Enabling Surgical Coaching through Artificial Intelligence: Enhancing Mastery with **Tool-Tissue Interaction** Feedback

List of deliverables needed from Lorenz

September 24th, 2025

Project Overview

Problem: Surgical complications are common

Current Limitation: Traditional coaching improves skills, but time and availability are limited

Research Question: Can an AI-based algorithms leverage tool-tissue interaction data to provide automated performance analysis and deliver tailored feedback?

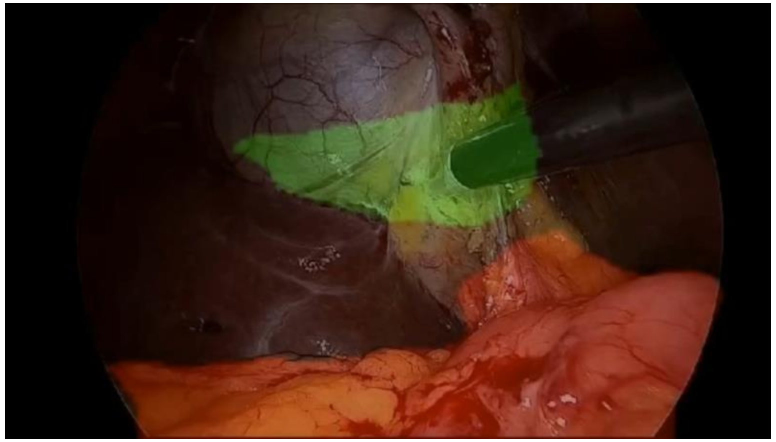
Next Steps in Evaluating Surgical Performance

- Go zone evaluates where is safe based on anatomical structure
- Need to know where surgeon interacts with tissue

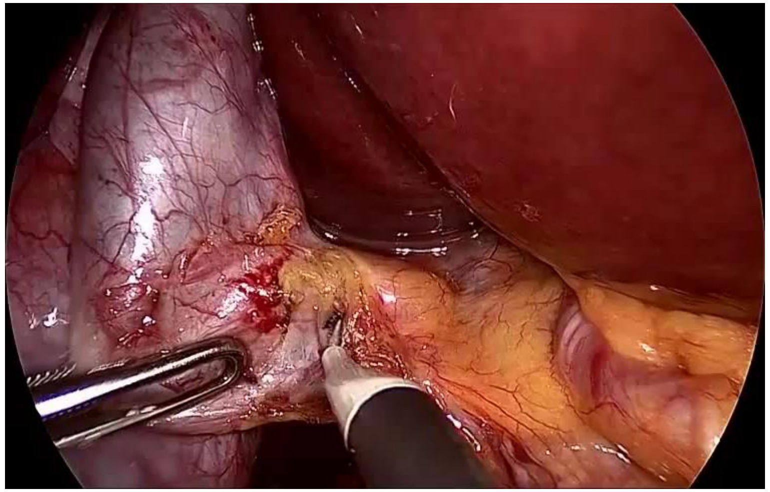
Objective:
Phase I- Develop a model that can detect Tool- Tissue Interactions (TTI)
Phase II- Showing Clinical Utility of the TTI model: External Validation on the an external dataset

Definition of TTI: Every time a surgical tool comes in physical contact with the tissue

Video 1. Go No Go Net in action



Video 2. An example of multiple tool-tissue interaction



Phase I- TTI Model Development

- Verify the metrics reported from the TTI model (accuracy, precision and so on)
- Compute metrics for the two other tasks (interaction type and tool type)

Estimated time of completion: **October 6th**

Phase II- Showing Clinical Utility of the TTI model: External Validation on the Safe Lap Chole+ BDI Dataset

1. **IoU/ Dice Score Calculation**
2. **TTI & GNG Overlap Analysis**
3. **Frame level -----> Interaction Level**
4. **Pixel Level Analysis**
5. **Q10 Extracted Frames**

Project i- IoU/ Dice Score Calculations

Dataset used: 11 Safe Lap Chol+ 6 annotated BDI videos

Comparison Groups: Comparing TTI model predictions (segmentations) with bounding box annotations I did

Estimated time of completion: September 28

Project ii- TTI & GNG overlap analysis

Main Research Question: Can an AI model detect differences in tool–tissue interactions between go and no-go zones across safe and BDI videos?

