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Robust Digitization of Perioperative Surgical Flowsheets From Low and Middle Income Countries

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5/2/2025

Project Team

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Background

Purpose

- Enhance a software package to extract data from paper charts
  - Store in database to facilitate improvements in care
- Python Package = *ChartExtractor*
- Phone Application = *EQUAL Anesthesia*

Motivation

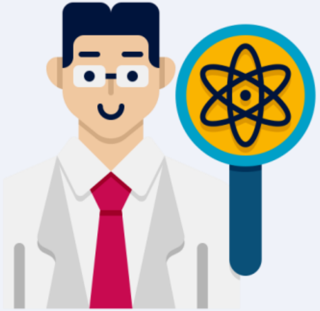
- Low and Middle Income Countries (LMICs) use paper charts
- Paper charts limit data availability
- Lack of quality improvement & real-time insights hinder developments in care
    - Contributes to worse surgical outcomes in LMICs

Sponsors

UVA Anesthesiology Department & Funded by the Center for Global Inquiry and Innovation

Stakeholders

VMED

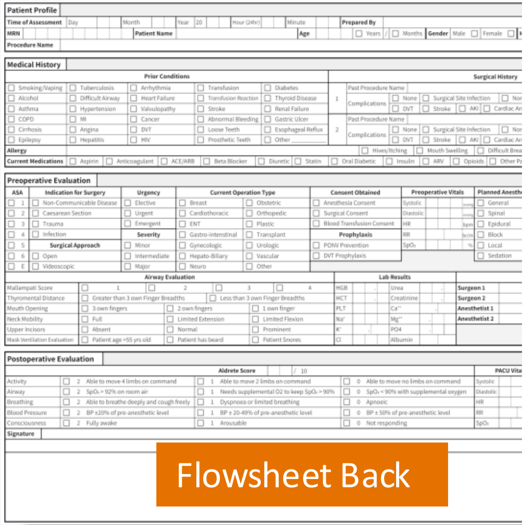


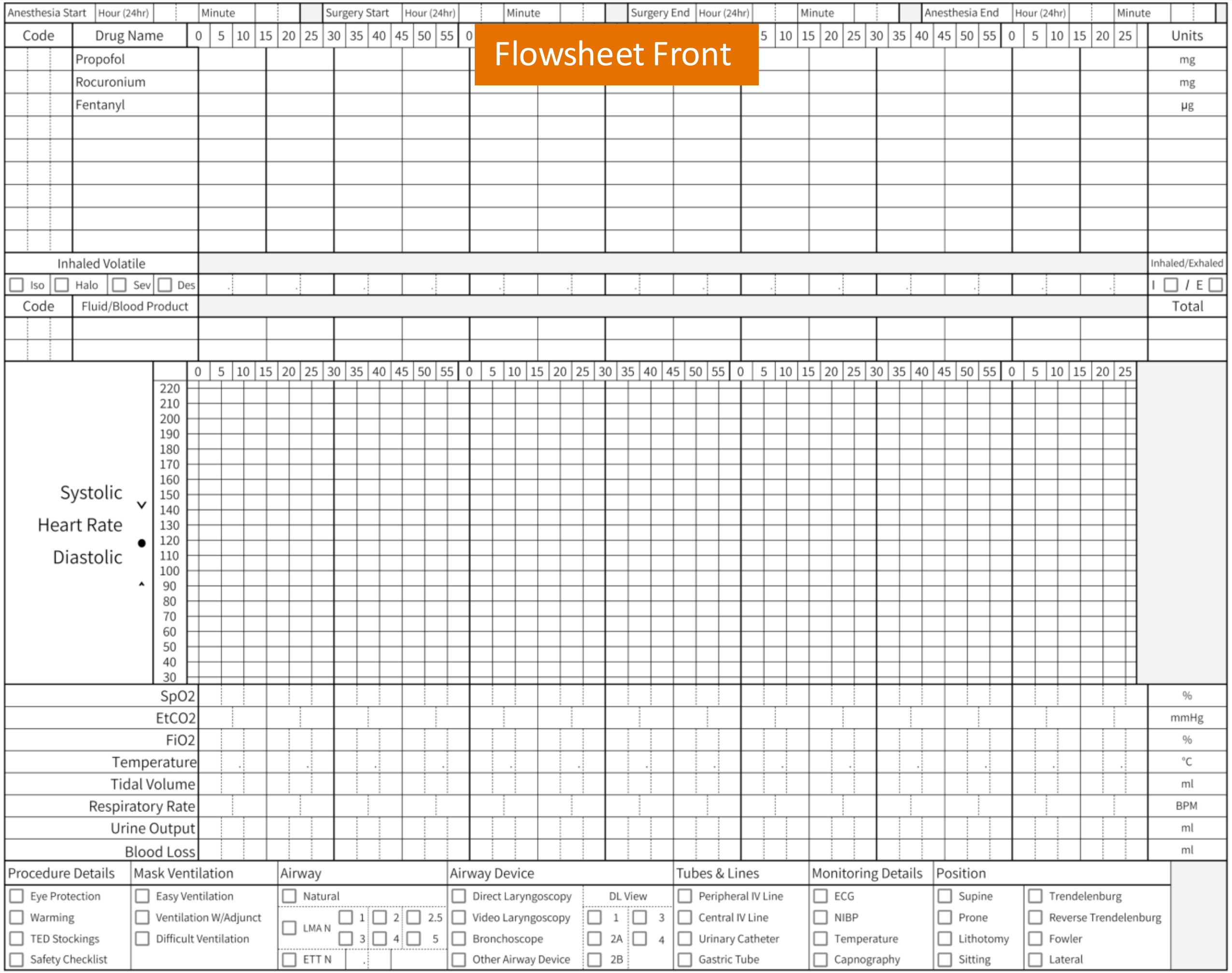
Previous Work

- Standardized anesthesia flowsheet was created
- Only linear transformations used for chart reformatting
- Single digit detections prevented proper vitals extraction
- YOLO detection models were good yet large & slow

