Capstone Project Proposal

Pediatric Laparoscopic Surgery Simulator

Augmented Reality Laparoscopic Surgery Training

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Report Date:

October 27th, 2023

SYSC 4907

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1. Introduction

This proposal outlines the research and development of the third iteration of the capstone project that centers on developing a cutting-edge Pediatric Laparoscopic Surgery Simulator, integrating augmented reality technology and machine learning to enhance its educational utility. The following sections of this proposal commence with a concise articulation of the project's primary objective, highlighting the need for innovative training tools in pediatric laparoscopic surgery. Subsequently, a comprehensive background is constructed, encompassing the essence of pediatric laparoscopic surgery, extant standards and requisites governing the domain of laparoscopic surgical training, and a discerning analysis of recent advances in simulation technology designed to augment the proficiency of laparoscopic surgeons. Furthermore, the exploration of specific contributions and competencies of each team member, leveraging the shared discipline of Biomedical and Electrical Engineering, as well as diverse practical experiences, reinforces the team's collective capability to undertake this complex endeavour. Moreover, a rigorous exposition of the planned methodologies is presented and supported by a designed Grantt chart to track the project's milestones and timeline. An extensive risk assessment and corresponding mitigation strategies are also delineated, followed by a listed inventory of specialized components indispensable for the project's successful handover.

2. Background

Laparoscopic surgery, often called ‘keyhole’ surgery, is a minimally invasive surgical (MIS) technique that differs from traditional ‘open surgery.’ Instead of making a large incision on a patient’s abdomen, laparoscopy involves several smaller, 0.5-1 cm diameter incisions, each called a ‘port’ [1]. A trocar placed inside a hollow sleeve or cannula at each incision or port is slipped through to create an access point for surgery [2]. A trocar is a pen-shaped instrument (triangular at one end) placed inside a hollow tubular instrument [2]. An image of a trocar is shown below in Figure 1.

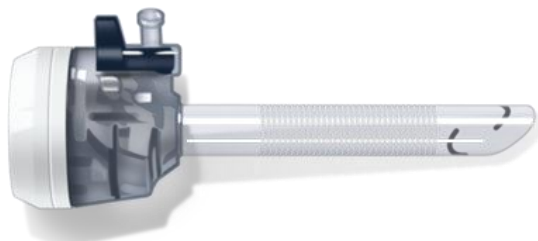

Figure 1 : Image of a trocar.[2]

In these incisions, the laparoscopic tools, a tube to pump gas into the abdominal cavity, and a specialized camera called a laparoscope are placed through [3]. A sample placement of these trocars is shown in Figure 2 below.

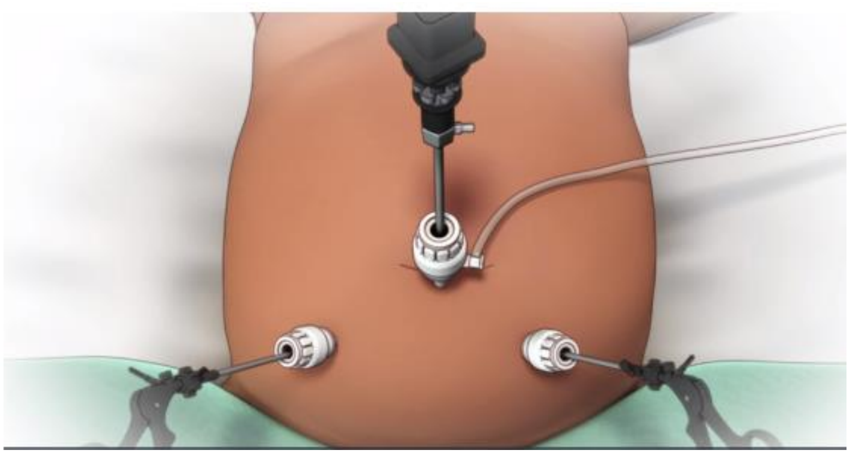

Figure 2: Pediatric laparoscopic surgery setup with a laparoscope and instruments inserted through trocars [3]

Various laparoscopic instruments available today are made of durable stainless-steel material with narrow shafts up to 3-5mm diameter to fit through the ports [2]. Along with a laparoscope, which is a thin telescope equipped with a camera and light source, there are a variety of other tools available for various functions [2]. Needle drivers, composed of handles, joints, and jaws, grasp suturing needles while securing wounds and surgical incisions [2]. Their tips may be curved or straight [2]. Bowel graspers, 3 - 5 mm in diameter, handle and grasp tissue, allowing surgeons to observe and perform various procedures [2]. Other instruments used in laparoscopy include scissors, suturing needles, and surgical meshes [2]. An image of these tools is given in Figure 3 below.

Figure 3: Laparoscopic instruments commonly used today. From left to right, laparoscope (top left), needle grasper (top right), bowel grasper (bottom left), and surgical mesh (bottom right) [2]

Additionally, in laparoscopy, surgeons are limited to four degrees of freedom of motion, which are the yaw, pitch, (counterclockwise/clockwise) roll, and (forward/backward) surge movements [4]. They lose the heave and sway motions due to the pivots that hold the instruments in place [4].

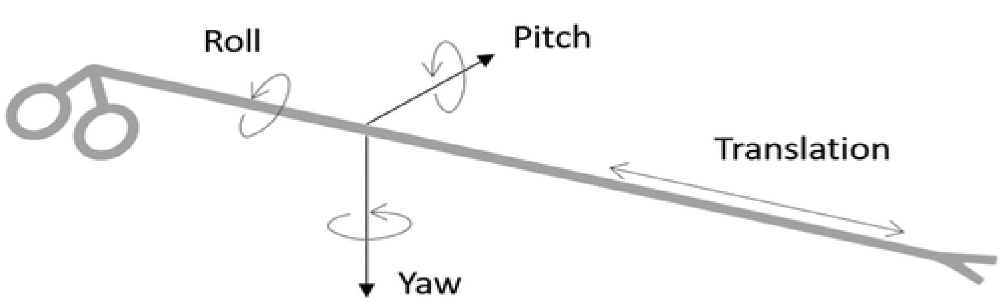

Figure 4:The four degrees of motion surgeons are limited to in laparoscopy are the roll, pitch, yaw, and surge (translation) movements [4]

Regarding postoperative outcomes, due to smaller incisions, laparoscopy is associated with reduced pain post-operation, reduced scarring, reduced hospital stays, and lower incidences of significant wound complications [5]. That means patients can return to everyday life and engage in normal activities much sooner after their operation than open-surgery patients [5].

