actions make laparoscopic cholecystectomy an ideal target procedure for surgical AI as mentioned in [34]. An important safety measure unique to this procedure is the so called “critical view of safety” (CVS). CVS is defined as the clear dissection and visualization of the cystic duct and cystic artery, the clearing of the hepatocystic triangle of tissue and exposure of the cystic plate in the cholecystectomy according to [35]. Specifically in cases, where safety is hard to achieve, automated recognition would augment surgical safety and provide additional supervisory clues to the surgeon. Within this concept model, the individual components of CVS are modeled as nodes and the overall achievement of CVS is defined as a relation. The cholecystectomy procedures videos recorded routinely have accumulated as a large and informative data source as stated in [36]. At the same time, little was explored in the qualitative or quantitative analysis regarding surgical context like bleeding in a crucial phase, significant anatomical structure injury, completeness of lymph node dissection, surgical steps and order, and operation duration, etc. The intraoperative information itself remains as a black box for surgical application. And AI serves as a promising tool in facilitating this process explained by [37, 38].

TABLE I. RECENT WORKS OF AI-ASSISTED APPLICATION AND PERFORMANCE IN SURGERIES.

Study	Year	Operations	No. of Video	Applications	Performance
Matava et al.	2020	Laryngoscopy and bronchoscopy	775	Anatomy classification in real-time	Overall confidence of classification ranges 0.54 to 0.82
Kitaguchi et al.	2020	Colorectal surgery	300	Surgical phase, action, and tool safety	Accuracy of 81.0%, 83.2%, and 51.2% respectively
Madad Zadeh et al.	2020	Hysterectomy	461 images	Anatomy detection	Accuracy of 24–97%
Morita et al.	2019	Cataract surgery	303	Surgical-phase and safety recognition	Mean correct response rate of 96.5%
Bodenstedt et al.	2019	Laparoscopic Procedure	80	Surgical-duration prediction	Overall average error of 37%
Hashimoto et al.	2019	Gastrectomy	88	Surgical phase and safety recognition	Accuracy of 82%
Korndorffer et al.	2020	Cholecystectomy	1051	CVS and intraoperative safety evaluation	Accuracy of 75%, and 99%
Mascagni et al.	2020	Cholecystectomy	100	Formalization of video reporting of CVS	Kappa scores of inter-rater agreements by binary assessment is 0.75
Yamazaki et al.	2020	Gastrectomy	52	Surgical tool detection and safety	Accuracy 86% accuracy

II. METHOD

A. Convolutional Neural Network - Constrained Local Models (CNN-CLMs) (Fig. 1 & Fig. 3)

Convolutional layer as images contains highly correlated 2D information (generally in three RGB-channels), the idea of local connections has been exploited by creating units in a convolutional layer which receive weighted input from local patches in the previous layer, referred to as their receptive fields (RF's). By relying on local RF's, this introduces sparse connections, rather than the whole-scale image statistics passed on to units and causing high-dimensional problems in fully connected feed-forward networks. The weight vector of a unit is also known as filter bank and through training the weights will be updated to filter for specific features, giving the units the behavior of filter detectors stated by [40]. The weighted inputs and additive bias are then passed through the activation function of said unit, where ReLU's have portrayed much faster learning in deep networks compared to other activation functions for laparoscopic cholecystectomy.