Data

Data





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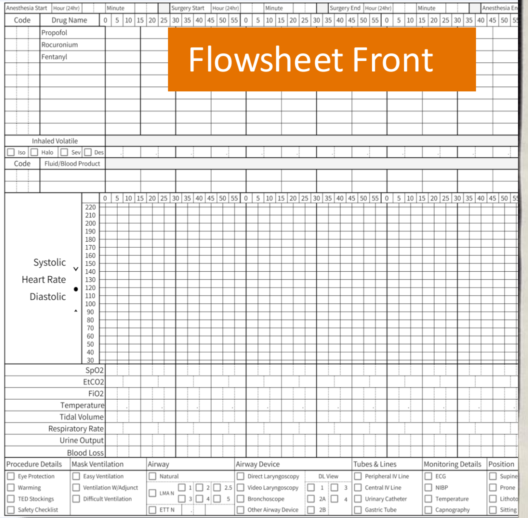
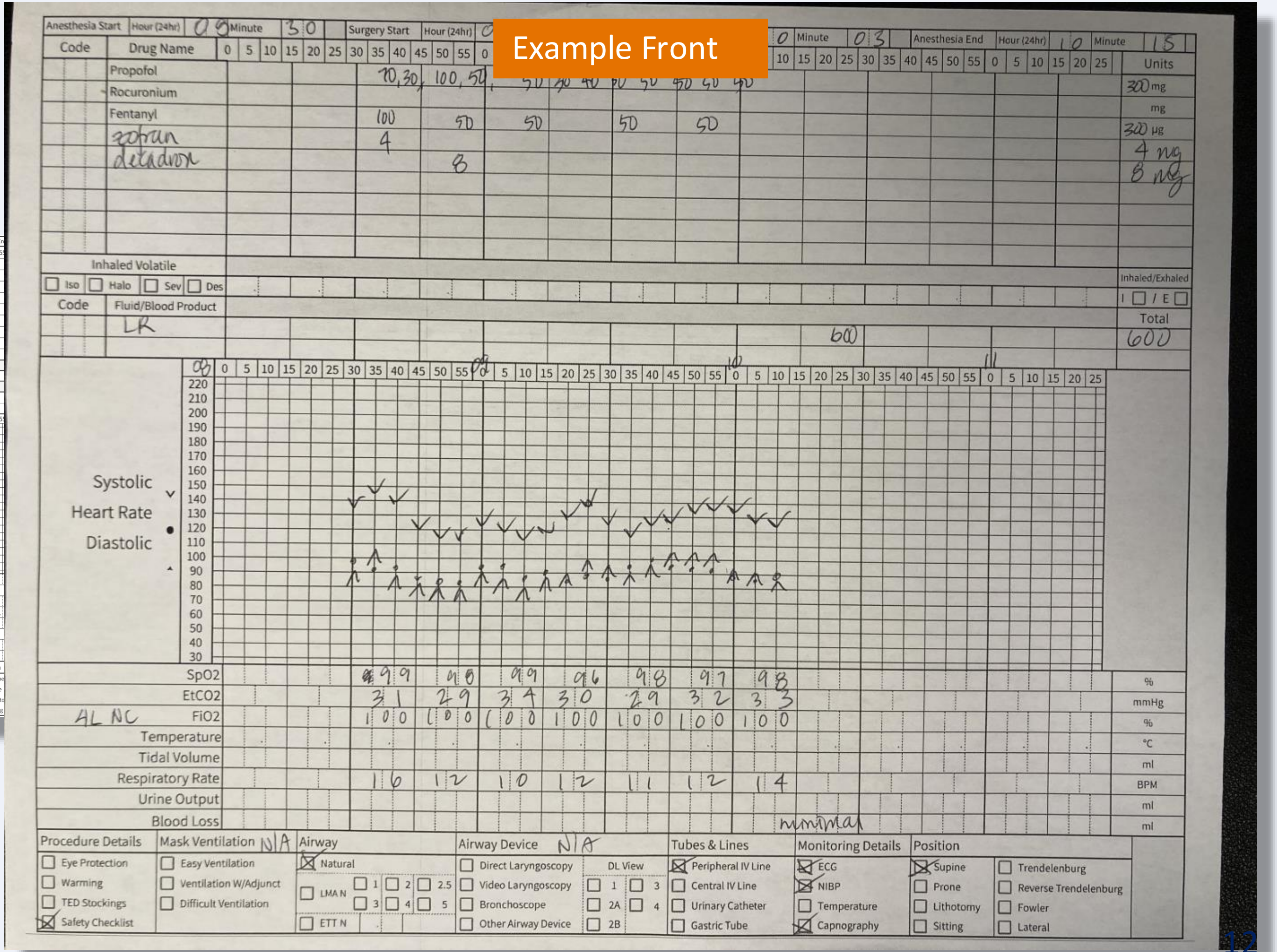
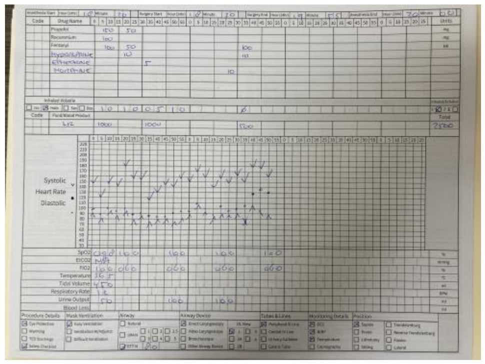
Data