However, laparoscopy is known to have a steeper learning curve for trainees than conventional open surgery, and each patient-specific procedure can present additional complications for surgeons and trainees [6]. Thus, training for laparoscopy is different from conventional open surgery training in several ways. Trainees must work within restricted spaces and exercise less intuitive and limited movement through the trocars [7]. They must also enhance their hand-eye coordination capabilities due to the added challenges of operating while looking at a screen instead of operating under direct vision, like in open surgery [7]. There is also an increased need to develop manual dexterity skills, like fine motor skills, since the long instruments used in laparoscopy amplify even small movements and errors made by the trainee [7]. Trainees also experience the fulcrum effect, which describes the inversion of movement while operating [7]. For instance, this refers to when the surgeon moves their hand to the right, and the instrument's tooltip is moved to the patient's left on the screen [7].

Additionally, trainees have to grapple with challenges like only using four out of six degrees of motion, the lack of physical sensation or touch from their hands, and the lack of 3-dimensional images like in open surgery [7]. In a clinical setting, laparoscopic training can largely depend on the variety of cases that arrive at the hospital [6]. Due to the increased need for the unique skills required for laparoscopy, a need arose to develop relevant simulators and training programs. Simulators provide trainees with a safe, ethical, and friendly learning environment to develop their hand-eye coordination abilities, improve their manual dexterity, and soften the learning curve of acquiring laparoscopic skills [6].

When minimally invasive surgery (MIS) was first adapted for infants and children, training surgeons and residents on pediatric laparoscopy presented additional challenges [8]. The use of smaller workspaces, shorter and narrower instruments, smaller margins of error, and the expansion of MIS in children and infants warranted the development of specific learning approaches and simulators for pediatric laparoscopy [8]. This type of procedure demands a more unique set of operating skills than adult laparoscopy. The abdomens of children and infants present a small workspace whereby damage to nearby vessels, the bowel, and other structures can quickly occur and lead to grave consequences [9]. While the instruments are smaller and narrower, surgeons must still maneuver these within smaller anatomical structures and a restricted operating field [9,10]. Due to these limitations, there also exists a lower tolerance of forces to surrounding tissues [10]. Thus, the demand for the unique skill set to perform the procedure has led to the use and development of pediatric laparoscopic simulators. These simulators must mimic the challenging surgical environments in their setup by using smaller instruments, smaller needles, more sensitive force-sensing devices, and more limited surface areas for training tasks [10].

The Fundamentals of Laparoscopic Surgery (FLS) was a program developed by the Society of American Gastrointestinal and Endoscopic Surgeons (SAGES) in 2004 to develop a framework that assesses knowledge and skills acquisition for laparoscopic surgery [11]. The program has been widely regarded as a valid and reliable tool and educational curriculum to train and assess surgeons [11]. The Canadian Association of General Surgeons endorses the FLS program as a valuable and comprehensive training and assessment tool to gauge residents’ knowledge and skills in basic laparoscopic training. The FLS examination consists of a web-based cognitive examination, followed by a manual-skills assessment on five fundamental laparoscopic tasks, namely, the peg transfer task, precision cutting task, ligating loop task, suturing with extracorporeal knot-tying task, and suturing with intracorporeal knot-tying task [11]. For now, and for our group's proposed surgical simulator, the focus will be on the peg transfer task and the suturing tasks with extracorporeal knot-tying and intracorporeal knot-tying [11]. More tasks may be added to our simulator if time, resources, and efforts allow.

The most straightforward task, the peg transfer task, involves using two Maryland grasper dissectors [12]. It gets trainees to grasp each ring with their non-dominant hand one by one and transfer it to their dominant hand in mid-air to place it on a peg on the opposite side of the board [12]. The process is repeated until all rings are on the other side of the board [12]. This process is then repeated in reverse, starting with the dominant hand and then transferring the rings to the non-dominant hand [12]. Penalties are applied if the ring falls out of the field of view or is no longer retrievable, but trainees are still expected to continue the procedure should this happen [12]. If a ring is dropped within the field of view, trainees can pick it up with their hands and continue the procedure [12]. The FLS recommends that trainees complete this entire procedure in 300 seconds, with the time starting from the minute the grasper touches the first ring till the time the grasper lets go of the last ring [12].

In the extracorporeal suturing task, trainees are expected to use two needle drivers (or one Maryland grasper and one needle driver) and endoscopic scissors to place a long suture through two marks in a Penrose drain and then perform three single throw knots (extracorporeally) to secure the slit on the drain [12]. Then, once the three throws are secured, both ends of the suture are cut [12]. Penalties are applied for a knot that falls apart, for deviating from the suturing marks on the Penrose drain, and for improper closure of the slit [12]. This procedure is expected to be completed within 420 seconds, beginning when the first tool is visible through the camera and ending when the cuts are made to either end of the suture [12].

Similarly, in the intracorporeal suturing task, trainees are expected to use two needle drivers (or one Maryland grasper and one needle driver) and endoscopic scissors to place a short suture through two marks in a Penrose drain and then perform three throws of a knot (one double throw, and two single throws) intracorporeally to secure the slit on the drain [12]. Then, once the three throws are secured, both ends of the suture are cut [12]. Penalties are applied for a knot that falls apart, for deviating from the suturing marks on the Penrose drain, and for improper closure of the slit [12]. This procedure is expected to be completed within 600 seconds, beginning when the first tool is visible through the camera and ending when the cuts are made to both ends of the suture [12]. While a scoring rubric from the FLS is not publicly available, plenty of scoring methodologies developed by medical professionals exist online. They can be used to assess the performance of trainees. For instance, many experts have developed independent scoring rubrics for the five basic laparoscopic tasks [13].

