

Detection and Guidance of K-Wire Placement in Pelvic Trauma Surgery

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Mentor: Dr. Ali Uneri

CIS2 Project

May 5, 2020

Motivation: K-wires in Pelvic Trauma Surgery

Motivation: Improve accuracy of K-wire detection to reduce injury while limiting radiation exposure

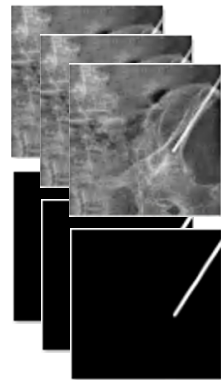
Objective: Use deep learning methods to:

- (1) Detect K-wires in 2D radiographs of the pelvis
- (2) Localize their 3D pose to provide surgical navigation

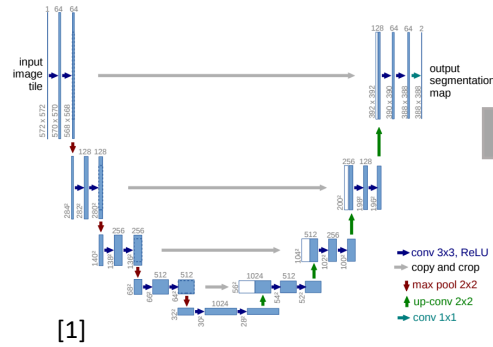


J. Goerres, et al. "Deformable 3D-2D registration for guiding K-wire placement in pelvic trauma surgery", Proc. SPIE 10135, Medical Imaging 2017: Image-Guided Procedures, Robotic Interventions, and Modeling, 101350A (3 March 2017);

Approach



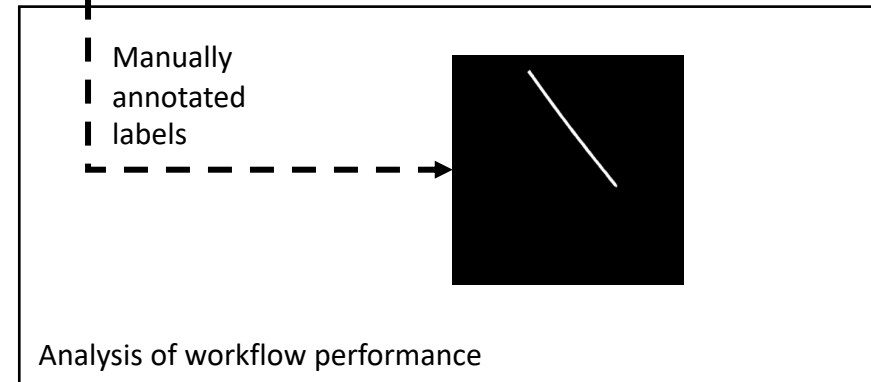
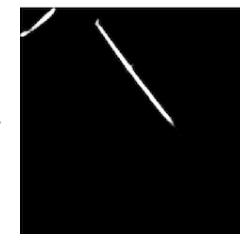
Images



Weights

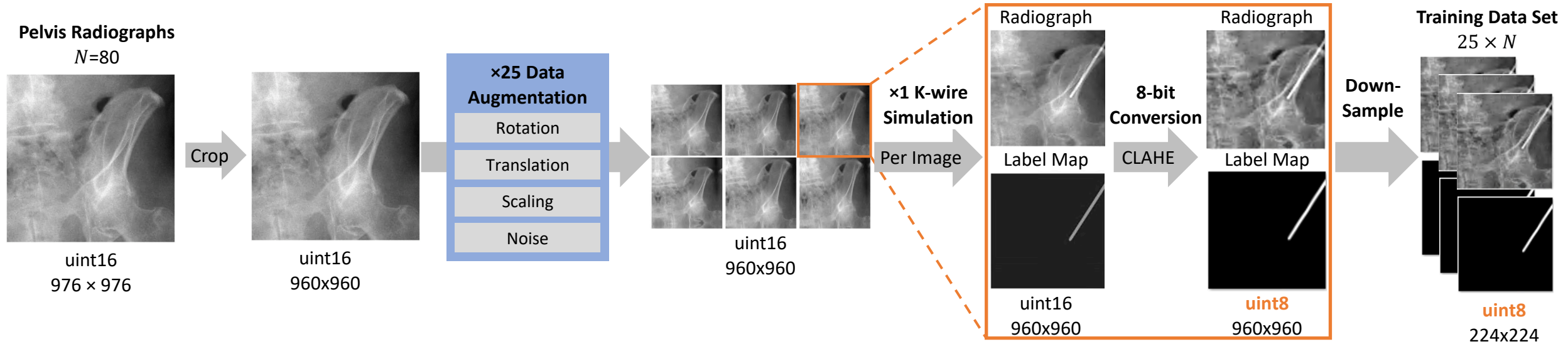


Output



[1] Ronneberger, Olaf, et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation." *Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, 2015, pp. 234–241., doi:10.1007/978-3-319-24574-4_28.

Dataset Generation: Transfer Learning



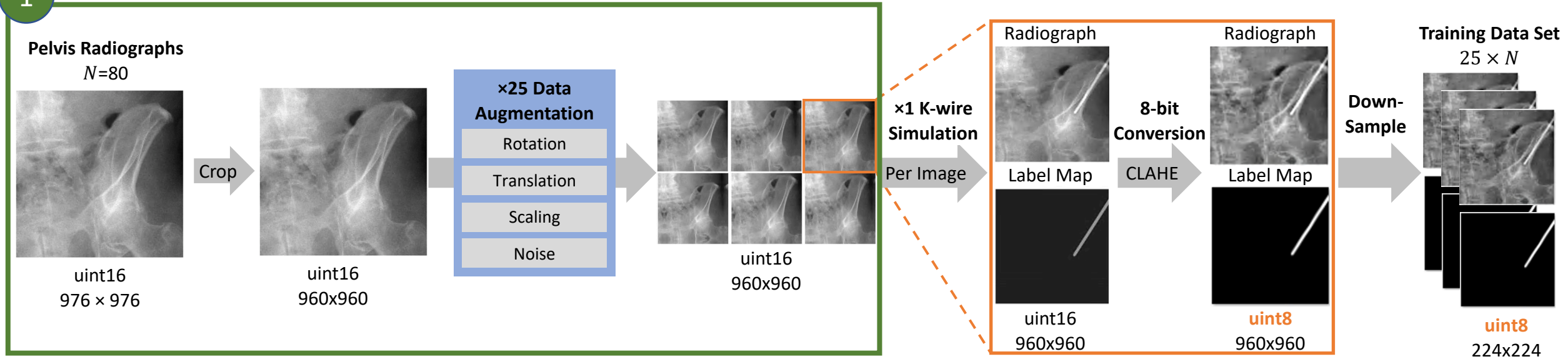
Access to quality, annotated training datasets remains a pain point for deep learning based medical image analysis