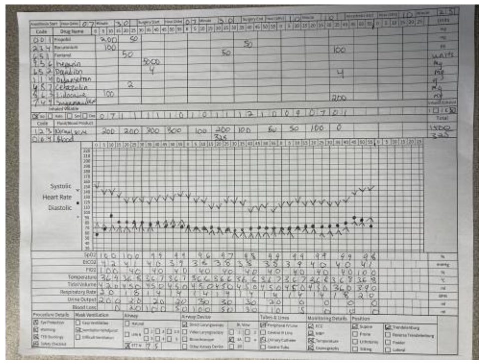

Flowsheet Front
Anesthesia Start
Code
Drug Name
Propofol
Rocuronium
Fentanyl
Inhaled Volatile
Fluid/Blood Product
Systolic
Heart Rate
Diastolic
SpO2
EtCO2
FiO2
Temperature
Tidal Volume
Respiratory Rate
Urine Output
Blood Loss

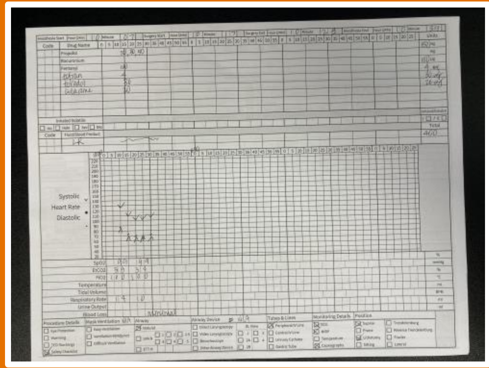

Example Front
Anesthesia Start
Surgery Start
Anesthesia End
Code
Drug Name
Propofol
Rocuronium
Fentanyl
Inhaled Volatile
Fluid/Blood Product
Systolic
Heart Rate
Diastolic
SpO2
EtCO2
FiO2
Temperature
Tidal Volume
Respiratory Rate
Urine Output
Blood Loss
Procedure Details
Mask Ventilation
Airway
Airway Device
Tubes & Lines
Monitoring Details
Position

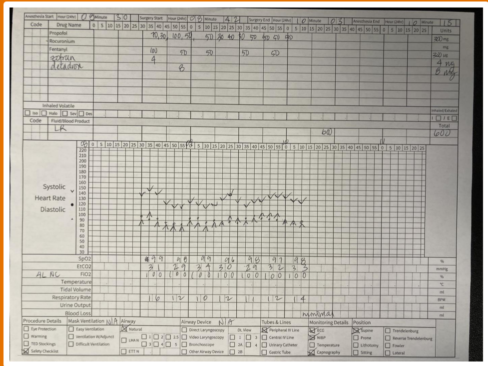
Assumptions & Limitations

- **Assumption:** Data Quality
- **Limitation:** Data Quantity









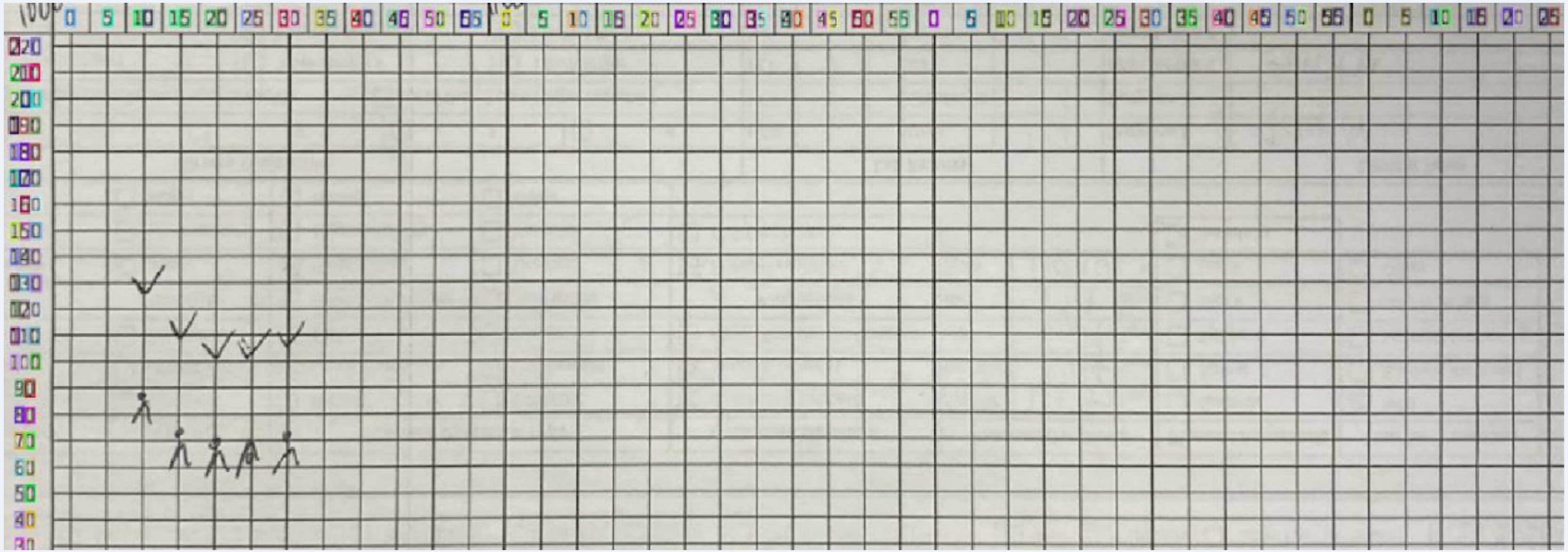
Contributions

Contributions

- Meaning extracted from vital sign chart
- Lightweight, faster, and more accurate object detection models
- Robust image registration techniques