To adapt the FLS training and assessment framework for pediatric laparoscopy, smaller and softer rings for the peg transfer task, as well as the 3 mm graspers instead of the 5 mm ones used for adult laparoscopy, should be employed [10]. The size of the Penrose drain used in the intracorporeal, and extracorporeal suturing tasks should be reduced by 6, and smaller needles and 3 mm instruments should be used [10]. Additionally, the surface area of the Velcro securing the drain to the board should be decreased by a factor of 5 to increase the risk of avulsion that can occur due to the application of even minimal force in pediatric laparoscopy [10]. The timing and penalty scores could be the same as that for adults, except additional parameters or penalties may need to be added to the scoring rubric for pediatric laparoscopies, such as assigning the trainee a score of zero if avulsion of the Penrose drain occurs [10].

2.1. Description of Current Surgical Simulators

The advent of surgical simulators has opened a new avenue in surgical training. It provides surgical residents and trainees with a safe, trainee-friendly learning environment to practice new instruments, procedures, and skills before operating on actual patients [1]. Due to the rapidly changing nature of instruments and laparoscopy's less intuitive techniques/procedures, it is difficult to use the traditional apprentice approach when teaching laparoscopic skills to novices [1]. Thus, many surgical simulators have focused on developing simulation training for laparoscopic surgery [1]. These have included low-tech and high-tech simulators like video-box trainers, organic simulators (on human cadavers and animal models), hybrid trainers, virtual reality (VR) trainers, and augmented reality (AR) simulators [14].

Video-box trainers resemble traditional box trainers in that they provide a box and holes for trocar insertion and various laparoscopic tasks, but also a camera projected on a monitor for the trainee [14]. While they can help practice hand-eye coordination skills and particular laparoscopic tasks, they need more objective expert feedback and focus only on specific tasks/techniques rather than an entire procedure [14]. They require the presence of an expert to assess the performance of a trainee, which is only sometimes available. The FLS uses the McGill Inanimate System for Training and Evaluation of Laparoscopic Skills (MISTELS) system to train novices on the five core laparoscopic tasks as part of its laparoscopic training program [14].

Hybrid trainers, or virtual reality (VR) trainers, integrate video-box simulators with virtual reality to guide a trainee throughout a performance with interactive haptic feedback and feedback metrics without needing an expert surgeon to be present [14]. The user can practice individual skills like suturing, knot-tying, etc. or go through an entire procedure in a realistic computer-generated environment in more advanced simulators [14]. Objective feedback can be in the form of time taken for a particular procedure or the strength of a knot [14]. Several VR trainers for different subspecialties have become available, including LapSim and Lapmentor simulators for laparoscopy [14]. Sometimes, these simulators may require additional time and effort to set up and maintain as they are not portable. However, they train residents to make sound decisions, preparing them for intense operating environments [14].

Finally, augmented reality (AR) trainers, which overlay computer-generated information into the user's field of view, connect the virtual world to the real world [14]. Some of the approaches covered by AR simulators include overlaying computer graphics on anatomical structures, mapping instrument paths during a procedure, creating a realistic training environment that involves real instruments interacting with actual artifacts in the surgical environment, and providing objective force, motion, and haptic feedback without the need of an expert observing the performance in real-time [14].

The current implementation of our Pediatric Laparoscopic Surgical Simulator project is an augmented reality (AR) simulator, overlaying the surgical environment in the box trainer with computer-generated information to guide the user through a laparoscopic task, like the peg transfer task. Currently, thresholds from sensory information regarding force, velocity, and acceleration of movement are used to assess trainee performance. Our current focus is to enhance the AR simulator by adding more advanced laparoscopic tasks and integrating it with powerful machine learning/data processing algorithms and an interactive user interface to enable it to recognize surgical gestures and classify a user's performance based on accurately collected expert data.

2.2. Machine Learning and Surgical Simulation

Current literature on laparoscopic surgical simulators has focused on applying artificial intelligence (AI) to surgical simulators. AI aims to mimic human intelligence by learning to predict, classify, and learn a particular task to make decisions [15]. AI can enhance surgical simulators today by assessing a trainee's performance, providing more personalized feedback, and enhancing the visualization of the surgical environment itself [15]. Among high costs and long-term maintenance, current VR simulators like LapSim and AR simulators like ProMIS present other limitations, like insufficient metrics/performance criteria to assess trainees [16]. For instance, the ProMIS AR laparoscopic simulator uses "time of performance," "path length," and "smoothness of motion" to assess trainee performance [16].

On the other hand, the LapSim simulator uses "time of performance," "tissue damage," and "path length" to assess trainee performance [16]. "Time of performance" cannot be the most important criterion with which to assess trainees, especially since the primary area of concern is often whether the trainee has used the correct technique and tied a knot properly [16]. Most current simulators do not accurately assess specific surgical techniques, compare a trainee's performance to an expert's performance and provide constructive feedback that the user can understand or implement [17]. Instead, they assume agreed-upon minimum threshold values for completion time, path length, collisions, force, or velocity to assess a user's performance [17].

Machine learning can evaluate performance more accurately and provide more personalized feedback to the user. For instance, machine learning algorithms can be trained to recognize patterns of movement and behaviour in novice and expert performers to provide more detailed feedback to the user. In this way, incorporating machine learning into our simulator will provide more instructional and informative feedback to the user, increasing the educational value and usefulness of the simulator itself.

There have been several AI-related applications in surgical simulators in recent years [15]. A group at McGill University developed a machine learning algorithm that classified the skill levels of surgeons during a brain tumour resection task and provided detailed feedback [15]. This was done by getting machine learning algorithms to select important performance metrics from an expert-defined list and use these to distinguish between the skill levels of surgeons in a virtual reality simulator [15]. The algorithms could select a novel list of performance metrics and achieve high classification accuracies when classifying trainee performances along training levels [15]. However, the challenges and problems introduced by applying AI and machine learning to surgical simulation training must be addressed. For one, the lack of valid and objective performance metrics for an algorithm to use, and another, the inability of the algorithm to accurately correlate between a trainee's performance on a simulator and in the operating room [15]. In addition, these algorithms may not consider the variety of methods and techniques trainees can use to achieve a particular goal. Potential solutions to these problems could be to divide a procedure into sub-tasks and obtain surgeon-led consensus on evaluation metrics in laparoscopy.