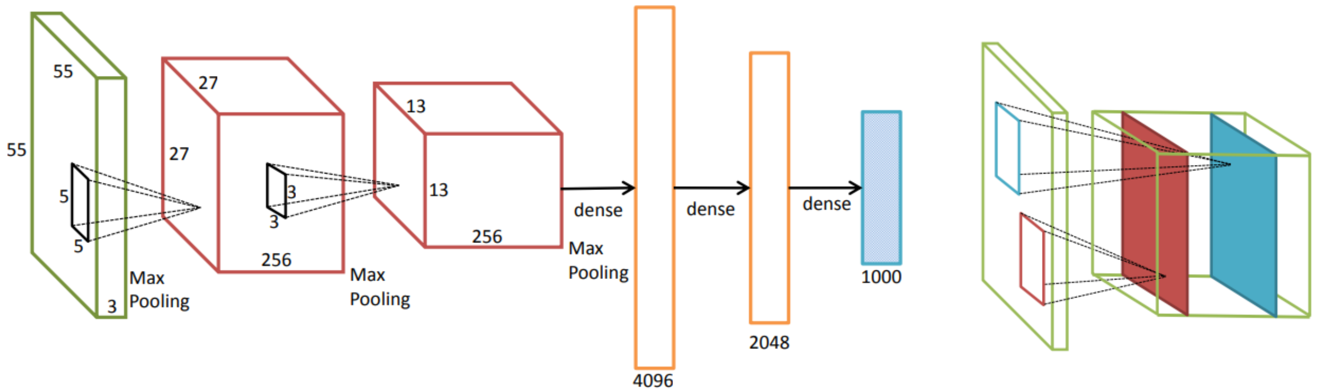

Fig. 1. Basic building blocks of CNN-CLM involving multiple layers.

On a structural level, the outputs of units with the same weight vector are organized in feature maps. Multiple feature maps (with different weight vectors) in each convolutional layer enable scanning for different features in each local image patch according to [39]. The optimal number of feature maps needed to capture the image dynamics tends to increase with the complexity of the input images. The flowchart depicts the framework of methodology being follow in the research study (Fig. 2).

1) Pooling layer: The feature maps in the convolutional layer serve as input for the next stage, being a pooling layer. Given that the relative location of features with respect to each other contains significantly more information than their precise pixel-location, further stressed by the notion that small shifts in the precise feature locations are to be expected in different images, the idea of local pooling of features to reduce spatial resolution is implemented at this stage using CNN-CLM. This result in a network invariant to small shifts in the images and the stages of convolutional/pooling layers equip the network to handle variable size inputs stated by [41].