Determining Heart Rate and Blood Pressure

The Problem:

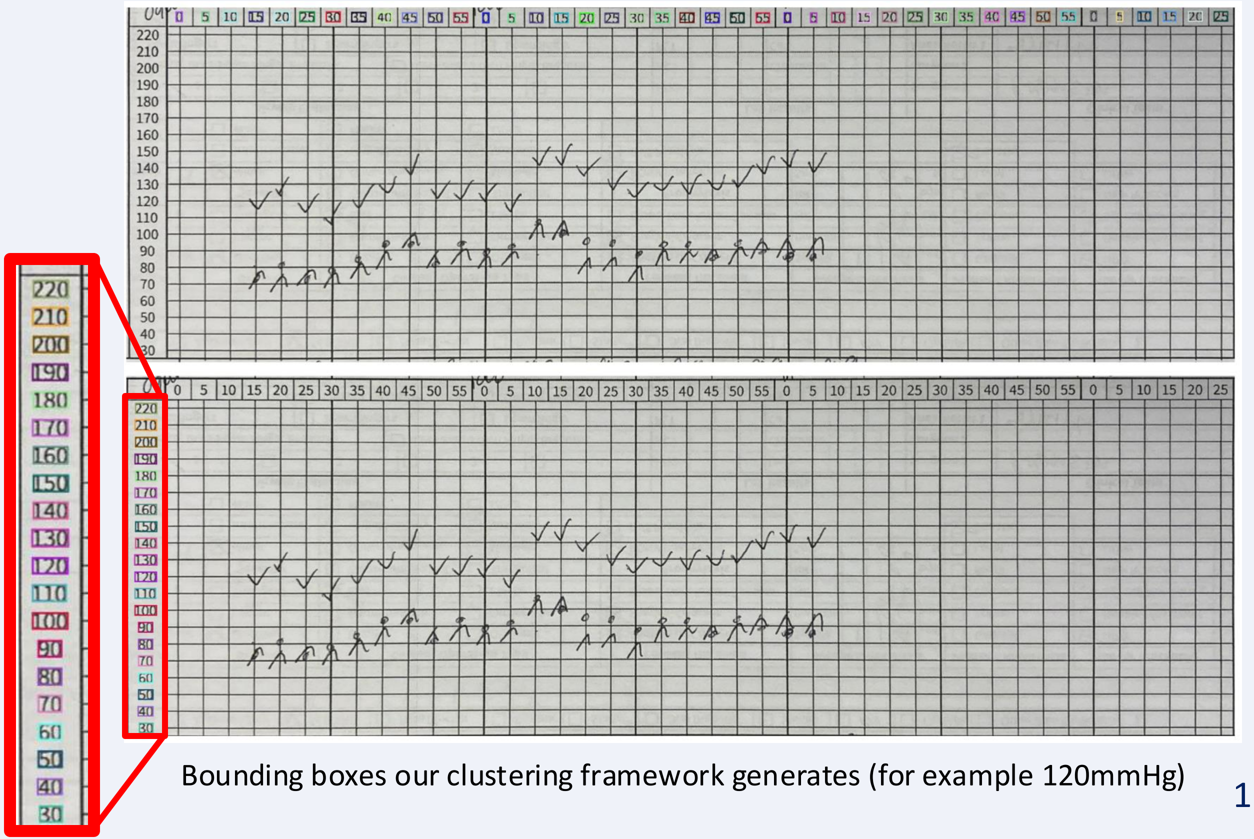


Bounding boxes YOLO object detection model gives are individual digits

Determining Heart Rate and Blood Pressure

The Solution:

- Use maximum density to dynamically separate X and Y axes
- Group digits using various clustering methods



Bounding boxes our clustering framework generates (for example 120mmHg)

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Performance of Heart Rate and Blood Pressure Determination

Clustering Method	W/O Erroneous Bounding Boxes		W/ Erroneous Bounding Boxes	
	Time Axis mAP	Number Axis mAP	Time Axis mAP	Number Axis mAP
K-Means	1.0	1.0	0.77	0.99
DBScan	1.0	1.0	0.81	0.99
Agglomerative	1.0	1.0	0.79	0.99

Mean Average Precision 50-95 (mAP) with and without introducing 2.5% bounding boxes randomly on the axis and removing 2.5% correct bounding boxes from axis

Retraining Object Detection Models

The Problem:

- Memory-intensive YOLO object detection models are expensive to host and run on the cloud
  - Can't embed models in *EQUAL Anesthesia* App
  - Mobile app requires internet connection to do object detection
- Larger object detection models are slow

Previous size and runtime:

- **220MB**
- **131 seconds**

Retraining Object Detection Models

The Solution:

- Trained and hyperparameter tuned 7 YOLO (nano) models -- the smallest available -- on Rivanna Computing Cluster