We aim to integrate our current AR pediatric laparoscopic surgical simulator with machine learning algorithms to 1) classify individual gestures or sub-tasks within a surgical procedure (like the peg transfer and suturing tasks) and 2) evaluate a trainee's performance and compare them to an expert's performance. Our conversation with pediatric surgeons Dr. Ahmed Nasr and Dr. Georges Azzie on September 27th, 2023, focused on how the machine learning algorithms that we will develop can assess a trainee's success in completing each sub-task of a procedure by evaluating their smoothness of movement, patterns of motion, and application of force. Each trainee's performance will be compared against the performances of actual, standard, expert data we have collected. Our methodology regarding our machine learning approach is explained in Section 6, our Methodology section.

3. Project Objective

The last iteration of the project focused on implementing a functioning box simulator equipped with proper sensors to measure the characteristics of a surgeon's hand movement and force. The simulator was interfaced with augmented reality to provide simple but overly mathematical feedback to the user through warnings and detailed graphs.

The primary goal of this capstone project is to develop a user-friendly training device for pediatric laparoscopic surgery, integrating an embedded system for real-time guidance and feedback. This iteration aims to reduce the reliance on expert surgical mentors, providing trainees with a versatile and safe platform to improve their surgical skills independently while comparing their performance to professional surgeons. Specific, measurable, functional, and non-functional criteria will be employed to measure progress effectively. Functionally, the device's sensors must accurately track intricate hand movements and measure applied forces on the training platform. This multifaceted sensor system will facilitate real-time feedback through an augmented reality interface to enhance the trainee's learning experience. However, the non-functional criteria will cover factors related to the system's back and front end. The backend evaluates data pipelines, signal processing, and machine learning model validation. The front end assesses the system interface's responsiveness and robustness in delivering consistent feedback, including labelled videos highlighting areas for improvement. A significant project objective is to enhance the existing training setup by integrating new hardware components and then building efficient data pipelines to process data from these integrated sensors and feed it to machine learning models. Lastly, the project's final milestone includes presenting this data through augmented reality to convey critical information and compare the trainee's performance to benchmarks supported by machine learning models. This project signifies a commitment to advancing pediatric laparoscopic surgical training by combining technological innovation and education, creating a transformative tool with significant potential to enhance surgical skills among trainees.

The design of this project will be executed in consultation with our supervisor, Dr. Carlos Rossa, as well as pediatric surgeons from CHEO and the SickKids Hospital in Toronto, Dr. Ahmed Nasr, and Dr. Georges Azzie.

4. Relevance to Degree Program

All members of the team - Atallah, Esraa, Huda, and Youssef - are currently in their final year of their undergraduate degree program in Biomedical and Electrical Engineering. The degree has equipped us with a shared foundational knowledge and skill set essential for our collaborative effort. While each member brings unique strengths and expertise to the project, we all share a solid academic background, ensuring that our overall project contributions will be closely aligned with our studies and objectives.

Atallah's academic journey has given him a deep understanding of concepts such as project design, biomedical instrumentation, digital and analog electrical circuits, and various programming languages. All these fundamental concepts come together to build his pivotal role in the project, where he will focus on enhancing the platform design, upgrading its instrumentation, and building the system data pipelines. His hardware, software, and electrical academic background equip him with the skills essential to the project.

Esraa will utilize her academic knowledge to give her the essential skills and ability to effectively contribute to gesture recognition of laparoscopic tasks. Her task will be accomplished using deep learning or deep convolutional networks, which will extract robust features from real-time data, and help provide several kinds of guidance according to the object states in training, to enable easily understandable real-time feedback.

Huda, throughout her degree, alongside her course work, has worked on several projects related to biomedical engineering in academics, research, and industry. Throughout these projects, she has gained experience in image processing, biomedical imaging, sensor analysis, software development, and project management. Huda's primary role in this project will consist of consolidating the machine learning aspects of the project (the performance assessment and gesture classification algorithms) with a powerful, interactive user interface (UI) that will guide and assess a trainee throughout their performance. She will also ensure that the laparoscopic tasks added to the project, such as the ring transfer and extracorporeal and intracorporeal suturing tasks, align with the Fundamentals of Laparoscopic Surgery (FLS) requirements. This will ensure that the laparoscopic surgical simulator functions correctly to give the user interactive feedback, as the performance assessment and gesture classification algorithms provide.

Youssef's degree has afforded him comprehensive exposure to hardware/software development, electrical engineering, and the intricacies of biomedical engineering. Beyond his academic studies, Youssef has garnered hands-on experience in medical imaging research, harnessing the power of deep learning. He has also honed his skills as a data science intern, adeptly utilizing machine learning and Python. Youssef's combined expertise will be beneficial as he works on developing the laparoscopic training simulator. His primary focus will be signal processing and utilizing machine learning for classification purposes. Leveraging his deep-rooted knowledge in biomedical engineering and data science, Youssef is poised to develop a robust signal classification algorithm. This algorithm will adeptly process simulation data to assess trainee performance accurately. Regarding signal processing, Youssef will adequately cleanse and standardize raw sensor data, structuring it into data frames and saving them as CSV files. This streamlined data will then be fed into the classification algorithm, offering insightful evaluations of trainee performance. Youssef's diverse techniques and methodologies during his studies and work serve as the foundation for his approach, promising users of the training simulator clarity and precision in results.

5. Skills and Expertise

Our project is structured around four primary aspects: *hardware development improvements*, *signal processing and classification*, *gesture recognition*, and *user interface (UI) enhancements*. Drawing upon the engineering and design skills we have cultivated at Carleton University, complemented by our co-op work experiences, our team is poised to execute these tasks proficiently.