Dataset used: 11 Safe Lap Choles +11 BDI videos

Models used: TTI Model and GNGNet (SegFormer) overlap

Step 1: Calculate the overlap between TTIs in a specific zone

Step 2: Classify TTIs as either in Go/No Go or (unclear zone) and calculate and average for each video

- Deliverable 1: There is a difference between safe and BDI videos in TTI and GNG overlap

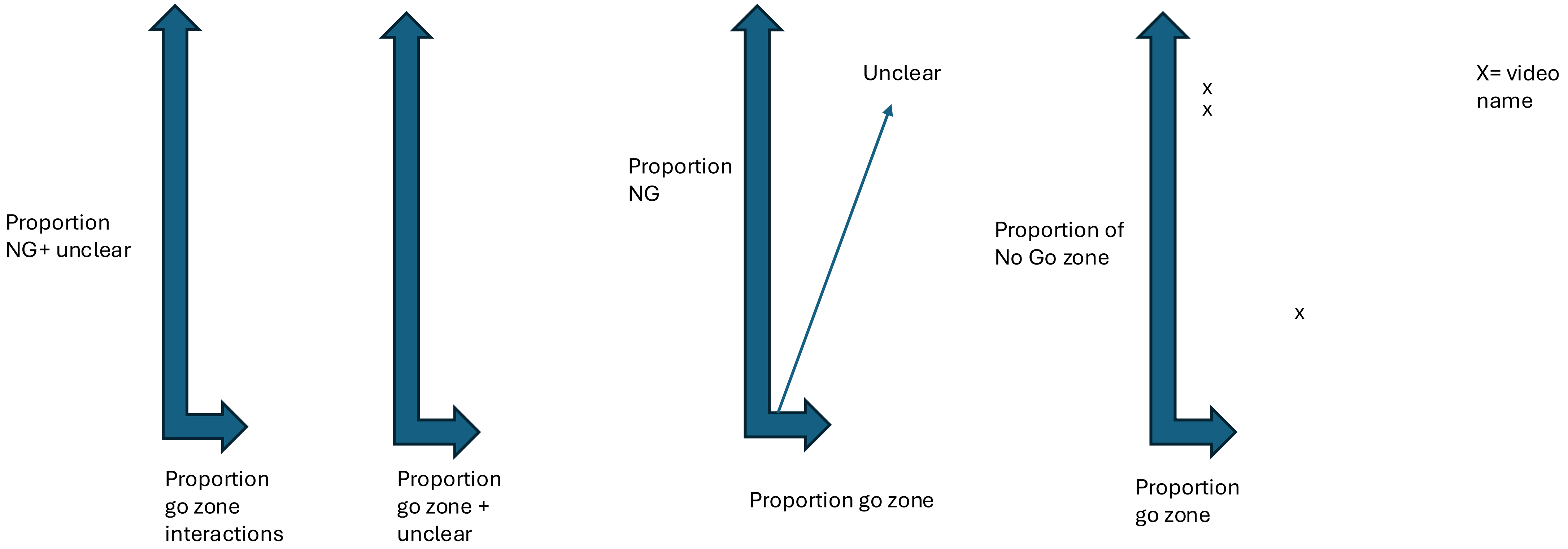
Conclusion (hopefully):

	Average proportion of TTIs in Gozone in all videos	Average proportion of TTIs in No Go zone
Safe Videos	High	Low
BDI	Low	High

Estimated time of completion: October 3rd

Project ii- TTI & GNG overlap analysis

<u>Graphs/visualizations:</u>



Estimated time of completion: October 3rd

Project iii- Shifting from frame to interaction level analysis

<u>Main Research Question:</u> What minimum proportion of frames must be detected within an interaction for it to be classified as a tool–tissue interaction?

Dataset used: 11 Safe Lap Choles

How was the dataset annotated:

- Beginning/ end of interactions + Beginning/ end of no interactions **[Temporal Determination]**
- Interaction site (bounding box)
- Tool type performing the interaction/ no interaction

Analysis needed:

- Use PR curve to calculate the threshold as to what % of frames need to be detected for that action to be classified as an interaction detected (reducing FNs is more important than FPs)
- Perform the analysis (regardless of interaction type/tool type) at the beginning and then add tool type and interaction type

  - **Deliverable 1:** Define a detected interaction as x% of frames detected within that interaction
  - **Deliverable 2:** Create a normal distribution curve of the interactions detected at different thresholds to justify the threshold we choose for our paper

Estimated Time of Completion= October 3rd

Project iv- Pixel Level Analysis

Dataset used: 11 Safe Lap Chol+ 6 annotated BDI videos

Comparison Groups: Comparing TTI model predictions (segmentations) with bounding box annotation

Analysis:

- Look at a single frame where there was a Ground Truth TTI and AI TTI and create the following table for me

	AI-predicted Pixel		
Ground Truth Pixel		TTI	No TTI
	TTI		
	No TTI		

\+ PR Curve

Estimated time of completion: October 3rd

Project v- Q10 extracted frames

A) ASSUMING THE GNGNet **works** well

<u>Main Research Question:</u> Can AI (TTI + GNGNet) predict safe and unsafe interactions in a manner comparable to human ground-truth annotations?