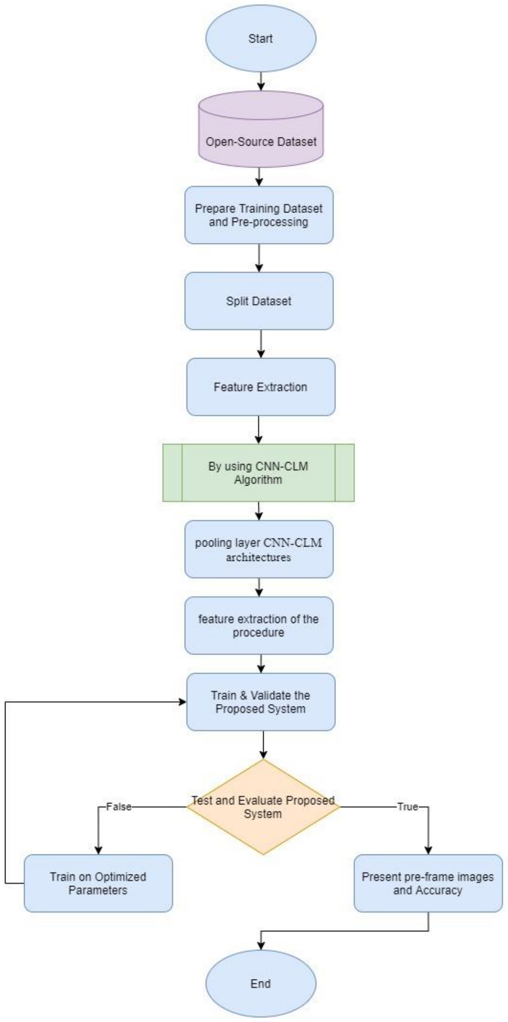

Fig. 2. Framework Flowchart

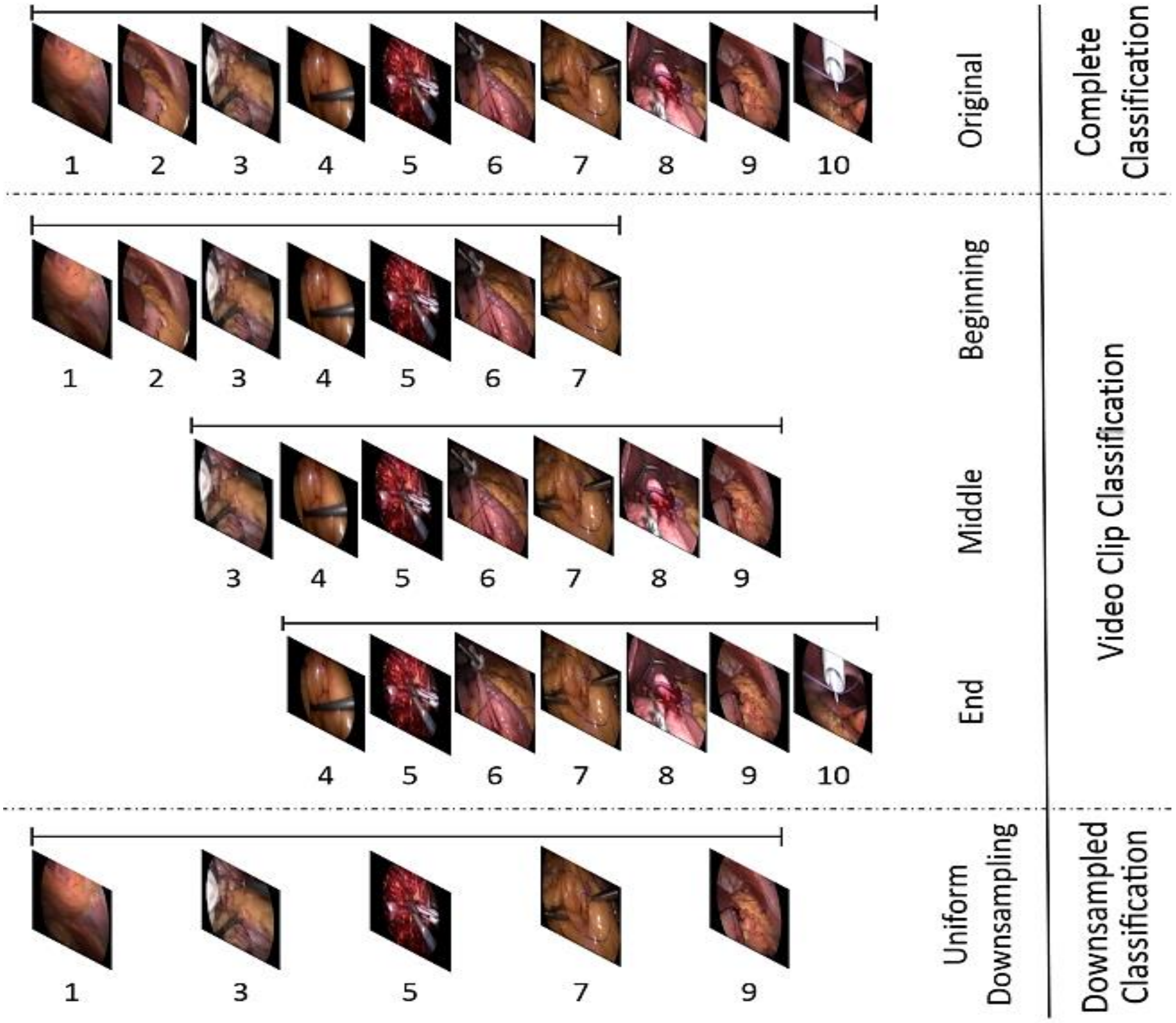

Fig. 3. The flow of convolutional layer serves as input for the next stage and sampling of laparoscopic cholecystectomy using CNN-CLM.