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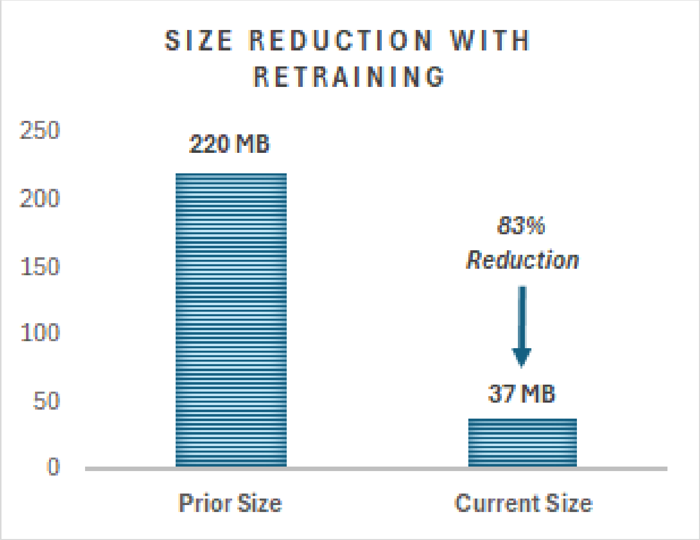
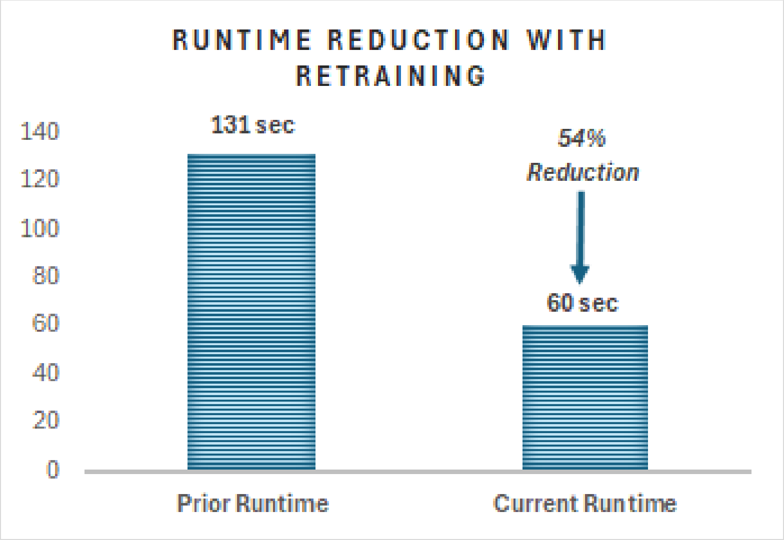
Retraining Object Detection Models

The Performance:





Improved or didn't change object detection **accuracy**

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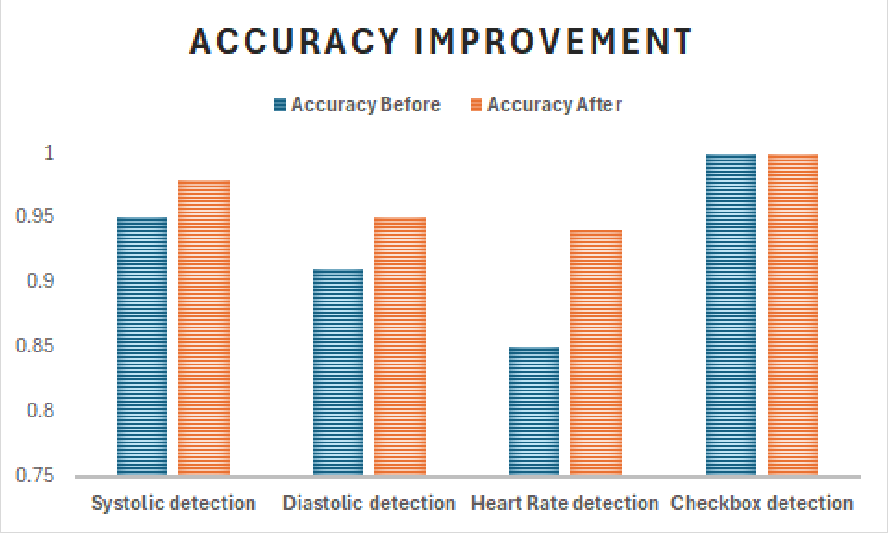
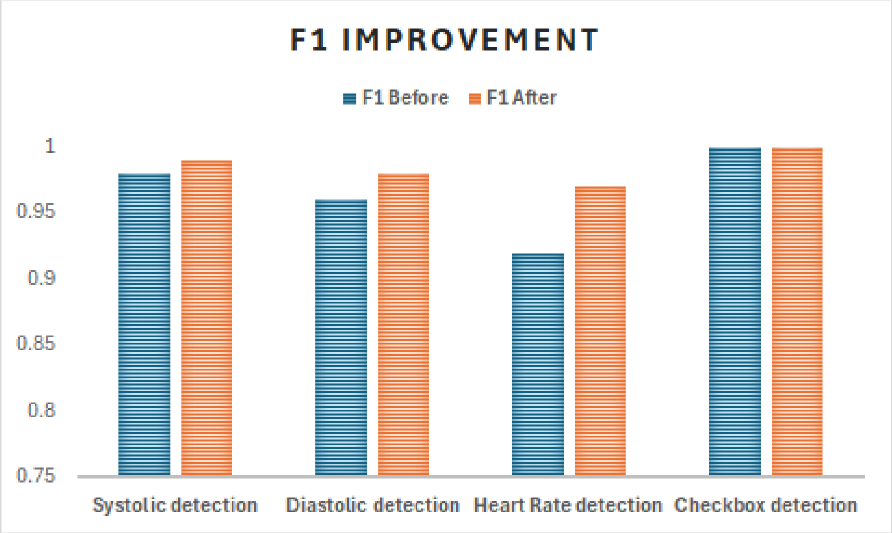
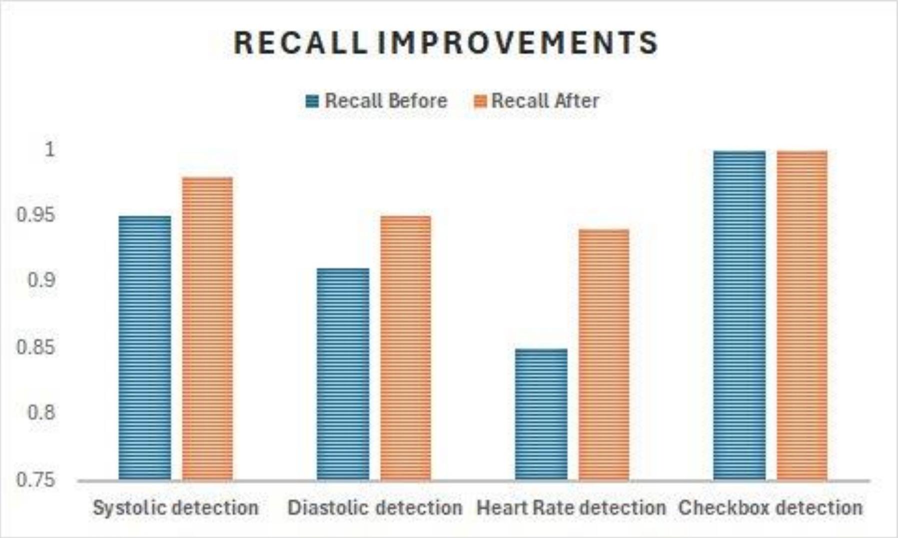
Retraining Object Detection Models

