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A Data-Driven Approach for Predicting Remaining Intra-Surgical Time and Enhancing Operating Room Efficiency

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Abstract:

Purpose: Efficient scheduling in Operating Rooms (ORs) is essential for optimizing corresponding costs and enhancing customer satisfaction in healthcare systems.

Design/methodology/approach: Conventional static scheduling methods rely on fixed historical surgery times and often lead to inefficient resource utilization and increased costs due to inaccurate predictions of surgical durations. In this regard, this paper introduces an innovative method that employs Convolutional Neural Networks (CNNs) to predict the remaining intra-surgical time through binary classification for the Gallbladder Dissection phase and to dynamically manage OR schedules. The study, although focused on laparoscopic cholecystectomy procedures, demonstrates a method adaptable to other laparoscopic surgeries. The dataset comprises labeled laparoscopic cholecystectomy videos (time labels for different phases) used to train and evaluate the CNN.

Findings: Results show that the proposed method reduces patient waiting times by an average of 87.3% and eliminates OR idle time compared to traditional fixed-time scheduling methods.

Originality/value: This paper introduces a new data-driven approach for predicting remaining intra-surgical time and enhancing OR efficiency. The study's novelty lies in its use of Convolutional Neural Networks (CNNs) to predict surgery completion times, a method that has not been extensively explored in this context. By providing accurate forecasts, this approach allows nurses to prepare for the next patient more efficiently and enables dynamic rescheduling when surgeries deviate from their planned timelines. This combination contributes to improved OR utilization and enhances patient satisfaction, offering a practical and innovative solution to a common challenge in surgical workflow management.

Keywords: remaining time predictions, operating room management, scheduling, convolutional neural network, machine learning

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1. Introduction

Managing healthcare systems is inherently challenging due to numerous constraints and competing priorities. Key issues include limited resources, high costs of medical technology and drugs, increasing demand, rising patient expectations, and insufficient planning tools. To address these challenges, healthcare organizations must focus on process optimization to control costs and improve care quality. Researchers have employed predictive models, Artificial Intelligence (AI), and Neural Networks (NN) to tackle various healthcare problems globally. For example, Lu, Yang, Yang, Li, Yin, Yin et al. (2024) used Long Short-Term Memory (LSTM) networks to track surgical instrument movements, while Gong, Zhang, Feng, Zhu, Deng, Ran et al. (2023) demonstrated the superior accuracy of computed tomographic angiography in diagnosing aortic coarctation. Fu, Duan, Zhong and Zeng (2024) compared keloid treatments through meta-analysis, finding that laser and steroid combinations resulted in lower recurrence and hyperpigmentation rates compared to surgery and radiotherapy. Nian, Pu, Li, Zhong, Ma and Li (2024) developed a CSIISM model to simulate intra-abdominal adhesions, providing insights into postoperative adhesion formation. Recent advancements in Machine Learning (ML) have further enhanced healthcare systems, as evidenced by studies from Qin, Shi, Tao, Yu, Jin, Xiao et al. (2024), Liao, Tang, Gao and Trik (2024), Li, Xia, Wang, Wang, Cui and Li (2023), Islam and Imtiaz (2024), Ayadi, Mezni, Alnashwan and Elmannai (2023), Howard (2023), Chen, Wu and Chiu (2024), and Rico, Alaeddini, Faruqui, Fisher-Hoch and Mccormick (2024), leading to more efficient and productive healthcare delivery.

Operating Room (OR) management is a critical component of healthcare systems, with scheduling being a complex task that involves prioritizing surgeries, allocating resources, and determining the sequence of procedures. Researchers have explored OR scheduling across various scenarios (Yang, Gajpal, Roy & Appadoo, 2022; Wang, Demeulemeester, Vansteenkiste & Rademakers, 2021; Miao & Wang 2023; Maleki, Hosseininesaz & Jasemi, 2023; Lotfi & Behnamian 2022; Fallahpour, Rafiee, Elomri, Kayvanfar & El-Omri, 2024; Dexter & Epstein, 2024). Two primary approaches to scheduling are static and dynamic. Static scheduling relies on historical data and remains unchanged regardless of real-time conditions, often leading to inefficiencies due to its inability to adapt to delays or unexpected changes. In contrast, dynamic scheduling continuously updates based on real-time data, offering greater flexibility and efficiency. This approach better handles unforeseen delays, variations in procedure durations, and changes in resource availability, ultimately optimizing resource use and minimizing idle and waiting times.

OR scheduling poses significant challenges due to its complexity and direct impact on efficiency and patient care. Traditional static methods often result in inaccurate predictions of surgical durations, leading to over- or underestimation of time requirements. This can cause prolonged idle times, underutilized resources, and increased patient wait times. Delays in one procedure can cascade, disrupting subsequent schedules and compounding inefficiencies. Variability in surgical durations, patient conditions, and unexpected complications further complicate scheduling, straining OR resources, reducing patient satisfaction, and increasing costs. To overcome these challenges, innovative approaches that integrate real-time data and dynamic scheduling are essential for optimizing OR utilization and improving patient outcomes.

Effective OR scheduling is vital for enhancing hospital efficiency, patient satisfaction, and the success of surgical services. By minimizing idle time, maximizing OR utilization, and reducing patient wait times, effective scheduling ensures optimal care delivery. It requires careful coordination of multiple factors, including surgeon and surgical team availability, equipment, anesthesiologists, supplies, and emergency cases. Additionally, it involves managing patient preparation, procedure types and durations, and contingency plans for unexpected delays or complications.

Over the past six decades, extensive research has been conducted on operating theater management. Magerlein and Martin (1978) categorized surgical demand scheduling into two main types: advance scheduling, which involves assigning a surgery date to a patient, and allocation scheduling, which determines the operating room and start time for the procedure on the scheduled day. Blake and Carter (1997) expanded on this framework in their review by introducing external resource scheduling, which involves identifying and reserving resources outside the surgical suite required for patient care before and after surgery. They further divided each domain into strategic, administrative, and operational levels, though these distinctions can often overlap and interrelate. Przasnyski (1986) organized the literature on OR scheduling around key themes, such as cost containment and resource-specific scheduling. Additional reviews addressing operating room management as part of broader healthcare services can be found in Boldy (1976), Pierskalla and Brailer (1994), Smith-Daniels, Schweikhart and Smith-Daniels (1988), Yang, Sullivan, Wang and Naidu (2000).

Historical data is very helpful in optimizing the OR scheduling process in hospitals. In practice, analyzing such data helps healthcare administrators to effectively forecast surgical demand, identify peak periods, and estimate procedure durations guided by similar past cases. With historical surgical patterns, hospitals can allocate their resources accurately and effectively, minimize idle time, and improve the overall flow of surgical operations. Moreover, historical data can aid in identifying and mitigating bottlenecks, enhancing staff and equipment allocation, and optimizing OR turnover times (Dexter, Macario, Qian & Traub, 1999; Leedal & Smith, 2005).

However, relying solely on historical data to schedule ORs in hospitals may not be the most effective approach due to different reasons, such as the variability in surgical cases, staffing, and resources, among others. For instance, each surgical case is affected by several factors, such as the patient's health condition, complexity of the procedure, surgeon professionality, and many other unexpected complications; in addition, staffing level of training, and available resources may differ from one surgery to another. Outliers and anomalies are very common problems in historical data as they can skew predictions. For instance, anomalies could arise from unusual cases, data entry errors, or atypical situations that are not representative of normal scenarios. Thus, relying on historical data only to schedule ORs in hospitals may not be the most effective or efficient approach.