We propose a transfer learning approach based on fully simulated training data

Dataset Generation: Transfer Learning

1

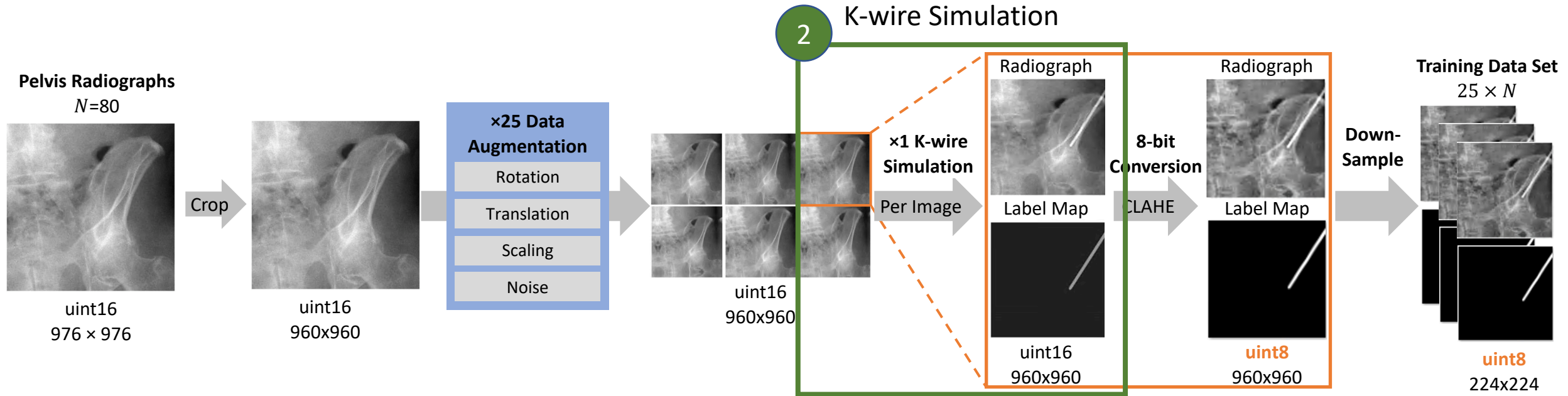
Augmentation of Real Cadaver Radiographs



Access to quality, annotated training datasets remains a pain point for deep learning based medical image analysis

We propose a transfer learning approach based on fully simulated training data

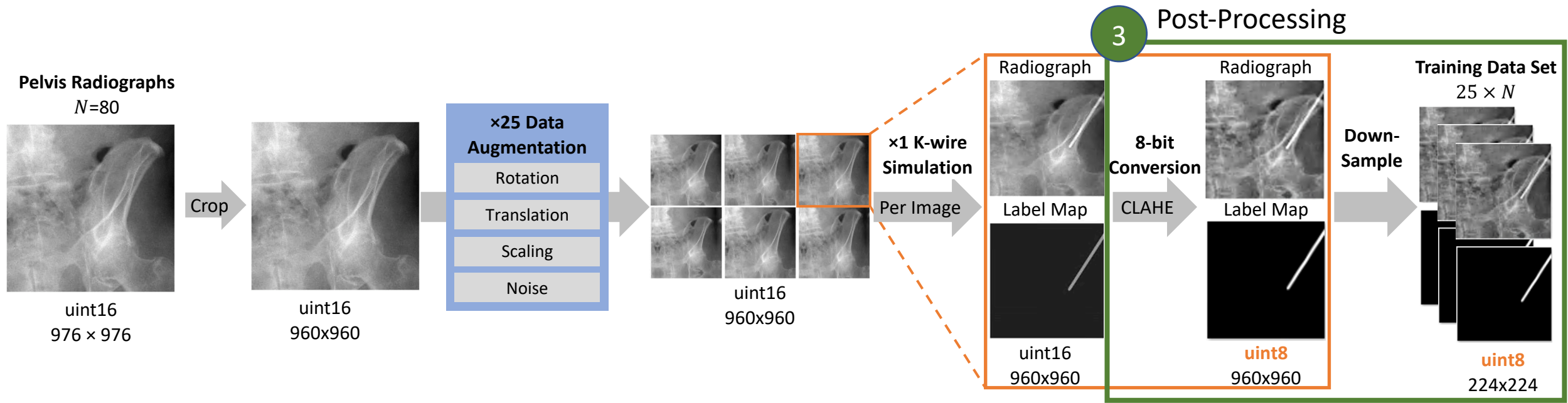
Dataset Generation: Transfer Learning



Access to quality, annotated training datasets remains a pain point for deep learning based medical image analysis

We propose a transfer learning approach based on fully simulated training data

Dataset Generation: Transfer Learning



Access to quality, annotated training datasets remains a pain point for deep learning based medical image analysis

We propose a transfer learning approach based on fully simulated training data

Training Dataset Generation: Examples

AP-like views

Single K-wire

Image sizes:

960x960

480x480

224x224

Dataset sizes:

250

500

1000

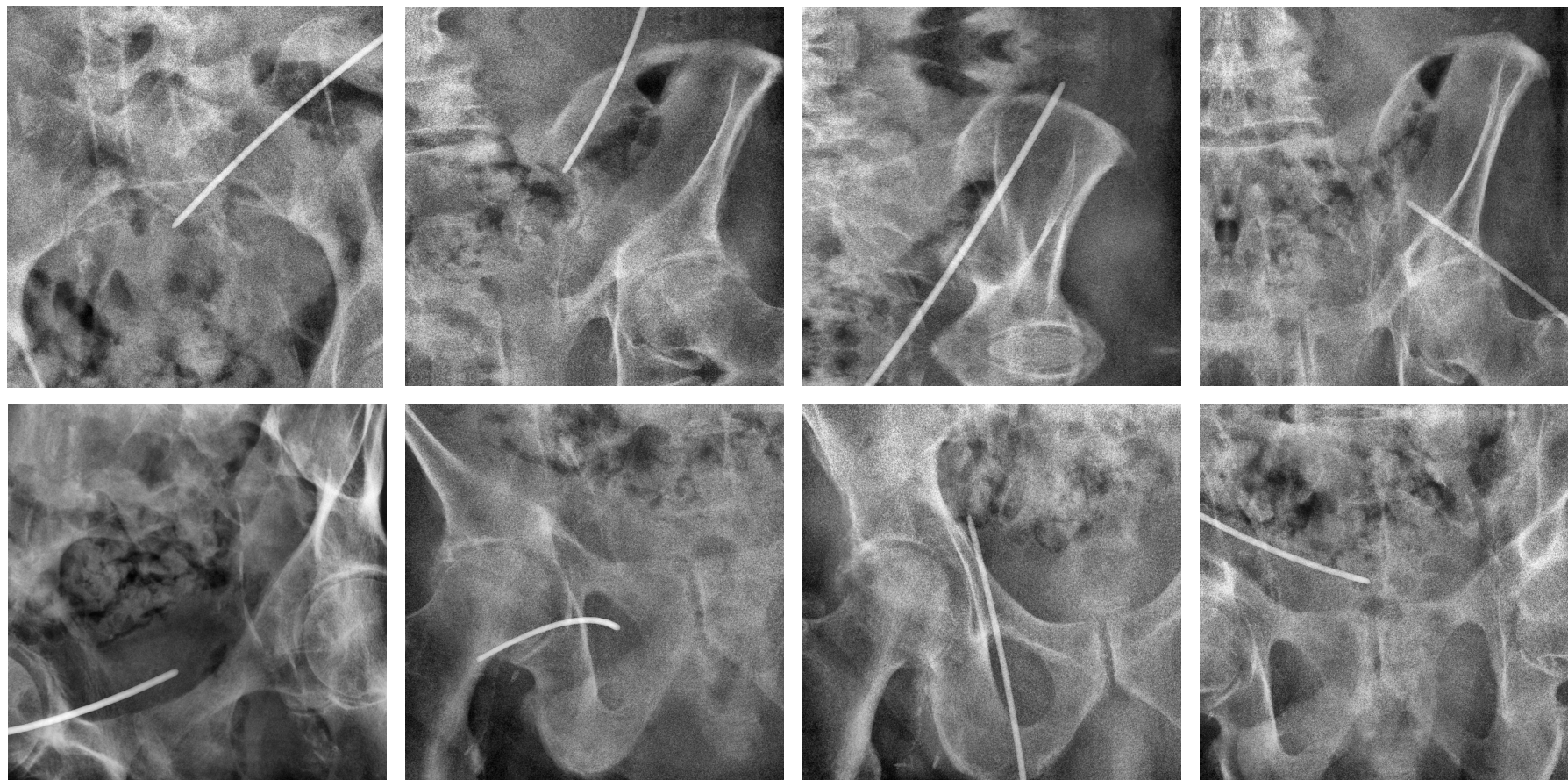
2000

4000

K-wire projection:

Deformed

Rigid



Test Dataset

IRB Approved Dataset

**Acquired using Cios Spin
(Siemens, Erlangen Germany)**

AP-like views, single K-wire

Raw Test Dataset:

Image Size: 976x976

7 Single K-wire Images

13 Multiple K-wire images

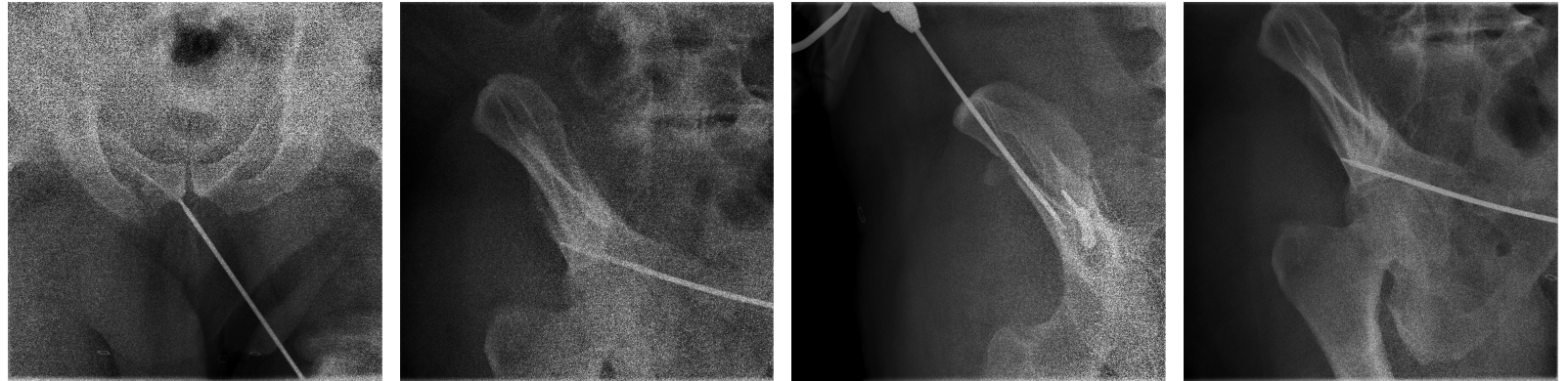


Test Dataset:

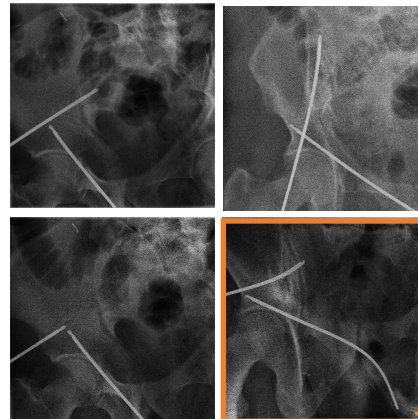
Image Size: 960x960

33 Single K-wire Images

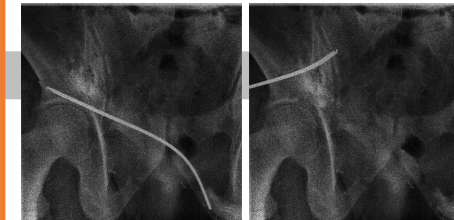
7 Single



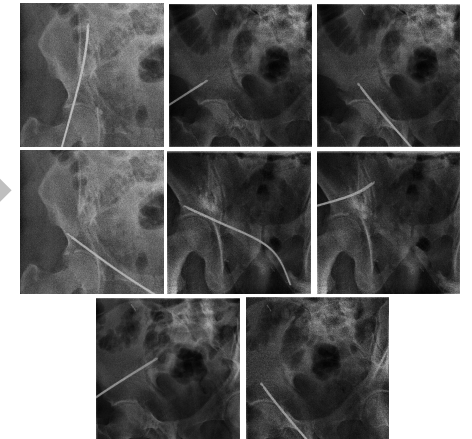
13 Multiple



Split based on Mask



26 Single



Figures of Merit: Standard CNN Prediction Metrics

Area under the Curve

AUC = Area under the TP Rate vs. FP Rate Curve

Precision

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score (Sørensen–Dice coefficient)

$$f1 \text{ score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

| | | Ground Truth | |
|------------|---|--------------|----|
| | | P | N |
| Prediction | P | TP | FP |
| | N | FN | TN |