Run TTI + GNGNet on extracted frames from Master List and automatically assign TTIs to either Go/No-Go Zone

Next Steps:

- What percentage overlap between tool–tissue interaction (TTI) and the Go/No-Go zone is required for a TTI to be classified within that respective zone? (Either TTI in Go or TTI in No-Go zone, no TTI in background)

Estimated Time of Completion= October 3rd

Once Phase I and Phase II metrics are computed

- Visualize the annotations and how many retract and grab were annotated, what tools were annotated and so on (Ziyad to send Lorenz JSON files of the ground truth annotations)

<u>End result:</u> Application of TTI+ GNGNet Model to Safe Lap Chole Videos (do the same for BDI videos

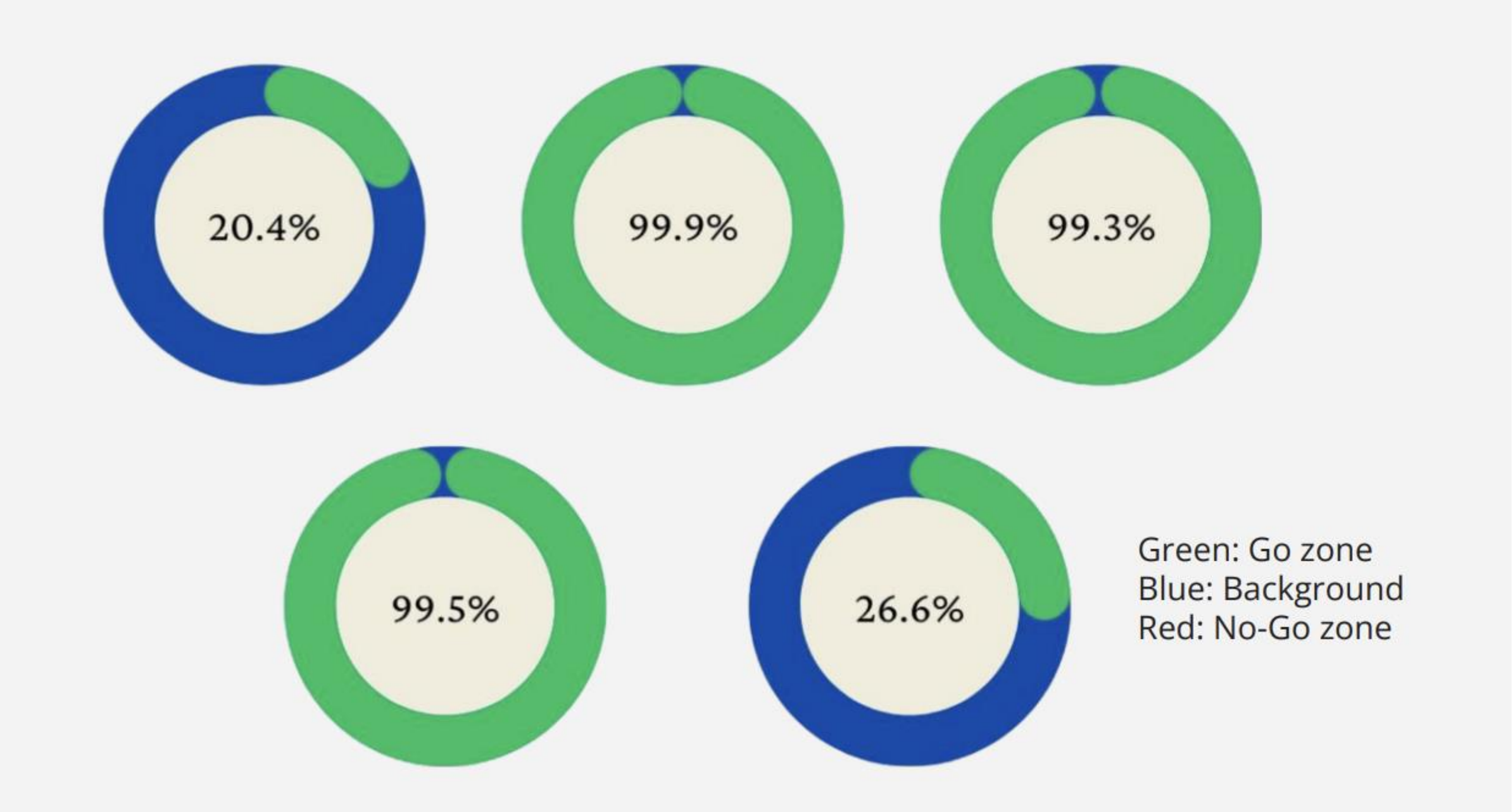


Figure x. Average percentage of TTI occurrence in Go, No-Go, Background zones in eleven safe lap chole videos
Compare them with BDI videos (hopefully there is some significance)