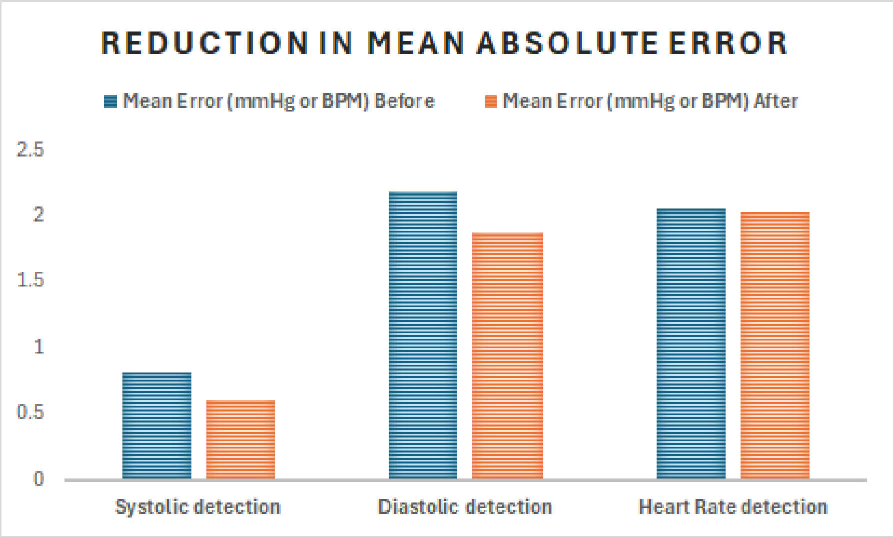




Change in performance before retraining and after. Precision was 1 across the board.

Retraining Object Detection Models





Change in performance before retraining and after.

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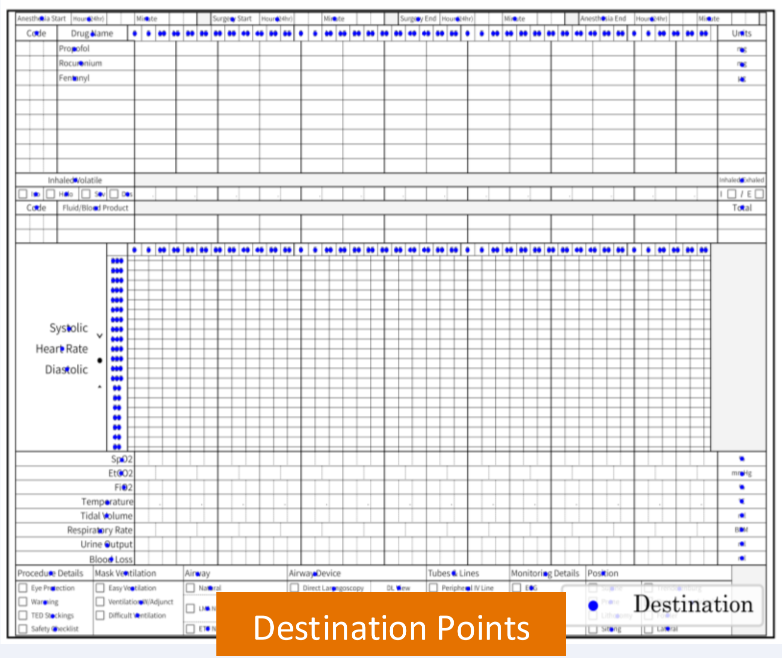
Retraining Object Detection Models Performance