ML algorithms can yield numerous benefits when integrated into OR scheduling, including predictive abilities, adaptability, and efficiency. Such algorithms can analyze historical data and reveal patterns that may not be detectable through manual methods. ML is a continuous learning and adapting technique based on real-time data. It can respond effectively to unexpected delays, emergencies, or changes in surgeon availability, which is not available in any other traditional scheduling techniques that are based only on historical data.

ML has become an effective tool for optimizing OR scheduling, especially for laparoscopic surgery. Laparoscopic procedures are characterized by small incisions and the use of a highly precise camera for visualization; thus, they require precise planning and resource allocation. ML algorithms can analyze historical surgical data, patient characteristics, surgeon availability, and equipment status to predict and optimize durations and scheduling for any surgical procedure; thus, minimize delays and enhance resource utilization. Researchers examined various ML techniques for effective OR scheduling processes; for instance, VanBerkel and Blake (2007) conducted a pilot study utilizing computer simulation to integrate anesthesia workload into the management of OR. The study aimed to optimize OR scheduling by incorporating anesthesia-related factors, considering their impact on the overall surgical process. The results showcased the potential benefits of this approach in enhancing OR efficiency and scheduling accuracy. Lazic, Hinterwimmer, Langer, Pohlig, Suren, Seidl et al. (2022) explored the application of ML to predict surgical duration specifically in total hip arthroplasty. The authors employed ML algorithms to analyze various factors and predict the duration of surgeries. The study demonstrated the effectiveness of ML in accurately forecasting surgical timelines, providing valuable insights for optimizing OR scheduling and resource allocation, particularly for total hip arthroplasty procedures. Schiele, Koperna and Brunner (2021) proposed a NN-based model to provide guidance and support to hospital managers in efficiently scheduling surgeries, focusing on the intensive care unit while incorporating elective/urgent patients, inpatients/outpatients, and all possible paths through the hospital. Various ML models were examined in Martinez, Martinez, Parra, Rugeles and Suarez (2021) to accurately estimate the surgery's duration using a large dataset of surgery records. Specifically, potential factors that can influence the surgery duration were analyzed. Eshghali, Kannan, Salmanzadeh-Meydani and Esmaieeli-Sikaroudi (2024) proposed a comprehensive model for enhancing the efficiency of OR scheduling, accommodating both elective and emergency patients, in a hospital. The proposed model incorporates various methods, such as Random Forest (RF) integrated with Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), to effectively estimate the emergency patient surgery duration.

Among ML models, the Convolutional Neural Networks (CNNs) have gained prominence in optimizing OR scheduling through their ability to analyze visual data. In fact, CNNs, in the context of OR scheduling, entails processing images or video data related to surgical procedures, surgical tools, or patient conditions to extract valuable insights for effective decision making. For instance, CNNs can analyze surgical videos to predict surgical duration, which is crucial for efficient OR scheduling. CNNs can also be exploited to assess surgical complexity based on visual cues, aiding in resource allocation and scheduling appropriate time slots. For example, Yuniartha, Masruroh and Herliansyah (2021) and Jiao, Xue, Lu, Avidan and Kannampallil (2022) utilized ML to predict surgery duration and complexity, demonstrating the potential of ANN in improving OR scheduling accuracy. Similarly, Al-Refaie, Judeh and Li (2018), Twinanda, Shehata, Mutter, Marescaux, De Mathelin and Padoy (2017), and Anteby, Horesh, Soffer, Zager, Barash, Amiel et al. (2021) argued that incorporating fuzzy scheduling and Deep Learning (DL) into OR scheduling process enhances the automation of data analysis, leading to more efficient scheduling processes and ultimately improving overall hospital efficiency and patient care.

As stated previously, optimal ORs scheduling is challenging due to many factors, such as the variability in surgical cases and staffing and resources. For example, general surgeons underestimated procedure time by 31 minutes on average, while anesthesiologists underestimated it by 35 minutes (Aksamentov, Twinanda, Mutter, Marescaux & Padoy, 2017). Guedon, Paalvast, Meeuwsen, Tax, van Dijke, Wauben et al. (2015) reported a high variability up to 37% in waiting and preparation time for patients in cholecystectomy procedures. This high variability indicates that effective scheduling is a very tedious job.

Riahi, Hassanzadeh, Khanna, Boyle, Syed, Biki et al. (2023) discussed various approaches proposed to preoperatively predict surgery duration, such as utilizing historical procedure-surgeon data, patient information (e.g., age), operational factors, and temporal factors. Ammori, Larvin and McMahon (2001) discussed traditional methods for dynamic adaptation of the schedule as a potential solution. Traditional methods involving verbal communication can disrupt surgical workflow and may compromise safety. Alternative approaches use signals, such as surgical tool usage, surgeon's hand movements, and low-level task representations for real-time prediction are limited by manual annotation and practicality, as discussed in (Twinanda, Yengera, Mutter, Marescaux & Padoy, 2019; Maktabi & Neumuth, 2017; Padoy, Blum, Feussner, Berger & Navab, 2008).

Over the past decade, the medical scientific community has been actively engaged in advancing the realm of intelligent ORs to enhance their efficiency and patients. This paradigm encompasses diverse domains, such as image-guided and robotic surgical systems, augmented reality, visualization, sensing devices, and Context-Aware systems within Computer-Assisted Interventions (CA-CAI). For instance, the works of Cardoen, Demeulemeester and Beliën (2010) and Meskens, Duvivier and Hanset (2013) are good examples of CA-CAI as the authors emphasized the importance of dynamic scheduling in optimizing OR utilization and improving customer satisfaction, highlighting its potential to contribute to efficient healthcare operations and enhanced patient experiences. The current study aligns with this trajectory, specifically focusing on CA-CAI.

The goal of this study is to develop a novel predictive model that leverages CNNs to estimate the remaining time of surgical procedures using real-time visual data from laparoscopic videos. While the model is implemented and validated in the context of cholecystectomy procedures, its primary focus is on advancing a generalizable framework for intra-surgical time prediction. Specifically, the model employs binary classification to identify the completion of the Gallbladder Dissection phase, a critical step in predicting surgery progression. By providing accurate and real-time predictions, the proposed model aims to support dynamic scheduling adjustments, enabling more efficient OR utilization and improved workflow management. This model-development effort is designed to address broader challenges in surgical time prediction, with cholecystectomy serving as a case study to demonstrate its applicability and effectiveness.

The remaining of this paper is structured as follows: Section 2 discusses the dataset being used in this work and data wrangling and augmentation strategy employed in this work for developing the proposed CNN model; Section 3 presents the structure of the proposed CNN and the dynamic scheduling aspects; Section 4 shows the application results and highlights the effectiveness of the proposed model. Finally, Section 5 concludes the work and highlights some future directions.

2. Data, Data Wrangling, and Data Augmentation

This Section illustrates the dataset being used in this work for the development of the proposed CNN for the prediction of the remaining surgery duration. The section also entails the data wrangling and augmentation steps employed to optimize the CNN model's performance and effectiveness.