2) Dataset Description: Cholec80 Dataset: A dataset of 100 laparoscopic cholecystectomy procedures was collected. The dataset was then annotated by clinical experts with regard to the critical view of the safety. Within the dataset, in a total of 50 videos CVS was achieved whereas in 50 videos CVS was not achieved. The videos were down-sampled to 1fps. A total of 50 frames were extracted and annotated prior to ’checkpoint 1’, directly before clipping of the cystic duct and artery, which served as a cutoff label as clipping of these structures demonstrated a ’point of no return’. Labels included all components of CVS as defined by the Society of American Gastrointestinal and Endoscopic Surgeons, including safety, cystic artery, cystic duct, two and only two ductal structures leading to the gallbladder, cystic plate being dissected and visibility of the liver between the two ductal structures. Videos are randomly split into a 90/10 ratio for training and testing. 5 random splits were used for the experiments.

3) Deep hierarchies: Finally, the use of many layers represents the different stages in the simplified model of the ventral stream. Features at higher-level stages results from combinations of lower-level features, thus enabling deep structures to capture the compositional hierarchy of natural images. Pooling units will scan the feature maps with (non-) overlapping p1 x p2 receptive fields and output a single value. Typical choices for pooling units are subsampling, where the output of a unit in the jth layer is the average of units in the receptive field, supplemented with additive bias b and passed through an activation function and max pooling.

B. Hybrid CNN-CLM Architecture for Laparoscopic Cholecystectomy (Fig. 4)

As profound learning strategies accept mathematical information as information, picture investigation could appear to be a straightforward instance of taking care of the organization with crude picture information. All things considered, pictures are only networks of numbers addressing pixel powers mentioned in [42-44]. Overall, this method can work well for simple acknowledgment projects with small, standard images. Unfortunately, versatility is the problem. The amount of necessary calculation explodes as the information size and number of layers increase.

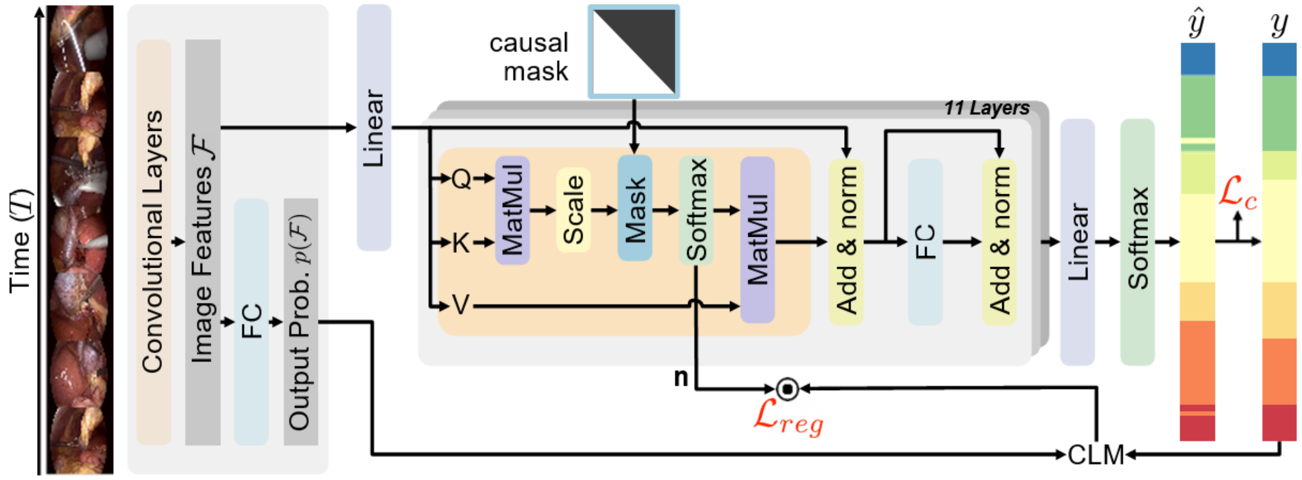

Fig. 4. Overview of the proposed hybrid CNN-CLM model for surgical safety automatic assessment of laparoscopic cholecystectomy and flow of data through 11-layers directly proportional to time also involving the casual mask.