As a Digital Hardware Co-op with deep expertise in embedded systems, Atallah's background plays a critical role in integrating new sensors. His skills in interfacing sensors with microcontrollers ensure precise data collection. As an Undergraduate Research Assistant, he excelled in optimizing data pipelines for complex CNN models in medical imaging. Atallah's skill in constructing efficient data pipelines, refined through academic and professional experiences, is vital for effectively managing data flow and processing. His proficiency in sensor integration, platform instrumentation, and data pipeline optimization is pivotal for hardware improvements with precision and excellence.

Esraa will leverage her grounding in biomedical and electrical engineering to harness the power of deep learning. Her role involves extracting pivotal features from real-time data, a crucial step toward achieving accurate gesture recognition. Gesture recognition will undoubtedly boost the simulator's training efficacy.

Huda will combine her biomedical, electrical engineering, and software development knowledge to create an interactive user interface (UI). Her vision also encompasses integrating advanced laparoscopic tasks, such as the extracorporeal and intracorporeal suturing tasks, into the simulator's existing setup.

With his biomedical and electrical engineering studies and a robust background in data science and software development, Youssef will be responsible for signal processing. He will further utilize Machine Learning algorithms for signal classification, aiming to enhance the trainee experience by providing constructive feedback that can serve as a blueprint for performance improvement.

With this diverse skill set, our team can handle individual responsibilities and provide collaborative support when required. We are confident in our ability to deliver on the project's expectations.

6. Methodology

6.1. Hardware Improvements

After conducting comprehensive testing and validating the project setup from the second iteration, several key issues were identified within the overall design. These issues included stability concerns, inaccuracies in readings, and inadequate housing for the sensors. Therefore, this iteration's primary objective is to address these concerns by redesigning the current platform and incorporating additional force sensors.

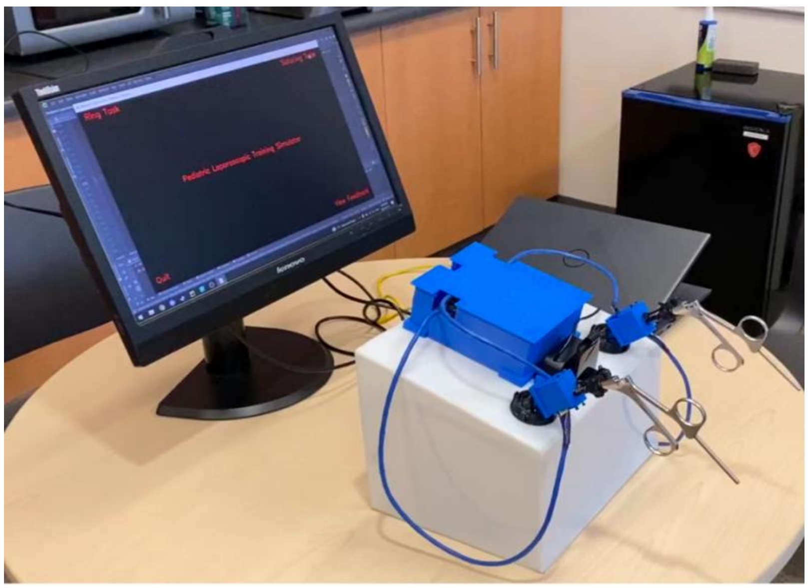

Figure 5: Current setup for the laparoscopic surgery trainer.

6.1.1. Force Sensors and Platform Redesign

For the force sensors, the current design allows the system to measure only the downward applied force by placing FC22-31 0000 0100-L at the bottom of the platform, as shown in Figure 6.

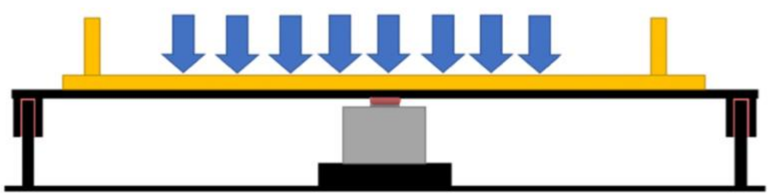

Figure 6: Current platform design with force sensor.

The sensor has a wide range of 0 to 100 ft-lb of force that can be detected [18]. The sensor output is amplified by AD620 operational amplifiers to have an output ranging from 0 – 5V, providing a higher resolution when converting the signal from analog to digital. A second force sensor will be placed to improve the current accuracy of the downward force by averaging two readings. Furthermore, two sensors will be added with an inverted configuration to collect upward forces. This will highlight the forces applied in both directions, which in real-world applications could damage and tear the patient's tissues in surgery.

To strengthen platform stability, a comprehensive redesign has been undertaken using Fusion 360 Computer-Aided Design (CAD) software. This redesign employs advanced CAD techniques to refine the platform's structural integrity. The primary objective of this redesign is to eliminate platform instability and reduce dependency on adhesives for stabilizing different procedural platforms, which may cause damage when they are swapped. Additionally, within this redesign, new space will be allocated for integrating new force sensors, improving the platform's capacity to gather precise data and overall performance.

6.1.2. Embedded System

The existing microcontroller, Arduino Mega 2560 Rev 3, has been replaced with an Arduino Nano Rev 3. This strategic transition was motivated by the imperative to maintain the existing level of functionality while concurrently achieving a substantial reduction in the physical footprint occupied by the microcontroller. This space will be occupied by a mounted screen and a compact computer to achieve a truly portable design. The data pipelines are essential for feeding data to the computer where the Python application runs to incorporate augmented reality experiences. Therefore, fast serial communication between the microcontroller and the computer is much needed. This can be achieved using a fast serial communication protocol such as I2C between the ends [19].

Clear and concise schematics are needed for a seamless hardware upgrade of the system. This requirement can be met by using KiCad software to develop new schematics and incorporate new components like force sensors and operational amplifiers. This simplifies the process and makes building and working with intricate circuitry easier while maintaining the system's functionality within spatial constraints.

6.2. Signal Processing and Classification

6.2.1. Sensor Data Collection and Initial Processing

During our simulator's most recent iteration, real-time data collected during simulations is handled by an Arduino microcontroller on our end. The fundamental nature of the Arduino makes it possible to acquire data from each sensor via the use of a signal controller in a seamless manner. Therefore, this produces a complete dataset that includes parameters such as rotation, position, speed, acceleration, and force. More classification is required to differentiate between the many measures each metric represents.