The dataset for Laparoscopic Videos used in this work comprises 20 video recordings obtained during laparoscopic surgical procedures in Al-Salt hospital in Jordan and the Cholec80 dataset (Twinanda et al., 2017) with a total of 100 videos. These videos capture the intricate movements and details of surgical activities performed by medical professionals. Temporal information indicating the duration of the surgery at different time points was extracted from the videos.

In CNNs, data wrangling and data augmentation play pivotal roles in optimizing model performance. For instance, the former involves the preprocessing and cleaning of raw data to ensure it is well-structured and suitable for training. This includes handling missing values, addressing outliers, and standardizing data formats. On the other hand, data augmentation is a technique employed to artificially increase the diversity of the training dataset by applying various transformations such as rotation, scaling, and flipping to the existing images. This augmentation helps enhance the model's robustness and generalization capabilities, enabling it to learn more robust features and patterns from the data. Together, data wrangling and data augmentation contribute significantly to the overall efficiency and effectiveness of CNNs by improving their ability to recognize and classify objects in diverse and real-world scenarios.

The dataset serves as a training and evaluation resource for a CNN tasked with predicting the remaining duration of a surgical procedure based on the visual information extracted from laparoscopic videos. The annotations associated with the videos provide ground truth labels for the model to learn the temporal dynamics and patterns within the surgical context. Establishing the temporal parameter corresponding to the conclusion of Gallbladder dissection Phase (Phase 4) in the laparoscopic cholecystectomy video is of paramount importance. The initial frame featuring the appearance of the white retrieval bag employed for gallbladder collection is indicative of the termination of Gallbladder dissection Phase.

The total number of Laparoscopic videos available is 100 videos. Out of these, 10 random videos were reserved for later use in the testing phase. A total of 240 frames were extracted from the remaining 90 videos for utilization in the training and validation steps. However, the available data proved to be insufficient for the proper execution and training of the model, resulting in low accuracy. Consequently, data augmentation was implemented to generate additional frames, leading to a total of 960 frames. This augmented dataset enhances the efficacy of the model training process, thereby contributing to an improved accuracy in predicting outcomes.

The training set consists of 80% of the training and validation data available (the 960 augmented frames), whereas the validation set consists of 20% of the training and validation data available (original 240 frames), and the test set consists of 10 full videos to generate the confusion matrix and Receiver Operator Characteristic (ROC) curve used as evaluation metrics for the model. The 960 frames were created by augmenting the original 240 frames, with each original frame producing four augmented frames. These original frames were randomly selected from a 3-minute time window surrounding the Gallbladder packaging phase. They primarily include the Gallbladder Dissection phase, the Gallbladder packaging phase, and the Cleaning Coagulation phase.

For clarification purposes, Figure 1 visualizes the segmenting of the dataset in the study, whereas Figure 2 visualizes the flowchart of the overall data segmentation process for an effective development of the CNN model as this segmentation helps the model increase result accuracies and predict more effectively and efficiently.

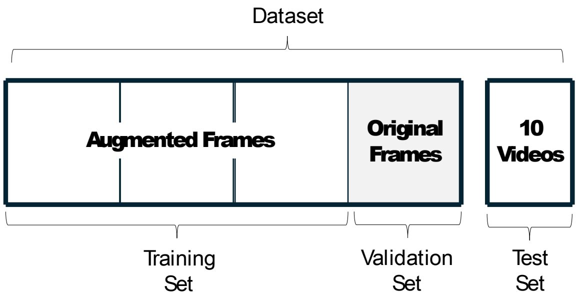

Figure 1. Dataset segmentation in the proposed CNN model

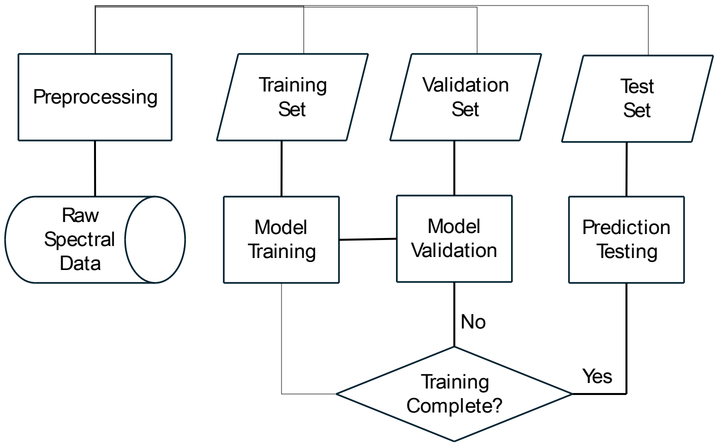

Figure 2. The dataset segmentation and CNN modelling framework

In the preprocessing stage, it is crucial to emphasize the discretization of the live video into individual frames using Python OpenCV library. Subsequently, the central regions of these frames are cropped. Additionally, binary labels are utilized to generate supervised learning labels for the CNN model. Within this framework, the label "0" is indicative of the termination of Gallbladder dissection Phase, whereas "1" denotes any time-point occurring before or after the conclusion of Gallbladder dissection Phase.

Figure 3 illustrates the temporal distribution of laparoscopic surgical procedures in a dataset comprising 90 surgeries. Analysis of the duration distribution shows a pronounced rightward skewness, accompanied by a notable high standard deviation of 17.1 minutes. The reliance on data characterized by high standard deviation presents challenges to scheduling due to the introduction of substantial uncertainty. This uncertainty can negatively affect the schedule as it can increase the likelihood of delays for patients and idle intervals in the OR. Such circumstances may cause complications in resource management and contribute to a reduction in patient satisfaction levels.

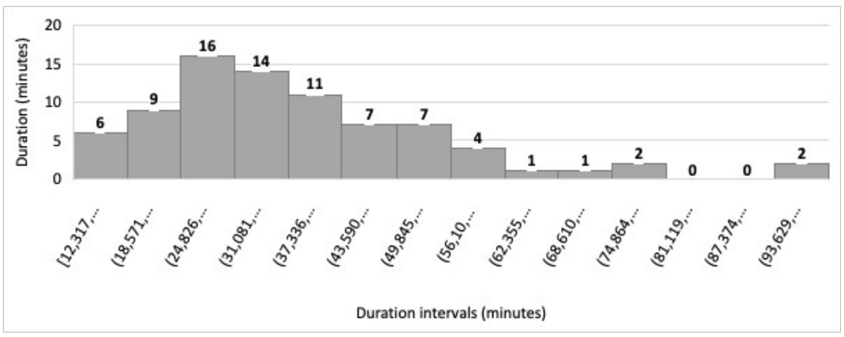

Figure 3. Temporal distribution of the 90 cholecystectomy surgeries

Examination of cholecystectomy procedures videos has identified seven primary phases that characterize the process, namely: Preparation phase (Phase 1), Calot Triangle Dissection phase (Phase 2), Clipping Cutting phase (Phase3), Gallbladder Dissection phase (Phase 4), Gallbladder Packaging phase (Phase 5), Cleaning Coagulation phase (Phase 6), and Gallbladder Retraction phase (Phase 7). The mean and standard deviation values related to phase durations across various phases in laparoscopic surgeries are presented in Figure 4. The Figure illustrates that the durations of these phases exhibit high standard deviations, indicating substantial variability. This significant variability in phase durations results in heightened uncertainty and makes scheduling challenging. Consequently, this difficulty in scheduling can lead to increased patient waiting times, prolonged OR idle time, decreased overall utilization of the OR, and introduces challenges in scheduling anesthesia.