C. *Training and Cross-Validation (Fig. 5 & Fig. 6)*

It is striking that the picture handling has progressively utilized further organizations however, progressed profound learning methods will give extraordinary effectiveness because of its engineering adaptability with picture handling calculation mentioned in [45-47]. Having more information models have more noteworthy authentic power making it conceivable to rough more intricate capacities. Additionally, quick advancement in the field ceaselessly presents new methods and models growing the tool stash for plan. Nonetheless, science has consistently embraced straightforwardness, and it is sensible to contend that the organization ought to be kept as basic as could really be expected [49-53].

Using CNN-CLM and picture handling strategies, a review looked at how common it is to use pooling and modern actuation capabilities in deep learning. Taking everything into consideration; they suggest employing merely intermittent layers with step and channel size boundaries that are appropriately selected. CNN-CLM architecture and design optimization is pursued in light of the current hype surrounding deep learning as stated in [54]. This section will therefore be devoted to some of the powerful CNN-CLM models that have been developed in the past few years and will be used throughout this work as stated in [55-58]. Specific, revolutionary design-elements that have assisted these improvements are marked throughout this discourse. The cross approval is utilized to approve the information in man-made brainpower-based frameworks, interpretable machine might even show people about how to settle on better choices according to [59]. To address the straightforwardness issue, representation procedures can be utilized to distinguish the picture areas generally significant for the model's expectation. Joining different perception procedures can deliver compelling visual clarifications for the CNN-CLM model's expectations as mentioned in [60]. To acquire better inclusion of the issue space, the quantity of preparing tests can be misleadingly extended. This strategy called cross approval implies changing examples with irregular changes like revolution and flipping, shifting properties like brilliance and differentiation or by adding arbitrary commotion [61].

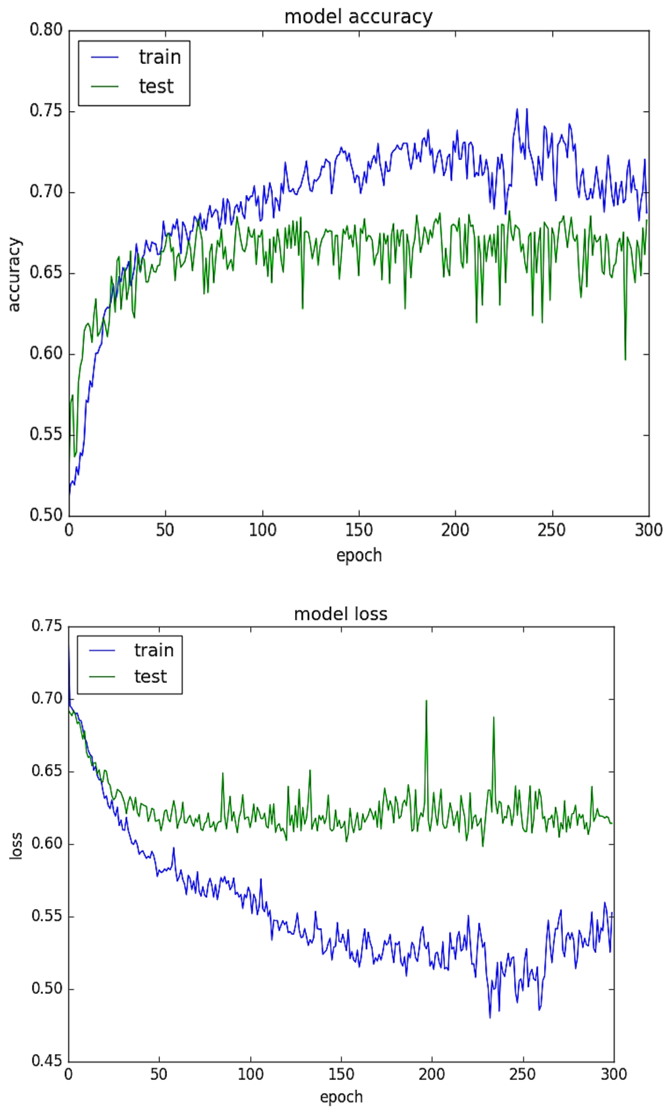

Fig. 5. The CNN-CLM Model Accuracy (accuracy vs epochs) Model Loss (loss vs epochs).