Figures of Merit: Standard CNN Prediction Metrics

Area under the Curve

AUC = Area under the TP Rate vs. FP Rate Curve

Precision

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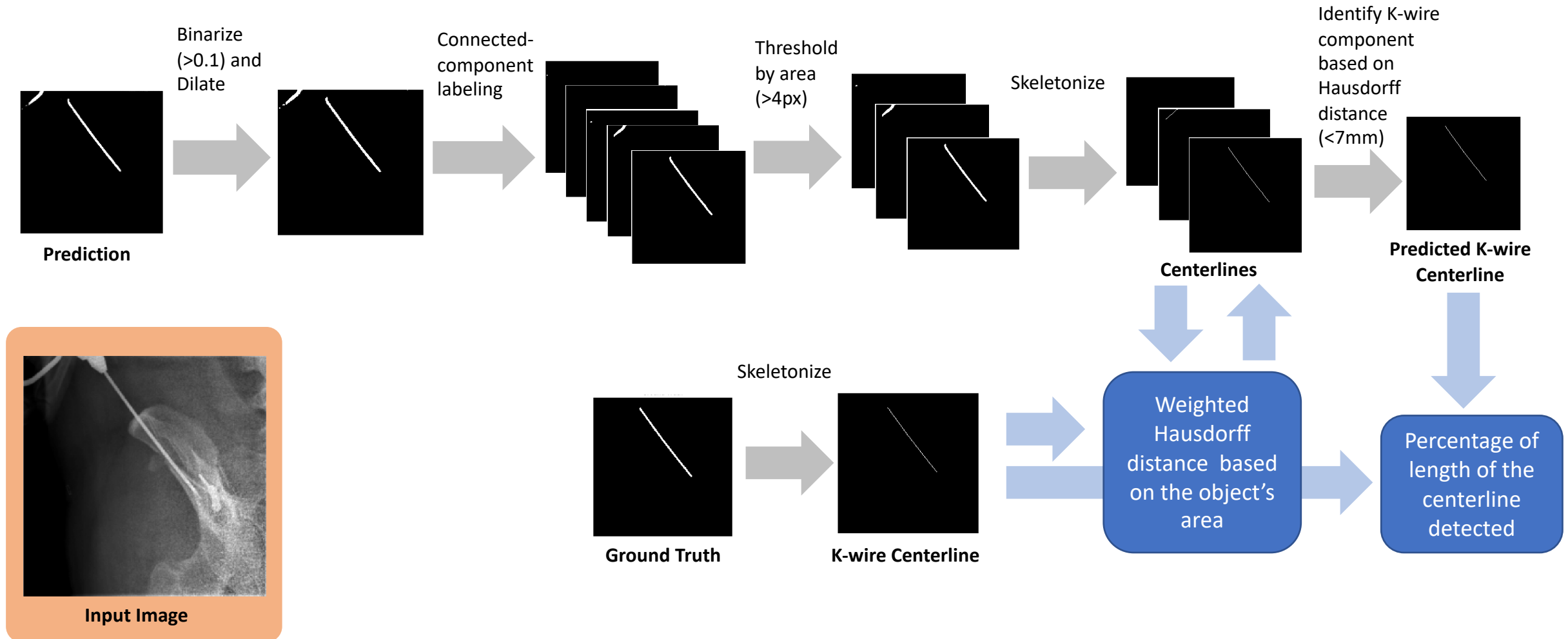
$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score (Sørensen–Dice coefficient)

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| | | Ground Truth | |
|------------|---|--------------|----|
| | | P | N |
| Prediction | P | TP | FP |
| | N | FN | TN |

Figures of Merit: K-Wire Detection Task Specific



Training Time

Binary Cross-Entropy Loss Function

$$L(y, \hat{y}) = -\frac{1}{N} (y * \log(\hat{y}_i) + (1 - y) * \log(1 - \hat{y}_i))$$