Figure 5 and Figure 6 illustrate the time distribution from the start of surgery to the end of Phase 4 and from the beginning of Phase 5 to the end of Phase 7, respectively, across 100 surgeries. For the 100 surgeries, the average time from the start of surgery to the end of Phase 4 is 19.55 minutes with a standard deviation of 10.30 minutes, while the average time from the start of Phase 5 to the end of Phase 7 is 5.91 minutes with a standard deviation of 2.89 minutes. This indicates that the majority of variability in surgical times arises from phases 1 through 4. Consequently, updating the schedule after the completion of Phase 4 can significantly reduce most of the scheduling uncertainty, thereby decreasing both OR idle time and patient waiting time.

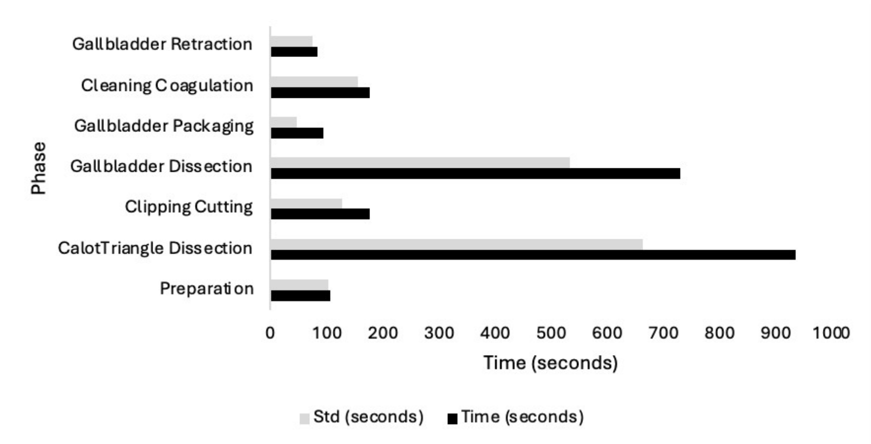

Figure 4. The mean and standard deviation for each phase time

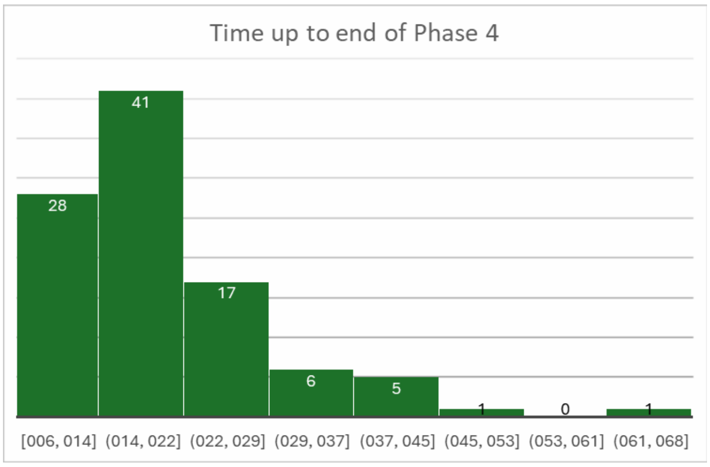

Figure 5. Total time up to end of Phase 4

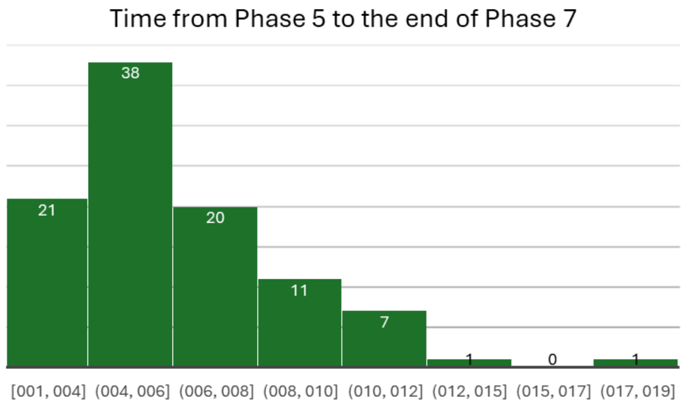

Figure 6. Total time from beginning of Phase 5 to the end of Phase 7

Further analysis has revealed key insights: Phase 2 (i.e., Calot Triangle Dissection) and Phase 4 (i.e., Gallbladder Dissection) are particularly critical, jointly consuming approximately 70% of the overall operation duration and contributing significantly to the variability in duration. Notably, the preparation time, averaging 25 minutes, underscores the temporal significance of the transition from Gallbladder dissection phase (Phase 4) to Gallbladder packaging phase (Phase 5). This stage is pivotal in determining whether an adjustment to the schedule for subsequent patients is necessary. The rationale lies in the fact that the average interval between the conclusion of Phase 4 and the termination of the surgery is approximately 6 minutes, necessitating an additional 50-minute interval between surgeries for preparation. Consequently, this cumulative duration of 56 minutes aligns with the anesthesia administration time (50-60 minutes), highlighting the crucial role of Phase 4's conclusion in determining the temporal alignment of the operation relative to the schedule.

Observations made during the analysis of frames in the latter part of Phase 4 and the initial segment of Phase 5 reveal a consistent positioning of the White Retrieval Bag (A bag used to extract the gallbladder or its fragments) at the center of the frame. Through the selective cropping of the central region of the frame, the importance of the white retrieval bag is highlighted. Consequently, this enhances the likelihood of accurate classification by the CNN, particularly in identifying frames corresponding to the conclusion of Phase 4. Refer to Figure 7 for a visual representation illustrating a randomly selected frame containing the white retrieval bag before and after the cropping process.

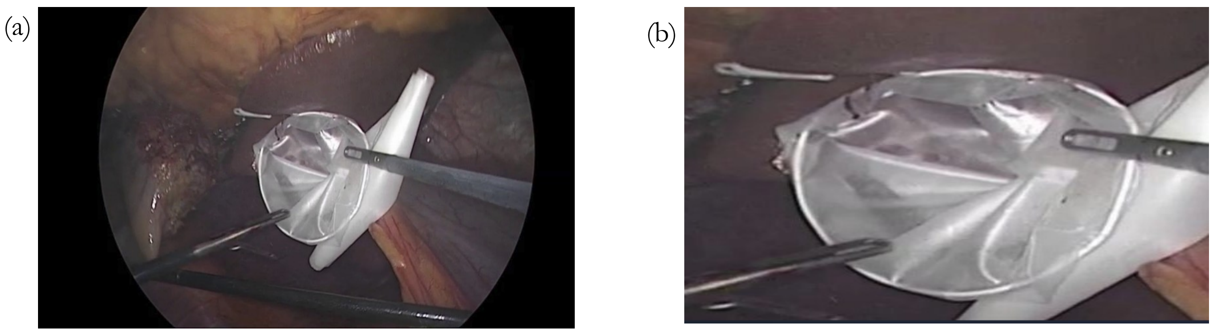

Figure 7. Frame (a) before and (b) after cropping

3. Methodology

In this study, CNNs are employed due to their superior ability to process and extract meaningful spatial features from visual data, such as laparoscopic videos, which are inherently rich in texture, shape, and temporal patterns. Unlike traditional ML methods that require manual feature extraction, CNNs automatically learn hierarchical representations of the data, making them particularly well-suited for tasks involving complex image analysis.