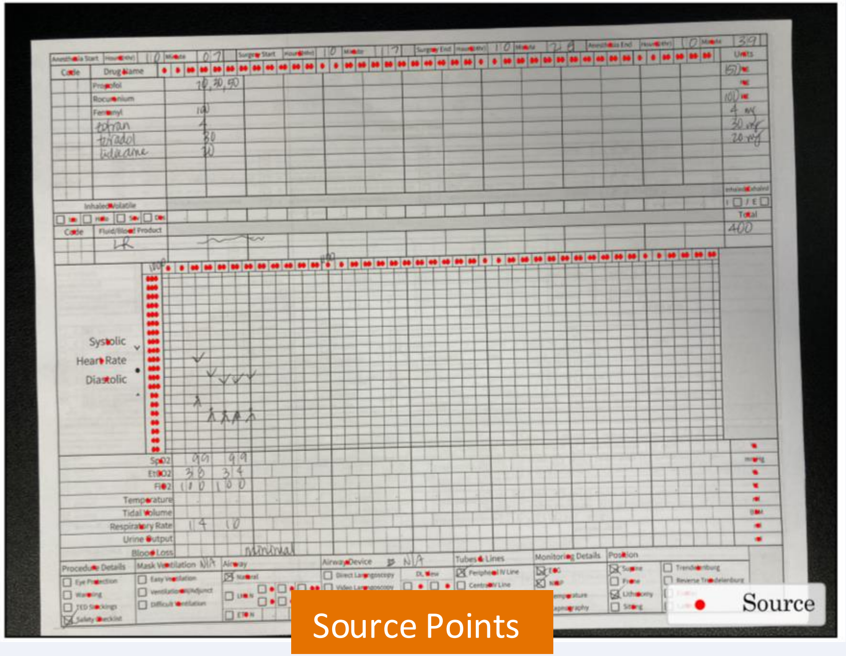
Detection Model	MAP 50-95		Precision		Recall	
	Before	*After*	*Before*	*After*	*Before*	*After*
Digit Detection	0.83	0.84	0.94	0.94	0.79	0.79
Intraoperative landmark detection	N/A	0.97	N/A	0.98	N/A	0.99
Pre/Postoperative landmark detection	N/A	0.99	N/A	0.96	N/A	0.99

Change in performance before retraining and after. Green symbolizes performance improvement. Gray is no improvement or worsening. New landmarks were included for both pre/post and intraoperative sheets so accuracy comparison could not be completed.