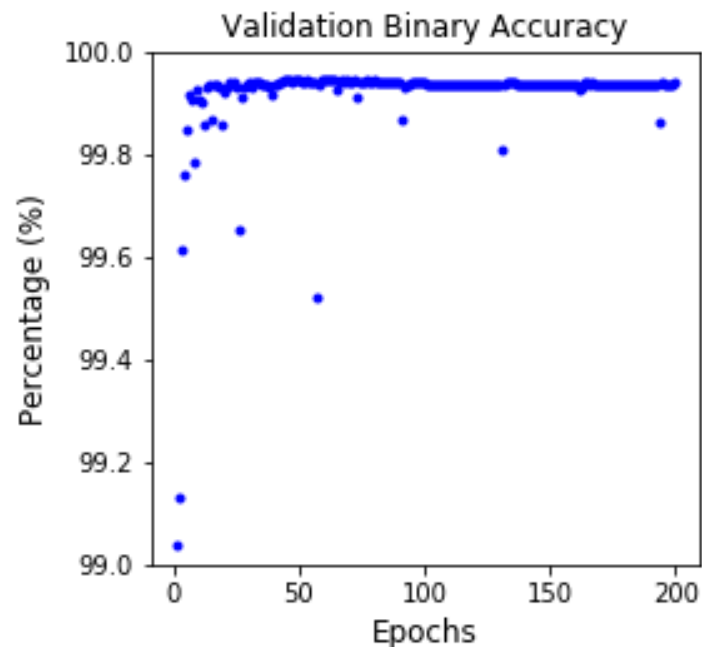
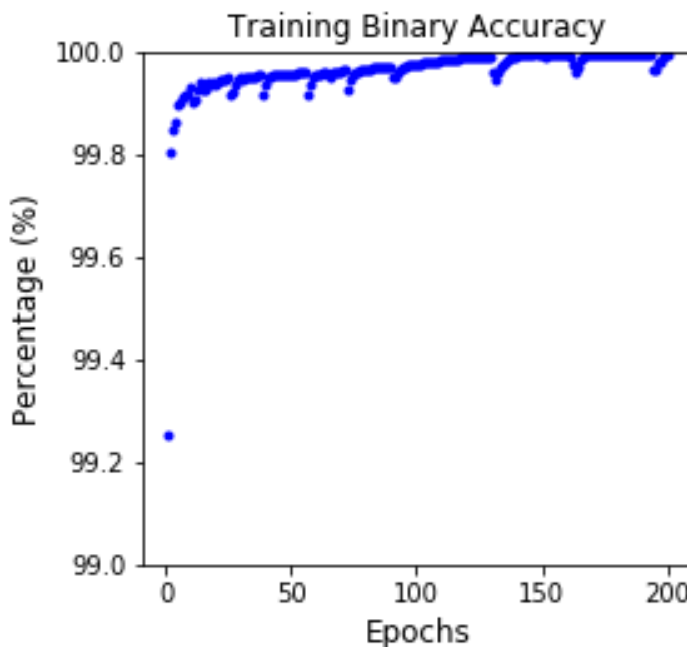
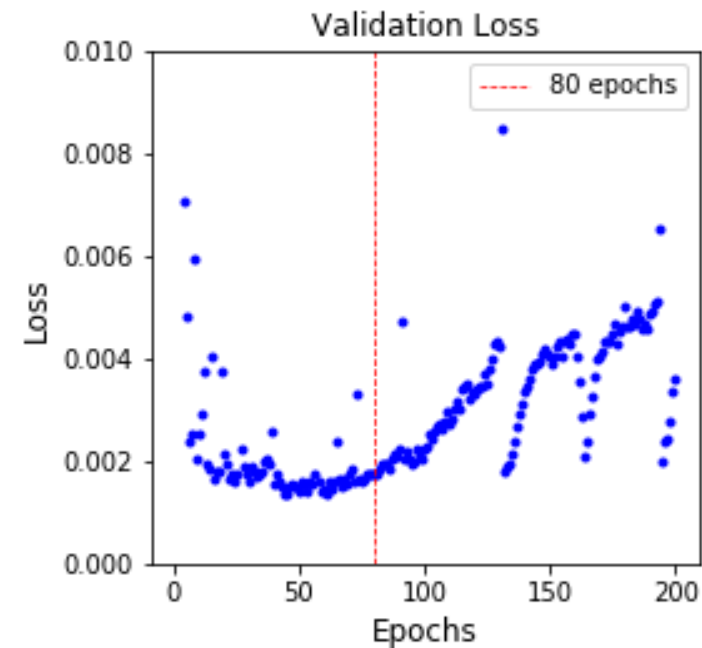
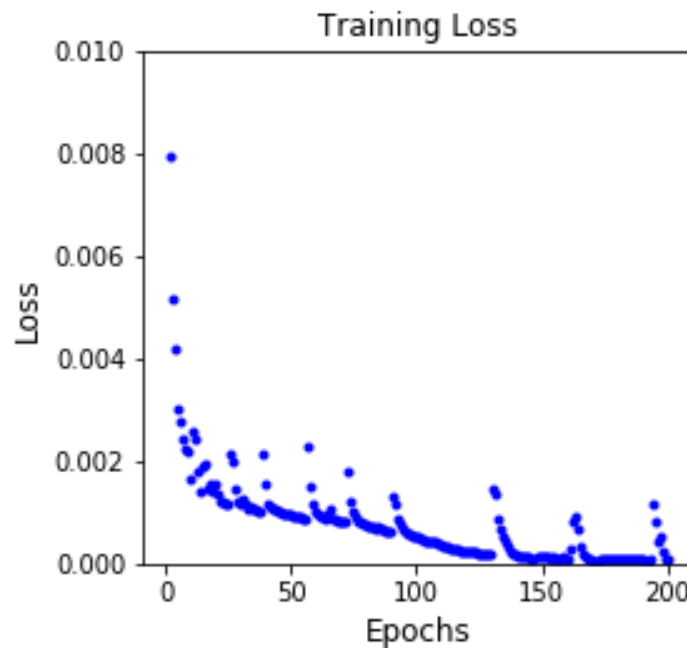
$$\text{Binary Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Training Dataset Size: 2000