Specifically, CNN is used to predict the end of Gallbladder dissection phase and hence gives enough time to reschedule the OR and the anesthesia. The architecture of CNN used in this work is depicted in Figure 8. The Figure represents the most important design parameters used in composing the model.

The model consists of various layers: a data augmentation layer, one convolutional layer, one maxpooling layer, one flatten layer, four dense layers, a dropout layer, and output layer. The hyperparameters were optimized for the data using the Optuna library in Python, a framework designed for automating hyperparameter tuning processes to efficiently discover optimal settings for machine learning models. A directional study was conducted with the objective set to 'Maximize', aiming to enhance model accuracy. Through 50 trials, Optuna identified the optimal hyperparameters: a learning rate of 0.0005, a batch size of 64, [16, 32, 64, 128, 256, 512] filters each of size 3 by 3, and Dropout of 0.2. The remaining hyperparameters were fixed as follows: 200 epochs, Adam optimizer, padding='same', ReLU activation for convolution layers, and Softmax for dense layers. Maxpooling with a size of 2 by 2.

The data augmentation layer (not shown in Figure 8) contains a set of operations that are applied to the input data during the training phase to artificially increase the diversity of the training dataset. This helps the model generalize better to variations in the input data and improves its robustness. The specific operations incorporated in the data augmentation layer include rotation (randomly rotating the image by a specified angle), horizontal and vertical flipping (mirroring the image horizontally or vertically), zooming (randomly zooming into or out of the image), translation (shifting the image horizontally or vertically), and contrast adjustment (randomly adjusting the contrast of the image). Rotation involves randomly rotating the image by a certain angle to help the model learn object recognition irrespective of orientation. Flipping mirrors the image horizontally or vertically, aiding the model in recognizing objects regardless of their alignment. Zooming simulates changes in camera distance by randomly zooming in or out, enhancing the model's ability to detect objects at various scales. Translation shifts the image horizontally or vertically, making the model robust to variations in object positioning. Contrast adjustment alters the image's light and dark areas to help the model adapt to different lighting conditions. Together, these techniques expand the dataset's diversity, improving the model's generalization and robustness. Figure 9 illustrates the outcome of applying the data augmentation operations to a frame from Phase4.

These operations introduce variability into the training data, facilitating improved generalization by mitigating the risk of overfitting to specific examples within the training set. It is noteworthy that data augmentation is exclusively applied during the training phase, and the original, unaltered images are utilized for validation and testing purposes.

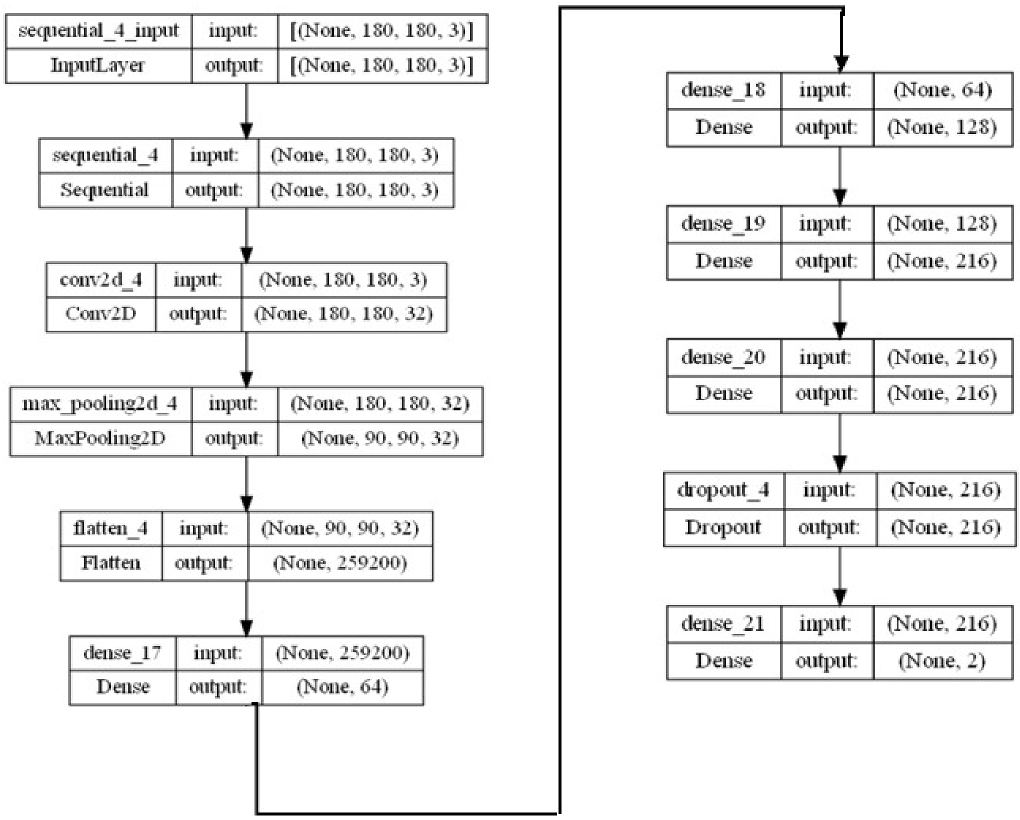

Figure 8. CNN model design parameters

Figure 9. Impact of augmentation on a frame from Phase 4

The algorithm takes a live laparoscopic surgical procedure video as input. It initiates a timer and captures a frame at regular intervals of 10 seconds from the ongoing video. The CNN component of the algorithm is responsible for determining the status of each captured frame, specifically whether it corresponds to the end of Gallbladder dissection phase (Phase 4) or not.

Upon classifying a frame as "end of Phase 4" the algorithm records the elapsed time from the timer, terminates the prediction loop, and proceeds to update the OR schedule accordingly. Conversely, if the CNN identifies the frame as NOT representing the "end of Phase 4" the algorithm continues the loop, capturing another frame. This iterative process persists until the CNN component eventually recognizes a frame as "end of Phase 4". The flowchart in Figure 10 visually depicts this procedural sequence.