Text files are used to store the raw data that is collected from the various sensors. Thus, a Python script was developed that uses the 'tkinter' library so that the data processing can be done more quickly. This script displays a dialogue window, which allows users to pick the appropriate text file containing sensor data. After the selection, the data is cleaned, organized into a DataFrame, and saved as a CSV file using the 'pandas' library. The visualization of data and its preparation for classification algorithms may benefit from this automation's acceleration.

6.2.2. Enhancing Training Experience through Machine Learning

A pivotal aspect of this project is enhancing the trainee experience. In order to achieve this goal, we are in the process of developing a machine-learning classification model. This model will categorize trainee-generated signals into one of three proficiency levels: "Novice," "Intermediate," or "Expert." The classification is achieved by comparing the trainee's signal against a benchmark 'expert' signal, which is the model's training data.

Considering the input provided by the surgeons, we are emphasizing our feedback mechanism. One strategy entails segmenting each task into smaller and more specific subtasks, providing trainees with detailed insights into areas of improvement. For instance, the 'ring transfer' task can be broken down into five distinct subtasks:

1. *Retrieving the ring from the initial peg.*
2. *Maneuvering the ring to the task area's center.*
3. *Transferring the peg between graspers.*
4. *Relocating the ring to the designated peg.*
5. *Securing the ring onto the destination peg.*

Given this segmentation, adopting a standardization approach from the 'sklearn' library is imperative, ensuring uniformity in data points for each subtask across all trainees.

6.2.3. Dynamic Time Warping for Segment Matching

We will employ the Dynamic Time Warping (DTW) algorithm, available through the 'fastdtw' library, to identify and extract segments from trainee signals that align with expert signal segments. The 'euclidean' distance metric from the 'scipy' library facilitates this comparison. DTW stands out as a time-series similarity measure, adept at countering the effects of temporal shifts and distortions. It achieves this by enabling elastic adjustments to time series, ensuring the detection of congruent shapes even if they manifest in differing phases [20].

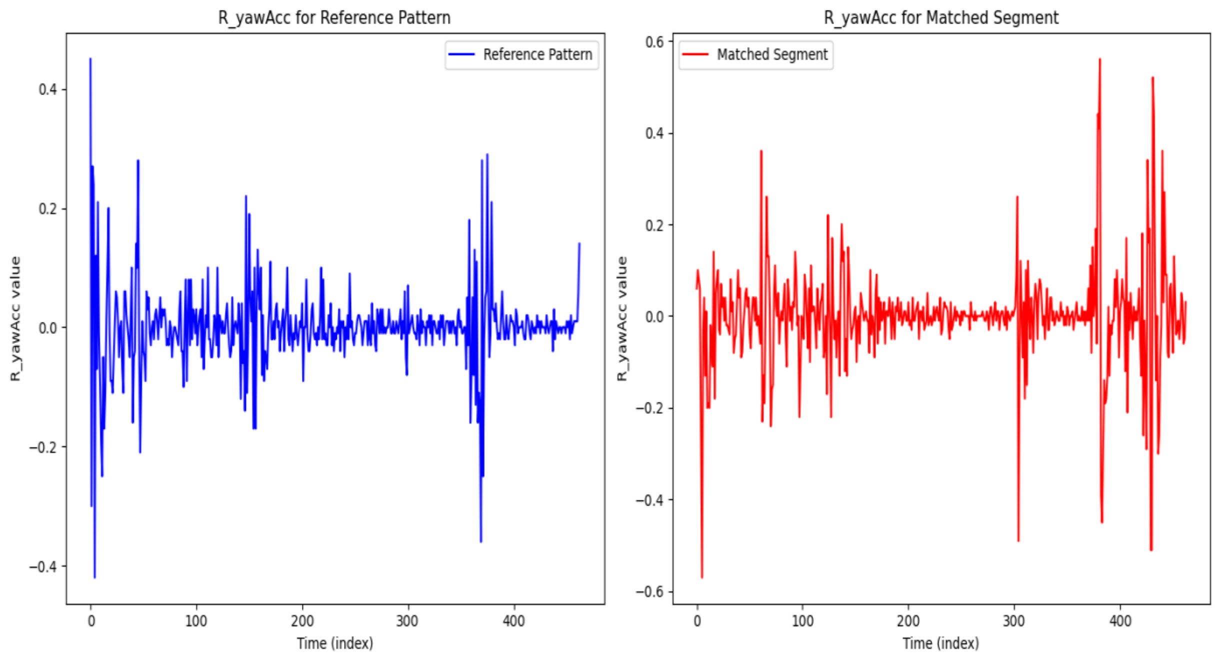

Figure 7: Comparative Analysis of ‘R_yawAcc’ signals: Reference Pattern vs. Matched Segment using DTW.

DTW's unique approach to time series comparison is essential in the context of our project. It guarantees that trainee movements are recognized and evaluated accurately, as Figure 7 shows, even if they are somewhat out of rhythm with expert maneuvers, delivering a fair and meaningful assessment. By combining these aspects, the classification algorithm promises to be a robust tool capable of providing informative feedback on trainees' performance and areas for potential improvement.

6.3. Object Recognition

Many surgery complications are caused by inadequate individual team performance, for which poor training and feedback play an essential role [21]. However, research indicates that half of the adverse surgical circumstances are preventable. One improvement could be objective feedback through an object detection approach providing real-time automated surgical video analysis. Hence, it is a way to evaluate the trainee's skills objectively and efficiently.

Deep learning-based approaches have two types: one-stage detectors and two-stage detectors. In two-stage detectors, using deep features, the object detection method is applied to locate and detect the developed semantic objects in an image [22]. Then, these components are used for the classification and bounding box regression for the object candidate. Also, it will achieve high detection accuracy [22].