Batch Size: 10

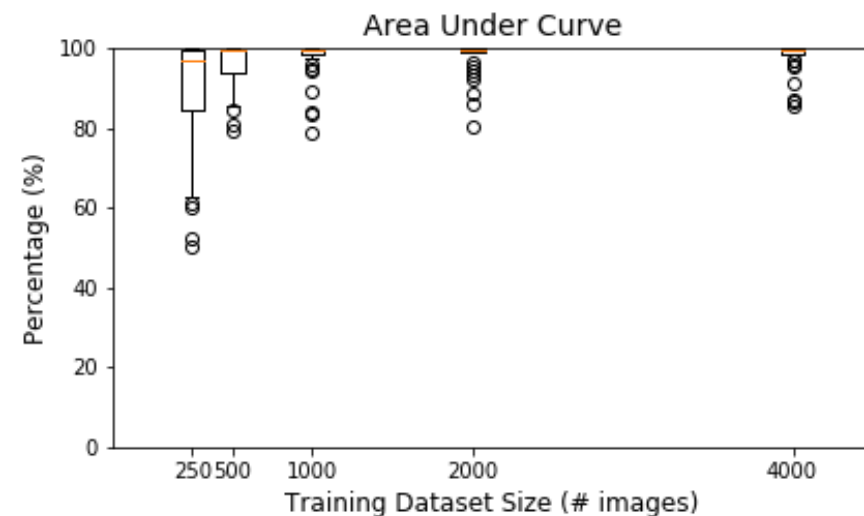
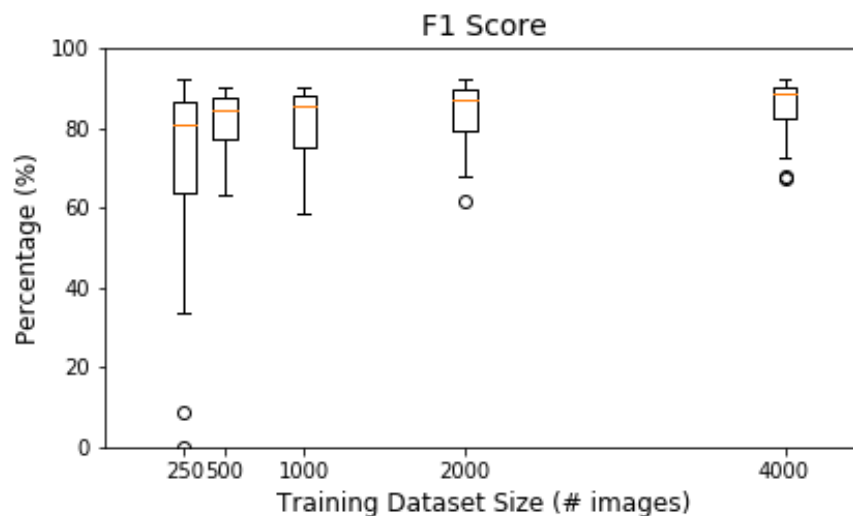
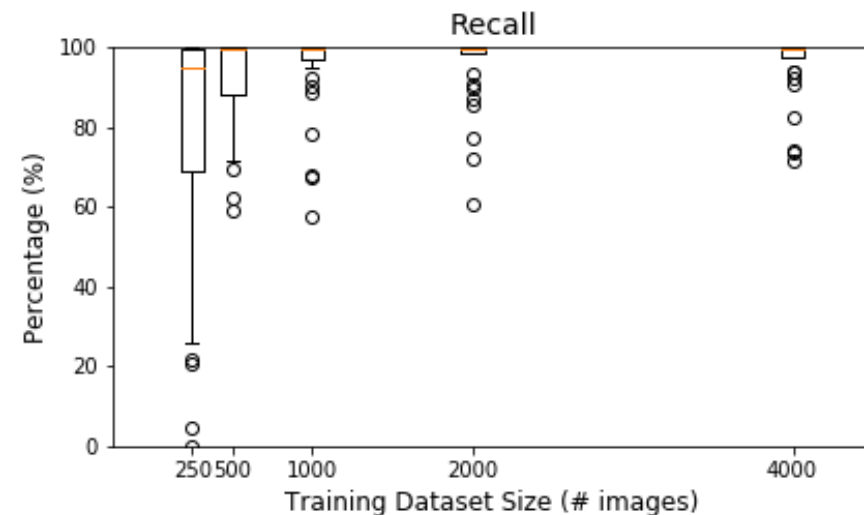
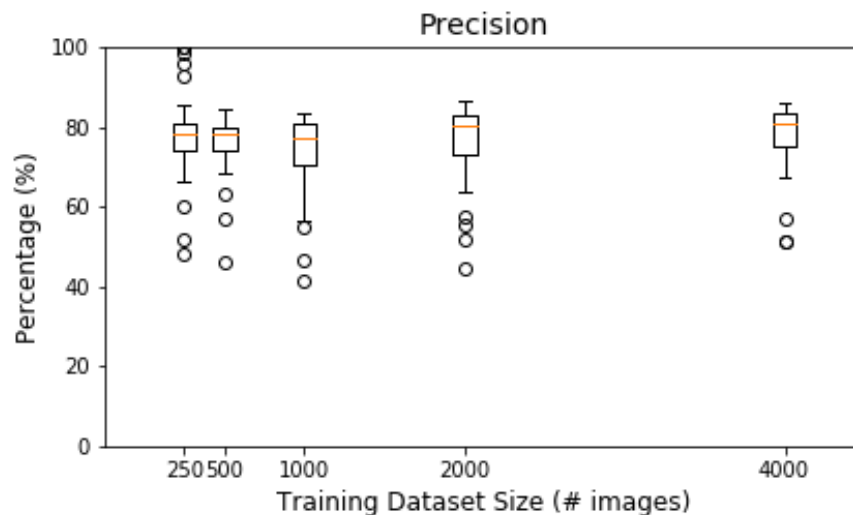
Epoch: 80