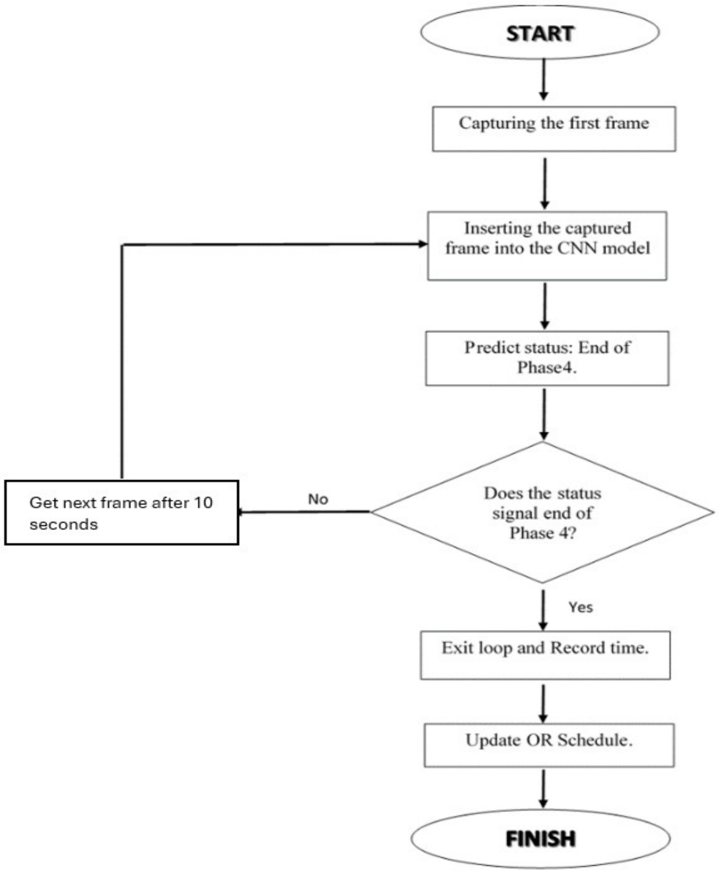

Figure 10. The flowchart of the proposed CNN approach

4. Results and Discussion

Loss and accuracy metrics serve as quantitative indicators of how well the model fits the data, with lower loss and higher accuracy signifying superior model performance. The term "epochs" denotes the number of complete iterations the model undergoes over the entire training dataset during the training process. While increasing the number of epochs has the potential to enhance model training accuracy, it concurrently introduces the risk of overfitting.

In the context of Figure 8, which portrays the progression of loss and accuracy across 200 epochs for both the training and validation (unseen data) sets, noteworthy observations emerge. The validation accuracy achieves an approximate value of 0.94, surpassing the training accuracy, which reaches 0.91. Simultaneously, the validation loss attains a level of around 0.28, slightly less than the training loss of 0.31. Figure 11 reveals a convergence of both training and validation accuracy, as well as training and validation loss, beyond the 150th epoch. This convergence suggests the absence of obvious overfitting in the model.

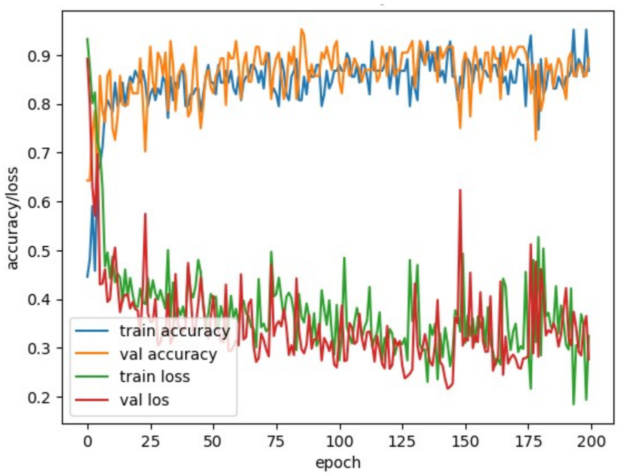

Figure 11. Loss and accuracy for training and validation sets across 200 epochs

Figure 12 and Figure 13 depict the confusion matrix and the ROC curve, respectively. The confusion matrix enumerates the instances of accurate and erroneous classifications conducted by the CNN relative to the true classes within the dataset. Evaluation of CNN's performance relies on this matrix, serving as a quantitative measure for assessment.

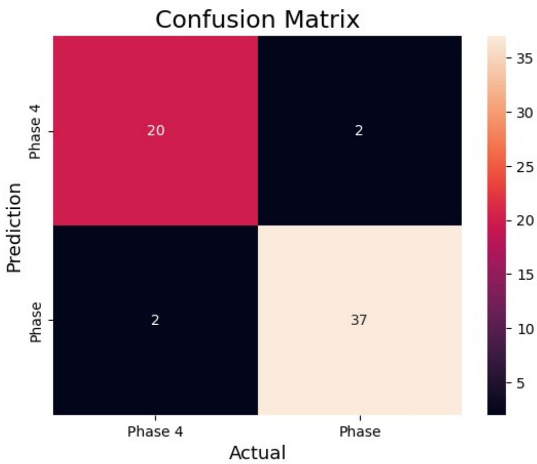

Figure 12. Confusion matrix for the proposed CNN

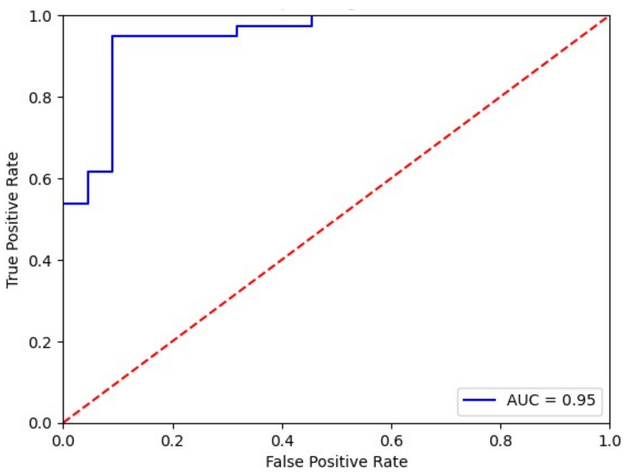

Figure 13. ROC curve for the proposed CNN

Specifically, five performance metrics are considered in this work:

- Accuracy (Equation 1). It quantifies the ratio of accurately classified frames, pertaining to both end of Phase 4 and non-Phase 4 categories, relative to the total number of frames classified by the model.

$$Accuracy = \frac{Total\ Correct\ Classifications}{Total\ Number\ of\ Classifications} = \frac{20 + 37}{20 + 37 + 2 + 2} = 0.92 \quad (1)$$

- Specificity (Equation 2). It denotes the ratio of frames accurately classified as non-Phase 4 by the CNN in relation to the total frames identified as non-Phase 4 by the CNN.

$$Specificity = \frac{Total\ Number\ of\ Phase\ correctly\ Classified}{Total\ Number\ of\ Phase\ Classified} = \frac{37}{37 + 2} = 0.95 \quad (2)$$

- Sensitivity (Equation 3). It represents the proportion of frames accurately classified as end of Phase 4 by the CNN among those frames identified as end of Phase 4 by the CNN.

$$Sensitivity = \frac{Total\ Number\ of\ Phase\ 4\ correctly\ Classified}{Actual\ Number\ of\ Phase\ 4} = \frac{20}{20 + 2} = 0.91 \quad (3)$$

- Precision (Equation 4). It signifies the ratio of frames accurately classified as end of Phase 4 among those frames identified as end of Phase 4.

$$Precision = \frac{Total\ Number\ of\ Phase\ 4\ correctly\ Classified}{Total\ Number\ of\ Phase\ 4\ Classified} = \frac{20}{20 + 2} = 0.91 \quad (4)$$

- Negative Predictive Value (Equation 5). It expresses the ratio of frames accurately classified as non-Phase 4 among those frames identified as non-Phase 4.

$$Negative\ Predictive\ Value = \frac{Total\ Number\ of\ Phase\ correctly\ Classified}{Total\ Number\ of\ Phase\ Classified} = \frac{37}{37 + 2} = 0.95 \quad (5)$$

The ROC curve serves as an evaluative metric for comparing the performance of the CNN against a random algorithm. Sensitivity and 1-specificity are respectively represented along the y-axis and x-axis. The area under the ROC curve is quantified as 0.95, signifying a markedly superior performance of the CNN compared to random classification. Specifically, an area under the ROC of 0.95 denotes that the likelihood of accurately categorizing a True end of Phase 4 frame as end of Phase 4 frame is 95% greater than the probability of misclassifying a non-Phase 4 frame as end of Phase 4.