Transforming Images with Non-Linear Registration

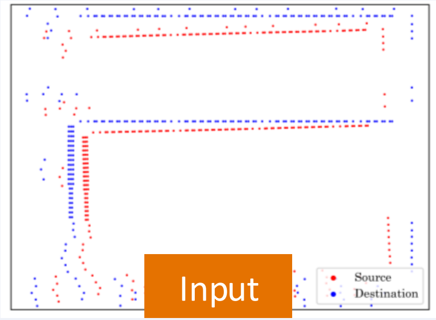
The Problem: User images are not ideal

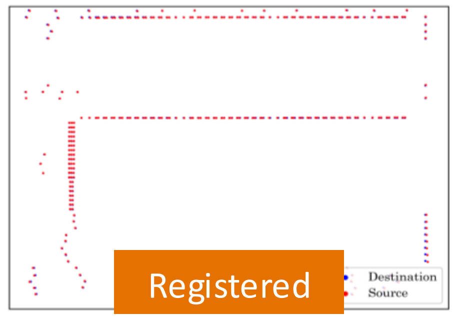


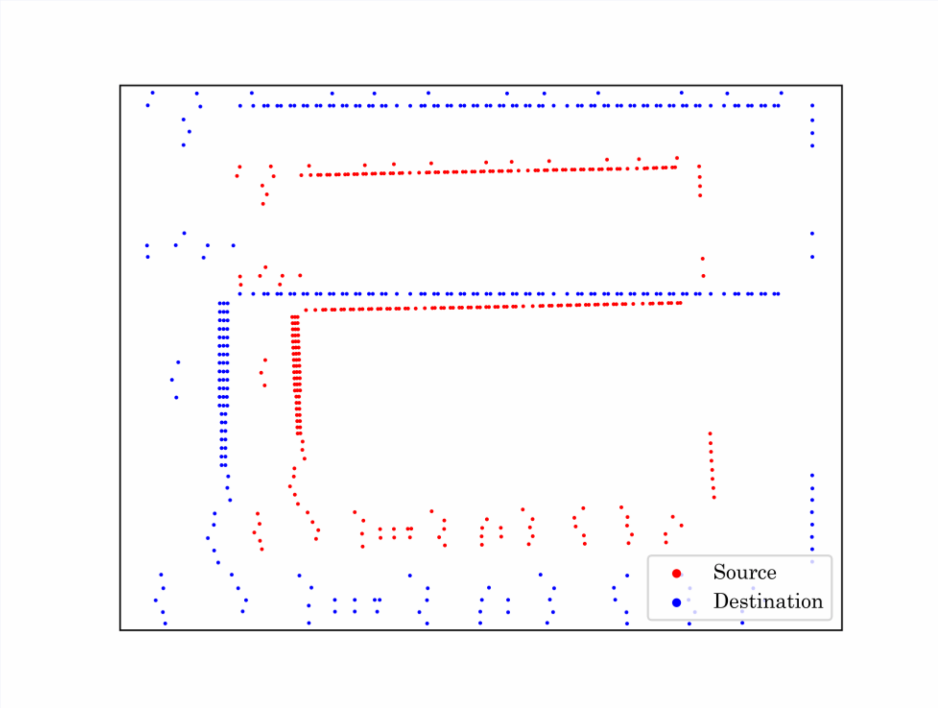


Transforming Images with Non-Linear Registration

The Solution: Coherent Point Drift, a registration algorithm



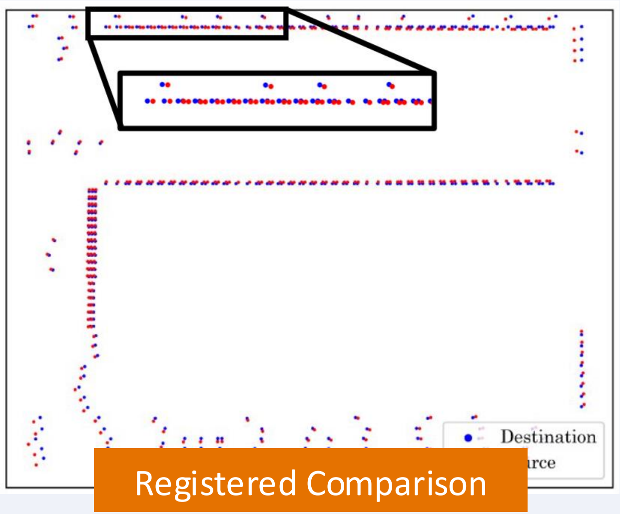


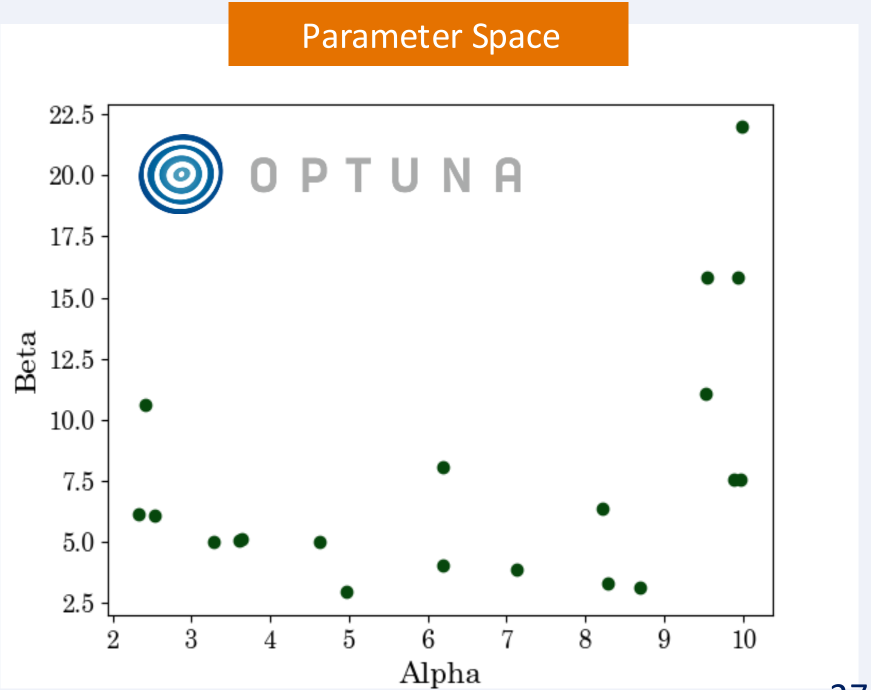


Non-Linear Registration Performance

The Performance: CPD is not generalizable yet

- Lays framework for further registration





Improving Image Registration with Thin Plate Splines

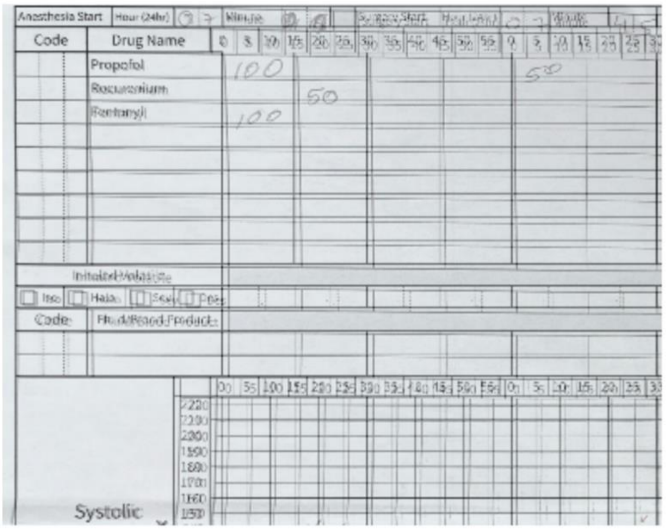
The Problem:

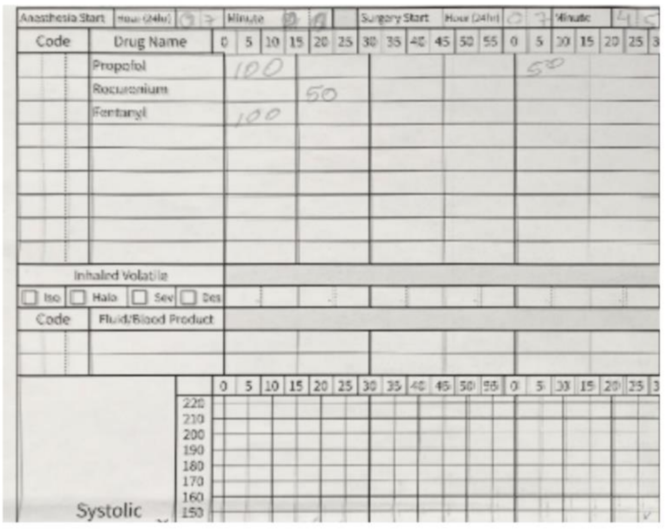
- Operational use of the system will encounter imperfect flowsheet images
  - Folded flowsheets result in distorted images
- Distorted images make object detection difficult

The Solution:

- Deploy Thin Plate Splines (TPS) to warp distorted images to align with an ideal flowsheet

Thin Plate Splines Performance





TPS Technique	Memory Increment (RAM)	Runtime
No Image Size Reduction	753 MB	3.6 seconds
0.5x Image Size Reduction	187 MB	1.1 seconds

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Conclusion

Summary

- **Contributions**
  - Facilitate extraction of semantic meaning from intraoperative vital sign chart
  - Detection model size reductions
  - Augmented image registration techniques

Acknowledgements

Dr. Mai Dahshan

Capstone Mentor

Ryan Folks

Capstone Sponsor

Dr. Bhiken Naik

Capstone Sponsor

Thank You!

Any Questions?