Image Size: 224x224



Training Dataset Size

General improvement as training dataset size increases



Training Dataset Size: 250–4000

Batch Size: 10

Epoch: 80

Image Size: 224x224

Training Dataset Size

Recall improvement is of particular interest

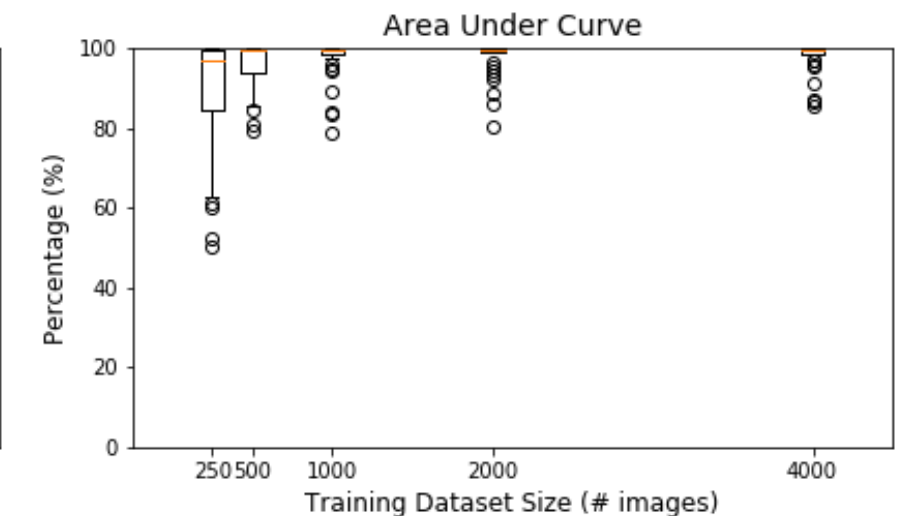
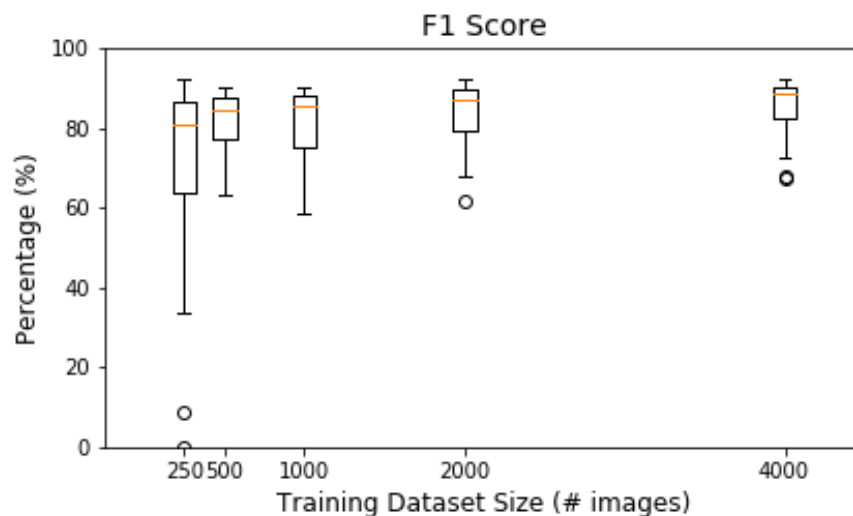
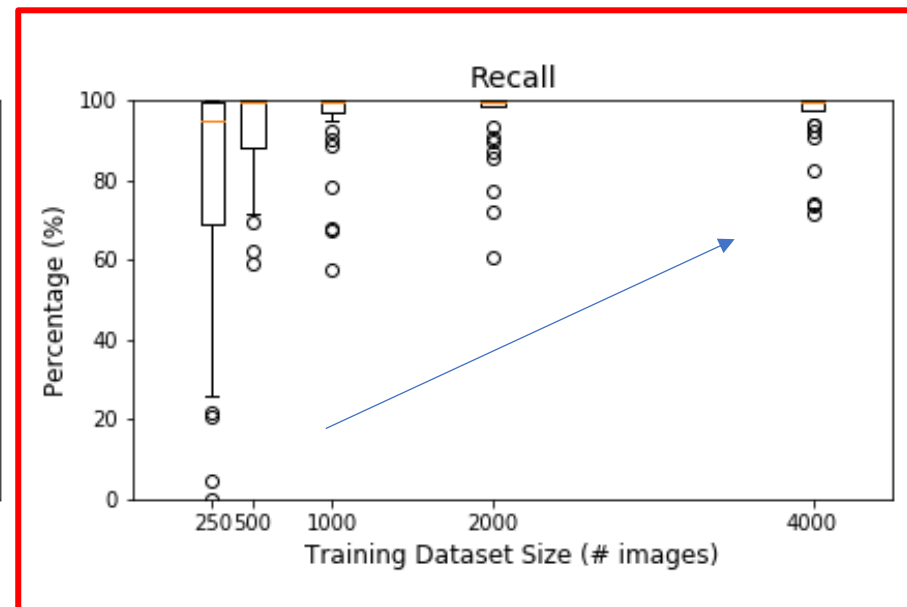
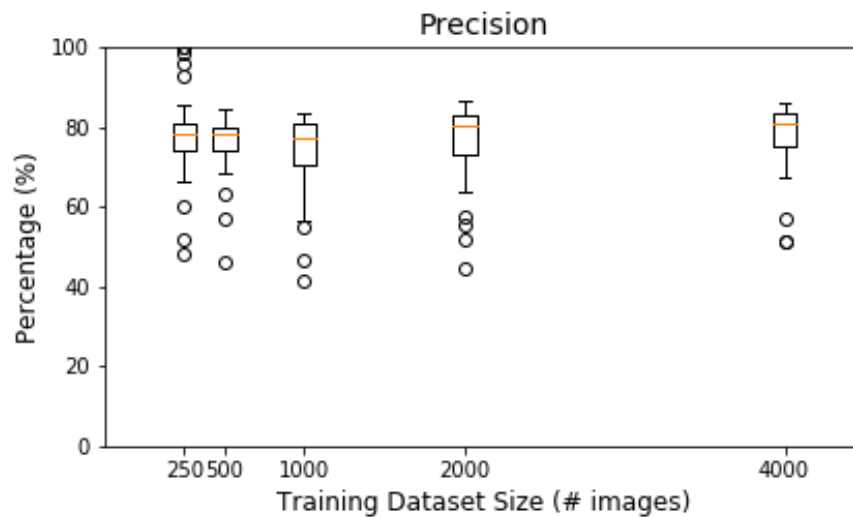
Hope to see false negatives decrease