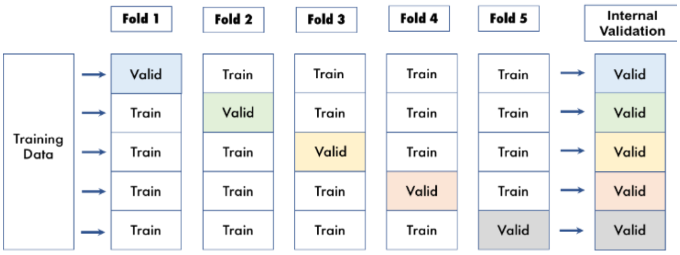

Fig. 6. An example of dividing dataset for cross validation.

III. RESULTS AND DISCUSSION

In this section we introduce the dataset, the detailed experimental settings, the evaluation metric, as well as the results on each specific task. It is especially important to improve surgical instrument detection techniques for physicians to perform surgical evaluations. With the rapid development of science and technology, the field of medicine is also seeing new breakthroughs. Compared with earlier hand-crafted features, features extracted by CNN can significantly improve network performance. Fig. 7 are the dataset-based predictions for safety assessment by CNN-CLM technique.

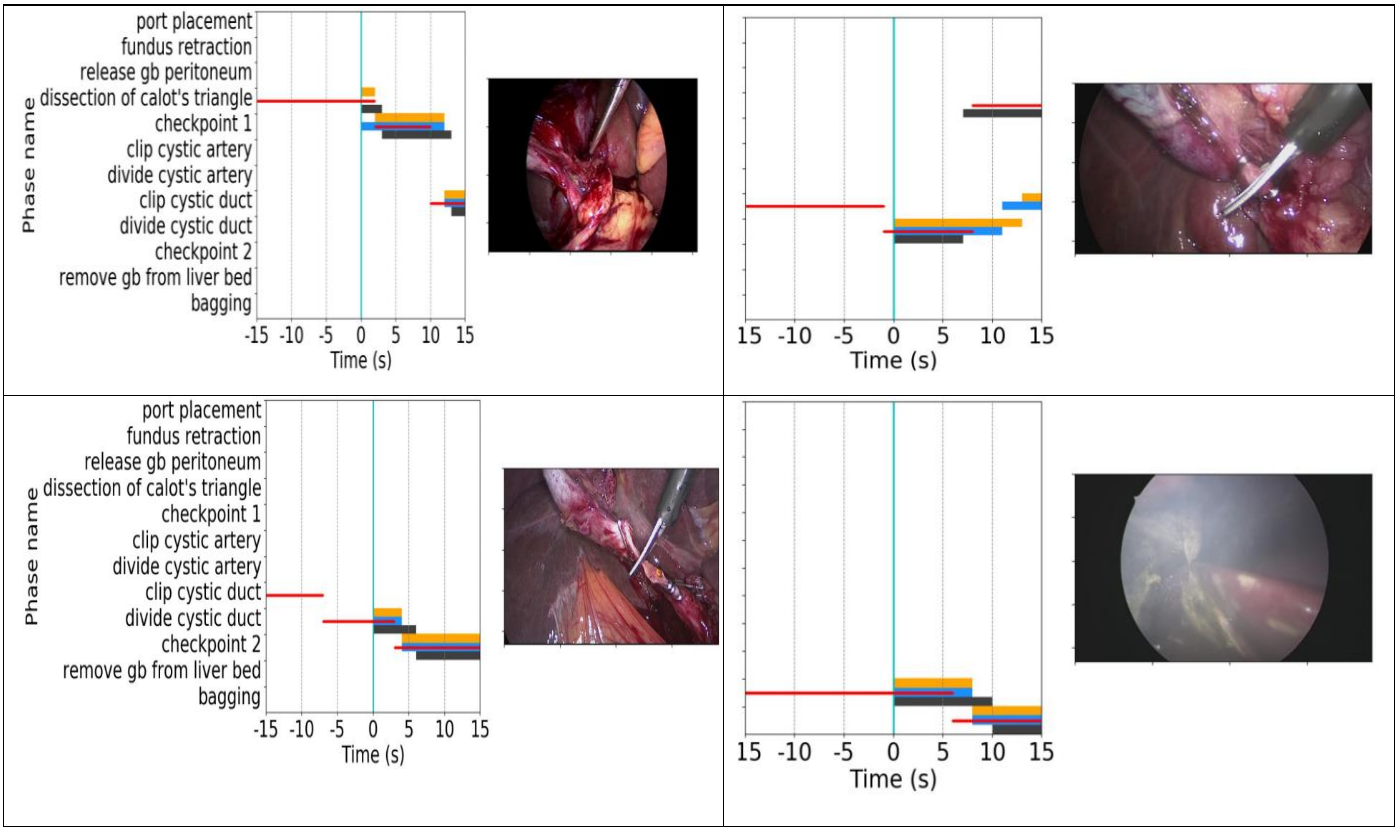

Fig. 7. Examples of prediction results by Cholec80 dataset. For every model, on the left, a chart of the periods of the activity was shown. The level hub demonstrates the time, going from the past 15s to future 15 seconds. The upward cyan bar demonstrates the "current" time point related with the video picture on the right side. Red level portions demonstrate the ground right directions in laparoscopic cholecystectomy.

Within the concept model, CNN-CLM dimension was set to 64 and the sequence length to 8. During training, the learning rate was 2 10 4, and the model was trained for 25, 20, 10 epochs for conv resolutions for the surgery safety, and CVS tasks separately. The Cross-entropy loss was applied to all the three problems. These image for the safety detections for the surgery's laparoscopic cholecystectomy is shown in Fig. 8.

Different metrics can be used by CNN-CLM to evaluate the performance of the proposed model of safety in surgery. In the Table 2, these are the metrices that are enabling machines to comprehend surgical workflow for safety by Dataset and assess these relevant concepts may significantly contribute to the application of CNN-CLM and artificial intelligence in the operating room, facilitating intraoperative decision making, risk mitigation as well as holding great teaching potential for trainees. In addition to accuracy, we also use average distance to measure the performance of the algorithm on the CNN-CLM, which is the distance between ground truth and the estimation. The model lends itself to straightforward partial supervision in training and explain ability in the resulting networks and their outputs.