On the other hand, bounding boxes are predicted over the images in one-stage detectors without the region proposal step [22]. This process does not consume time and can be used in real-time devices. Hence, for our design, our model's performance will rely on the object recognition capability of the selected detection method and implementations of the different state-of-the-art techniques that propose several efficient solutions and new directions as the plans to provide an overview of how other deep learning models are used in generic object detection, specific object detection, and object tracking [22].

Therefore, this task has two objectives: 1) The object modelling for the training task and 2) Object detection using deep learning to support real-time application of the simulator.

6.3.1. Object Modelling

Object modelling in machine learning refers to characterizing and describing objects to allow machine learning algorithms to understand and work with them. Object modelling involves determining a structured representation of objects, usually as attributes. The main objects for this task are the left grasper, right grasper, and the ring states. The object model contains two fundamental attributes for each target object:

- *Location*: to determine the exact pixel coordinates for the grasper.

- *Movement*: Our design considers movement a relationship between the objects and any other object, such as holding the ring together with the left grasper, that indicates a movement of "Ring transfer."

Thus, each target object may have several object movements, as shown in Table 1, and objects such as the ring and the grasper are required to know their movement. However, when objects are represented in semantic modelling along with their semantic attributes and relationships, machines can understand their meaning [23]

The semantic object model offers a method of representing objects in a task by combining movement and object type attributes into a single attribute: location. The advantage of this semantic object technique is the simplification of object state detection, as it will only detect the location of the objects. This simplification can direct to efficient object detection methods.

Table 1: The Objects Classification by Movement and Location.

Gesture Index (R: Right) and (L: Left)	**Objects Movement**	**Jaws (Open or Closed)**
RG0	Ring on peg: Idle state (or hovering)	C
RG1	Right grasper: Moving vertically downwards towards peg on right side of operating table	O/C
RG2	Ring out peg: Positioning ring between the jaws and clasping it	O
RG3	Right pick ring: Moving upwards with clasped ring	O
RG4	Right Carry ring: Moving to center of operating table to meet left grasper	O
RG5	Right carry ring: Hovering with ring between jaws for left grasper to pick	O
RG6	Ring transfer: Holding ring together with left grasper	O
RG7	Right pick ring: Opening jaws to let go of ring	O
RG8	Moving aside	O/C
LG0	Idle state (or hovering)	C
LG1	Left grasper: Moving to center of operating table to meet right grasper	O/C
LG2	Left pick ring: Positioning ring between the jaws	O
LG3	Left pick ring: Clasping ring	O
LG4	Left carry ring: Moving horizontally (straight or diagonally) towards a peg on left side of operating table	O
LG5	Left carry ring: Positioning ring over peg	O
LG6	Ring on peg: Opening jaws and dropping ring through peg	O/C
LG7	Ring on peg: Moving aside after transferring all three rings	O/C

6.3.2. Object detection using deep learning: Single Shot Detection

A single-shot detector is a one-phase detector that predicts multiple classes. In other words, a real-time object detection framework that merges the tasks of object localization and type into a single unified architecture [24]. In this task, after modelling the semantic objects. The primary plan concept is Multiscale Bounding Box Prediction and the training.

6.3.2.1. Multiscale Bounding Box Prediction

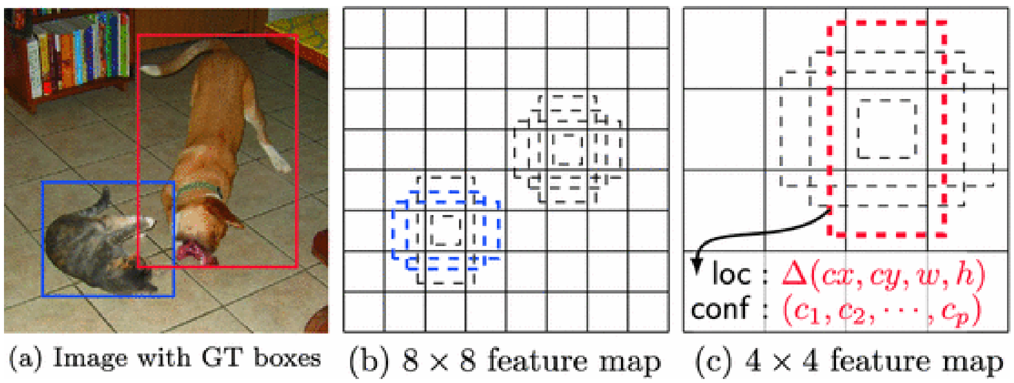

Figure 8: The figure shows SSD framework (a) Image with GT box. (b) 8×8 feature map. (c) 4×4 feature map.[24]

The SSD approach's target output is to predict an object's presence on different scales. This multiscale technique allows SSD to detect objects of various dimensions and positions in the input image. The approach is as follows:

- Input Image and Ground Truth: The SSD only needs an input image with objects to be detected. The object in the image is associated with a ground truth box for each object during training, as shown in Figure 8 (a) [24].
- Convolutional Neural Network (CNN): using CNN to detect objects of different sizes and forms, these boxes are considered at multiple positions on different feature maps of various resolutions (as shown in Figures 8 b and c: 8x8 and 4x4).

- Multiple Fixed Scale Grid Feature Maps: generates multiple fixed-scale grid feature maps and captures segments at various spatial resolutions within the image shown in Figure 8(b) and (c).
- Default Boxes: A collection of default boxes is connected per location on the feature maps and operates as reference templates for object detection.
- Multiscale Bounding Box Prediction: aims to predict objects' existence at multiple scales.
- Final Feature Map: All the feature maps from other scales are compiled into a final feature map containing the predictions for shape offsets, classification scores and attributes for each default box.

6.3.2.2. Training

*Dataset Preparation***:** A training dataset is prepared that contains labelled images. Each image should have ground truth information that needs to be assigned to specific outputs in the fixed set of detector outputs [24].

- The loss function and backpropagation: The loss function generally has object localization and classification components. Represent a loss function quantifying the discrepancy between the model's predictions and the ground truth information.
- Default Box Selection
- Ground Truth Label Conversion: The ground truth information for the training images is converted to correspond to the output format expected by the SSD model.
- Dataset Augmentation: Each training image is randomly sampled to construct a better and more robust model with different input object dimensions and shapes [24].
- Training Iterations: In each iteration, the model processes small batches of images and updates its parameters using a matching optimization algorithm.