The excellent outcomes observed in both the confusion matrix and the ROC curve indicate that the CNN model has undergone effective training with minimal overfitting. Consequently, we have confidence in utilizing this well-trained CNN model.

The CNN model, which has undergone training, will be employed on the test set comprising 10 new videos of laparoscopic cholecystectomy procedures. A detailed analysis of the results for the first video will be presented, followed by a subsequent enumeration of the outcomes for the remaining nine videos. Figure 14 presents the temporal details for the first video.

The total duration of the entire surgery is approximately 29 minutes, with Phase 4 lasting about 8.4 minutes. Notably, the CNN model successfully identified the conclusion of Phase 4 at the 24-minute mark by recognizing the appearance of the white retrieval bag employed to collect the patient's gallbladder. Figure 15 depicts the specific frame detected by the CNN model, signifying the conclusion of Phase 4.

Table 1 presents the OR timetable generated using the traditional static scheduling method, which serves as a baseline for comparison with the proposed algorithm. In this traditional approach, the schedule is constructed based on an average surgical duration of 40 minutes and an average interval of 45 minutes allocated for OR preparation and sanitation. This method relies solely on historical surgery times and does not account for real-time variability in surgical procedures. By contrasting this static scheduling approach with the dynamic updates enabled by the proposed algorithm, the study highlights the limitations of traditional methods and underscores the advantages of incorporating real-time predictions for optimizing OR efficiency.

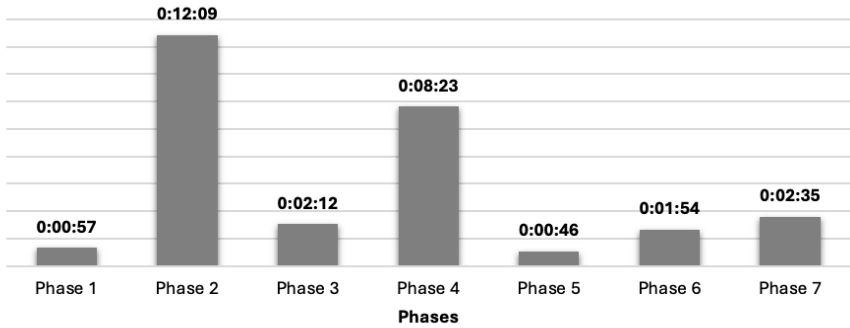

Figure 14. Temporal details for the first surgery

Figure 15. The specific frame detected by the CNN model to signify the conclusion of Phase 4

Operation number	*TST*	*AST*	*AOT* (Min)	*AET*	*CPOR*	*ORIT*	*WT* (Min)
1	7:00 AM	7:00 AM	29	7:29 AM	8:14 AM	0	0
2	8:25 AM	8:14 AM	40	8:54 AM	9:39 AM	11	0
3	9:50 AM	9:39 AM	54	10:33 AM	11:18 AM	11	0
4	11:15 AM	11:18 AM	44	12:02 PM	12:47 PM	0	3
5	12:40 PM	12:47 PM	27	1:14 PM	1:59 PM	0	7
6	2:05 PM	1:59 PM	57	2:56 PM	3:41 PM	6	0
7	3:30 PM	3:41 PM	49	4:30 PM	5:15 PM	0	11
8	4:55 PM	5:15 PM	43	5:58 PM	6:43 PM	0	20
9	6:20 PM	6:43 PM	56	7:39 PM	8:24 PM	0	23
10	7:45 PM	8:24 PM	39	9:03 PM	9:48 PM	0	39

TST: Theoretical Starting Time; *AST:* Actual Starting Time; *AOT:* Actual total Operation Time; *AET:* Actual Ending Time; *CPOR:* Cleaning and Preparation of OR; *ORIT:* Operating Room Idle Time; *WT:* Patient Waiting Time

Table 1. OR schedule without the utilization of the proposed algorithm

The Theoretical Starting Time (TST) for a surgical procedure is defined as the sum of the previous TST and 85 minutes. This duration comprises 40 minutes for the average surgical procedure and an additional 45 minutes for Cleaning and Preparation of the OR (CPOR). The Actual Starting Time (AST) is determined by adding 45 minutes to the Actual Ending Time (AET) of the preceding surgery, accounting for cleaning and preparation activities. The AET, in turn, is calculated by summing the AST and the duration of the surgical procedure. Thus, the OR Idle Time (ORIT) and the patient Waiting Time (WT) are calculated using Equation 6 and 7, respectively, as follows:

$$ORIT = \begin{cases} TST_{i+1} - CPOR_i \,, \forall\, TST_{i+1} > CPOR_i \\ 0, \quad otherwise \end{cases} \tag{6}$$

$$WT = \begin{cases} AST_i - TST_i, \forall\, AST_i > TST_i \\ 0, \quad otherwise \end{cases} \tag{7}$$

Where *i* is the index of the operation. Table 2 shows what the CNN model predicts for when each operation starts and ends, creating a schedule in real-time. In this way of planning, nurses get notifications about 51 minutes before the next surgery begins. These 51 minutes can be divided into 6 minutes until the current surgery ends and 45 minutes for CPOR. This gives enough time for updating schedules, getting ready for the next patient, and preparing anesthesia. As you can see in Table 2, the CNN model effectively reduced patient waiting time and eliminated OR idle time by making a real-time scheduling.

Operation number	*TST*	*AST*	*AOT* (Min)	*CET*	*AET*	*CPOR*	*ORIT*	*WT* (Min)
1	7:00 AM	7:00 AM	29	7:28 AM	7:29 AM	8:14 AM	0	0
2	8:13 AM	8:14 AM	40	8:56 AM	8:54 AM	9:39 AM	0	1
3	9:41 AM	9:39 AM	54	10:30 AM	10:33 AM	11:18 AM	0	0
4	11:15 AM	11:18 AM	44	12:02 PM	12:02 PM	12:47 PM	0	3
5	12:47 PM	12:47 PM	27	1:13 PM	1:14 PM	1:59 PM	0	0
6	1:58 PM	1:59 PM	57	3:01 PM	2:56 PM	3:41 PM	0	1
7	3:46 PM	3:41 PM	49	4:26 PM	4:30 PM	5:15 PM	0	0
8	5:11 PM	5:15 PM	43	5:54 PM	5:58 PM	6:43 PM	0	4
9	6:39 PM	6:43 PM	56	7:42 PM	7:39 PM	8:24 PM	0	4
10	8:27 PM	8:24 PM	39	9:05 PM	9:03 PM	9:48 PM	0	0

CST: CNN predicted Starting Time; AST: Actual Starting Time; AOT: Actual total Operation Time; AET: Actual Ending Time; CET: CNN predicted Ending Time; CPOR: Cleaning and Preparation of OR; ORIT: Operating Room Idle Time; WT: Patient Waiting Time

Table 2. The OR schedule with the utilization of the proposed algorithm

The implementation of the CNN significantly reduced patients' WT, achieving a remarkable 87.3% decrease from 103 minutes to just 13 minutes. This efficiency is achieved through the real-time schedule, wherein nurses receive timely notifications, enabling simultaneous preparation of the OR and patient readiness for anesthesia. The CNN's application not only minimizes costs but also enhances patient satisfaction by eliminating unnecessary waiting and repetition of the anesthetization procedure. Figure 16 provides a comparison of patient waiting times under two schedules: one without the application of the CNN model and the other with the utilization of the CNN model.