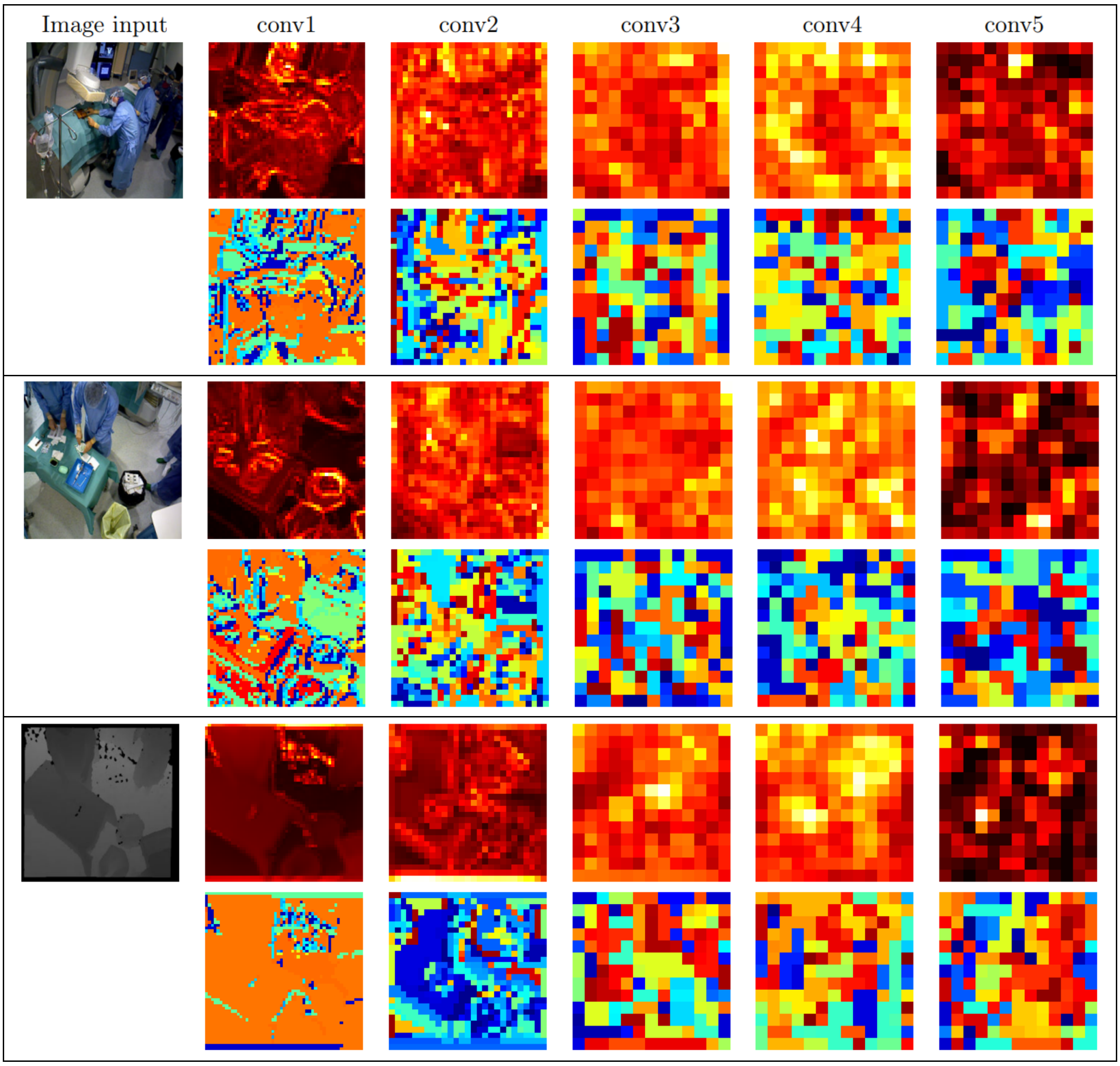

Fig. 8. The progress of laparoscopic cholecystectomy visualization of activation of CNN-CLM layers closely related to the invention of new surgical instruments and evolvement for detection and recognition of laparoscopic in the sample images. This is due to its high frequency, stable field of view, procedural standardization and well described conceptual notions, as a safety measure for prevention of accidental clipping. The CVS process of safety has statistical measures for implementation, some of the measures can be seen in Table 2, using the proposed technique.

TABLE II. LABELS INCLUDED IN THE DATASET.

Class	Description	Per-frame labels
CVS	CVS is achieved	yes, no
Cystic plate	Cystic plate is exposed	yes, no
Two	Two and only two structures are dissected and exposed	yes, no
Cystic artery	Cystic artery is exposed	yes, no
Cystic duct	Cystic duct is exposed	yes, no

IV. CONCLUSION

The research evaluated the assessment on the automated surgical safety with the novel dataset which challenge, one of specific approach provided. The study uses one of the top three performing methods CNN-CLM for the evaluation and yields. The great performance of recognition of surgical safety and anatomical structures in laparoscopic cholecystectomy surgery requires a large amount of multi-dimensional image data and excellent AI algorithms to support proposed by this study. In the future, AI may be deployed to carry out more challenging works like real-time anatomical variations. We demonstrate the framework for temporal analysis of surgical video data for safety evaluation. It is a general assessment which affords easy embedding of surgical concepts via structured network and demonstrate superior results on various surgical safety notions and several important surgical applications and is generalizable across the different surgical procedures. By reviewing AI in other surgical fields, we proposed the prospect of videos-based CNN-CLM display for laparoscopic cholecystectomy surgery safety assistance and try to illustrate in a flow, including construction of safety videos database, annotation of surgical data, identification of instrument and anatomic structure, and automated recognition of surgical phases, etc.

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