- Validation and Thresholding: A threshold is used to select which object detections are proper based on confidence scores. Detections with scores beyond the threshold are retained.

6.4. User Interface Design

The design of the user interface will be implemented using Python's tkinter package, which is a standard interface for a GUI toolkit [25]. This package provides an efficient way for us to implement buttons, display screens, menus, and images that will guide the trainee throughout the execution of their training program. This user interface will be implemented through object-oriented programming, a programming paradigm that defines classes of independent objects with inherited methods and variables but their states [26]. This will allow for code reusability, efficiency, and extensibility and is usually the default programming paradigm for a program of this type and scale.

6.5. Laparoscopic Training Tasks

This project will implement the peg transfer task and the intracorporeal and extracorporeal tasks from the FLS program. While the current implementation of the peg transfer task is set up with three pegs on either side of the board and three rings to transfer, the suturing task has yet to be formally set up in the previous implementation of this project. A durable silicone suturing pad will be sealed to the platform of the box simulator. Materials needed for the suturing task will be 2/0, 3/0 or 4/0 curved suturing needles of the longest available size, like 25 mm or 17 mm needles (for ease of visibility through a camera), as well as two needle drivers, and one pair of endoscopic scissors to perform the task.

7. Project Timetable

A *Gantt chart* is a project management tool visually representing a project's timeline and objectives. It displays tasks on the vertical axis and time on the horizontal axis, enabling team members to visualize the project's progression and discern the interrelation between various subtasks.

Every member has described their responsibilities for the 2023-2024 year and estimated the duration required to complete their tasks. Also, we have set collaborative milestones, such as the final project deliverable, based on contributions from all the team members. Everyone must dedicate at least 8 hours weekly to the project throughout the year. The Gantt chart detailing this can be found attached in Appendix A.

8. Risk Assessment and Mitigation

Considering potential risks and developing mitigation plans is crucial for effective project management. This approach helps the project team to be prepared for uncertainties and enhances the possibilities of project success. Identifying potential issues that could occur during the project is a crucial initial step, such as the change from the Arduino Mega 2560 Rev 3 to the Arduino Nano Rev 3. This change carries potential risks, specifically regarding software compatibility and unexpected hardware adaptation challenges. However, a well-defined plan has been set to manage these circumstances, including comprehensive testing and validation procedures to ensure a smooth transition, thereby reducing the risk of functional disruptions. Other team members have also implemented and thoroughly reviewed a detailed schematic model to minimize errors and ensure the seamless integration of new components. These measures are created to mitigate potential risks to the project timeline and ensure these critical hardware advancements are successfully implemented.

Instability during the training box platform assessment was observed and identified several risks. A platform redesign using Fusion 360 (CAD) software was proposed to address this issue. However, due to potential design compatibility problems, new structural changes and force sensors could result in unexpected issues. To mitigate these risks, the supervisor will conduct design reviews and implement trial-and-error plans to ensure the seamless integration and compatibility of the changes.

Furthermore, storing project information and data is essential to ensure the project's continuity and success. We use cloud services, such as OneDrive for files and documentation, GitHub for software, and Fusion 360 for design backups, to mitigate the risk of data or information loss. However, despite the reliability of these cloud services, there is always a potential risk of data loss. To address this, we will schedule regular backups to ensure redundant storage across multiple locations. Also, automated backup and version control systems will be implemented to minimize the risk of data loss.

9. Special Components and Facilities

As we begin the third iteration of our project, we will use a wide range of specialized tools and components.

1. *3D Modeling & Printing:*

- Modelling Software: We will utilize AutoDesk Fusion 360 for 3D modeling.
- 3D Printer: The DREMEL from Digilab, located in the Biomechatronic lab, will print our designs.
- PLA Filament: Used for 3D printing components, it emulates the physical environment of a pediatric abdomen during laparoscopy.

2. *Sensor Communication & Control*

- Microcontroller: The Arduino Nano Rev 3 will interface with the PMW 3389, MPU 6050, and FC2211-0000-0025-L sensors
- Development Environment: The open-source Arduino IDE ensures seamless sensor communication.

3. *Software Development & Data Processing*

- Python Language: A versatile choice for augmented reality, signal processing, classification algorithms, and gesture recognition. It is also compatible with the Arduino Nano Rev 3 for serial data communication and supports machine and deep learning applications.

4. *Simulator Design & Components*

- AutoCAD: Precision design software for crafting the platform housing diverse laparoscopy tasks.

- Force Sensors (FC2211-0000-0025-L): Vital for tactile feedback simulation during laparoscopic procedures, aiding trainees in honing their touch and dexterity.
- Operational Amplifiers (AD620): Four amplifiers will condition and amplify signals from the force sensors.
- Suturing Equipment: A suturing pad and 26mm needles enable realistic suturing technique practice.
- PWM 3389 and MPU-6050: Essential for the four degrees of movements

5. *Components depend on the approval of additional funding.*

- Mini PC: This acts as the simulator's computing heart, orchestrating software simulations, performance metric recording, and trainee feedback.
- LED Matrix: The matrix gives a realistic representation of the surgical field, while the wires cater to circuitry needs.
- Display & Feedback System: An IPS display, and FOV web camera collectively create an immersive training interface.

With this comprehensive suite, we are poised to deliver a simulator that offers trainees a holistic, realistic, and educative experience.

10. Report Contributions

Table 2: Outline of each member's contribution to the proposal report

Contributor	Section
Atallah Madi	• Introduction • Project Objective • Relevance to Degree Program • Methodology (Hardware Improvements)
Esraa Alaa Aldeen	• Relevance to Degree Program • Methodology (Object Recognition) • Project Timetable • Risk Assessment and Mitigation
Huda Sheikh	• Background • Relevance to Degree Program • Methodology (User Interface and Design Laparoscopic Training Tasks)
Youssef Megahed	• Relevance to Degree Program • Skills and Expertise • Methodology (Signal Processing and Classification) • Special Components and Facilities

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Appendix A (Grantt Chart)