Table 3 presents the precision of our model in forecasting the conclusion of a Phase 4 across ten surgical procedures. The second column denotes the Actual End of the phase (AE_{Phase}), while the third column represents the Predicted End of the phase made by the proposed algorithm (PE_{Phase}). The accuracy can be calculated by Equation 8 in seconds. As per the tabulated results, 40% of surgeries were accurately forecasted with zero instances of misclassification. Among the remaining six instances, the most significant deviation was approximately 2.27%. The average error across all predictions was a mere 0.69%. This minimal average error underscores the overall high accuracy of the proposed model.

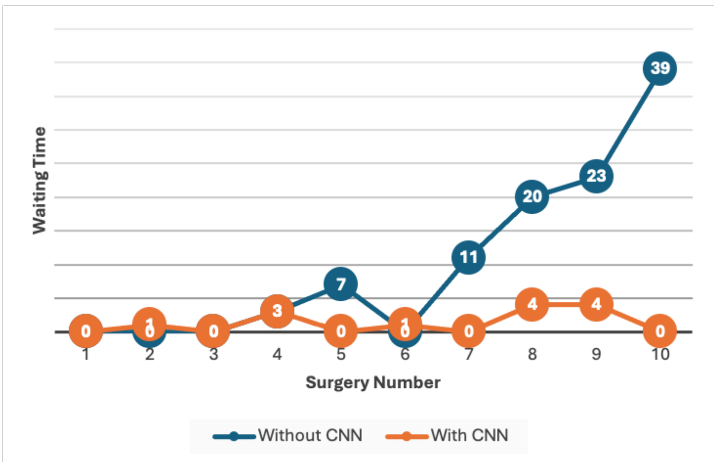

Figure 16. The waiting time (in minutes) comparison chart with and without the utilization of the proposed CNN algorithm

$$Accuracy = \left|PE_{Phase_i} - AE_{Phase_i}\right| \tag{8}$$

Operation Number	AE_{Phase} (Min)	PE_{Phase} (Min)	*Accuracy*	$\|Error\|$ (%)
1	24	24	0	0.00%
2	32	32	0	0.00%
3	43	42:30	30	1.16%
4	36	36:20	20	0.93%
5	22	21:30	30	2.27%
6	50	50	0	0.00%
7	41	40:50	10	0.41%
8	36	36	0	0.00%
9	44	44:10	10	0.38%
10	28	28:30	30	1.79%
			Averages	0.69%

Table 3. Absolute error percentages of the proposed CNN model

Figure 17 depicts the errors linked to CNN's predictions of the conclusion of Phase 4. The Figure demonstrates that the errors are randomly distributed, indicating that the proposed algorithm exhibits no apparent bias and hence the model does not exhibit systematic errors and provides predictions or estimates that, on average, are correct and free from any systematic deviation from the true values.

The proposed CNN sometimes misclassified images with rolled retrieval white retrieval bags as the end of phase 4. This mistake extended the duration of phase 4 and delayed the schedule update, increasing the error in detecting the end of phase 4. Providing more data could mitigate this issue by improving the model's training. Figure 18 shows an example of such an image.

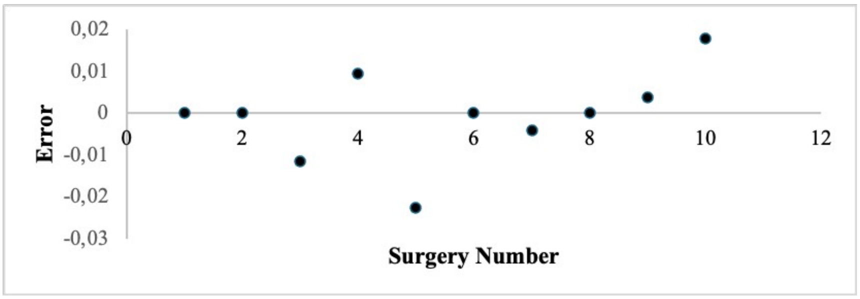

Figure 17. Errors linked to CNN's predictions

Figure 18. An image featuring a rolled white retrieval bag

It is important to note that in this study, 10 test videos (surgeries) were used to create a surgery schedule based on traditional static scheduling methods. The same 10 videos were then used to generate a schedule using the proposed method. The schedules produced by the traditional method and the proposed method were subsequently compared. Unfortunately, achieving statistical significance in the results necessitates repeating the processes multiple times, which requires a large number of datasets. The authors, however, do not have enough data to construct confidence intervals, or conduct hypothesis tests regarding the reduction in idle and waiting times.

5. Conclusions and Future Directions

This study demonstrates the potential of data-driven approaches, particularly machine learning, to address the challenges of dynamic Operating Room (OR) scheduling by leveraging real-time visual data from surgical procedures. Traditional static scheduling methods based on historical data often fall short due to the inherent variability in surgical cases, staffing, and resources. To address these challenges, the study proposes a Convolutional Neural Network (CNN) model that predicts the conclusion of Phase 4 in laparoscopic cholecystectomy procedures, allowing for dynamic updates to the OR schedule.

The results demonstrate the effectiveness of the CNN model, achieving an accuracy of approximately 92% and reliably predicting the conclusion of Phase 4. This accurate phase detection contributes to more precise scheduling, minimizing patient waiting times and OR idle time. The real-time schedule generated by CNN significantly outperforms traditional scheduling methods, reducing patient waiting times by 87.3% and eliminating OR idle time.

However, there are two notable limitations in this study. First, only 10 test videos (surgeries) were used to create a surgery schedule based on both traditional static scheduling methods and the proposed method. These schedules were subsequently compared. Unfortunately, achieving statistical significance in the results requires repeating the processes multiple times, necessitating a large number of datasets. The authors do not have enough data to construct confidence intervals or conduct hypothesis tests regarding the reduction in idle and waiting times. Second, the proposed CNN sometimes misclassified images with rolled white retrieval bags as the end of Phase 4. This mistake extended the duration of Phase 4 and delayed the schedule update, increasing the error in detecting the end of Phase 4. Providing more data could mitigate this issue by improving the model's training.

While the CNN model demonstrates promising results, ongoing research and refinement are essential to further enhance its accuracy and applicability across diverse surgical scenarios. Future work may explore expanding the dataset, refining the CNN architecture, and considering additional factors for a more comprehensive predictive model. Additionally, the methodology used in this study can be adapted for other laparoscopic surgeries, such as laparoscopic appendectomy and hernia repair. These applications could provide a more comprehensive evaluation of the proposed CNN model's effectiveness, further validating its applicability and enhancing its robustness in optimizing OR scheduling. Nevertheless, the findings of this study underscore the potential of data-driven models, particularly machine learning, in revolutionizing intra-surgical time predictions and optimizing OR management for improved patient care and resource utilization.

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Declaration of Conflicting Interests

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Data Availability Statement

Data will be available on request.

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