Training Dataset Size: 250–4000

Batch Size: 10

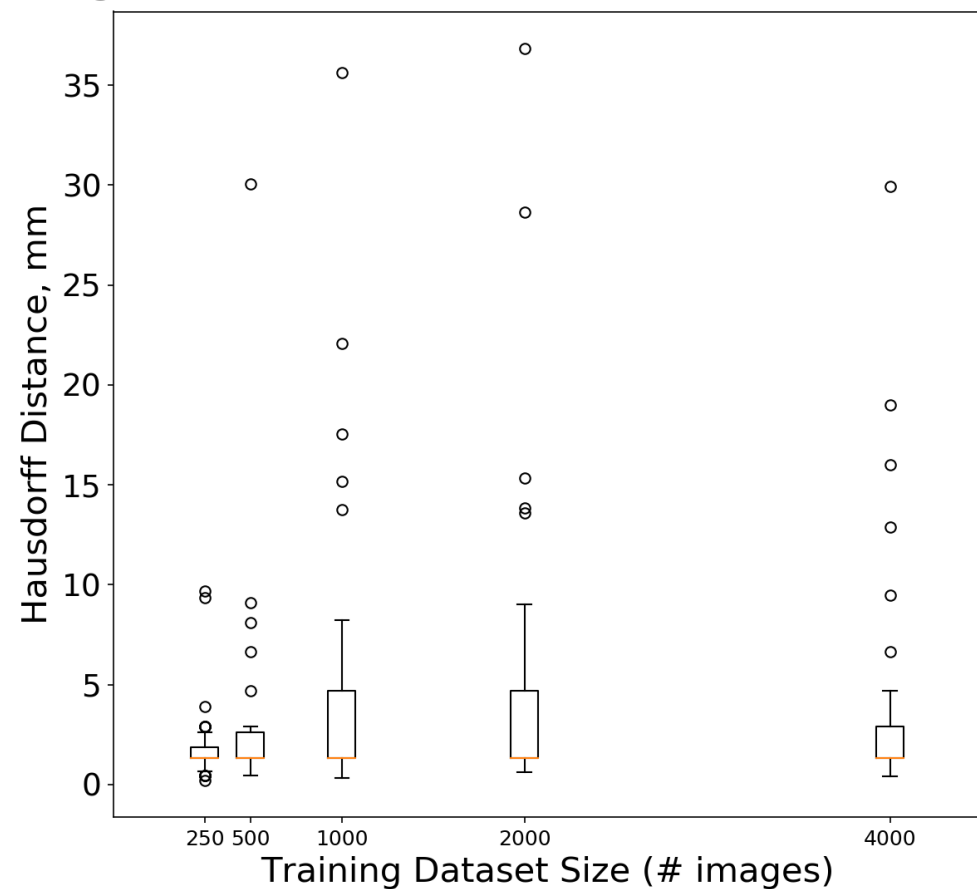
Epoch: 80

Image Size: 224x224

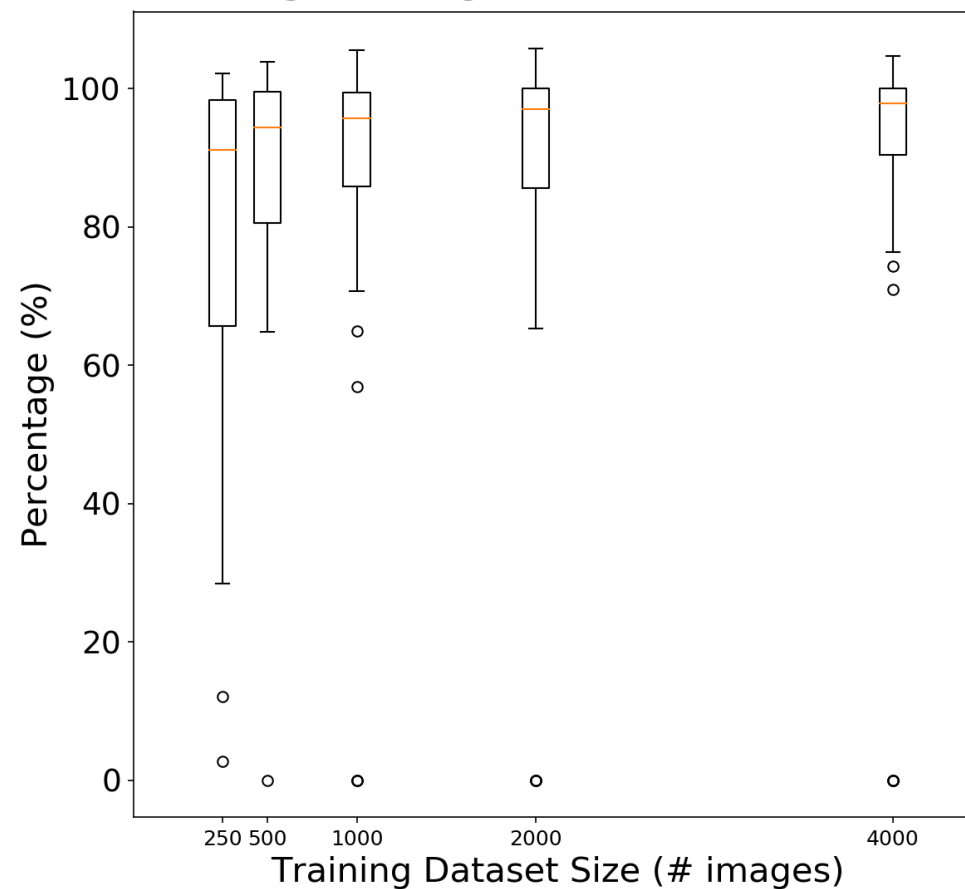


Training Dataset Size: Centerline Metrics

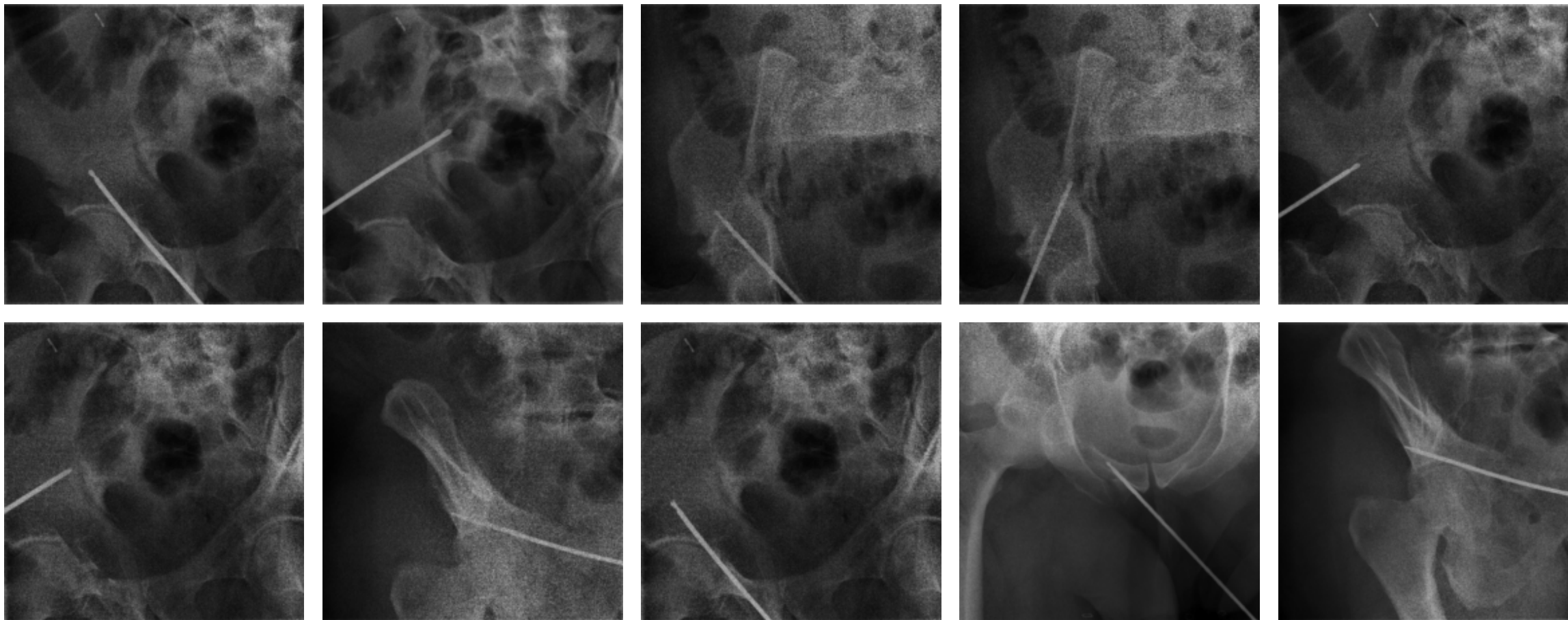
Weighted Distance between Centerlines of K-wires



Percentage of Length of K-wire Identified



Prediction Examples



Prediction Examples

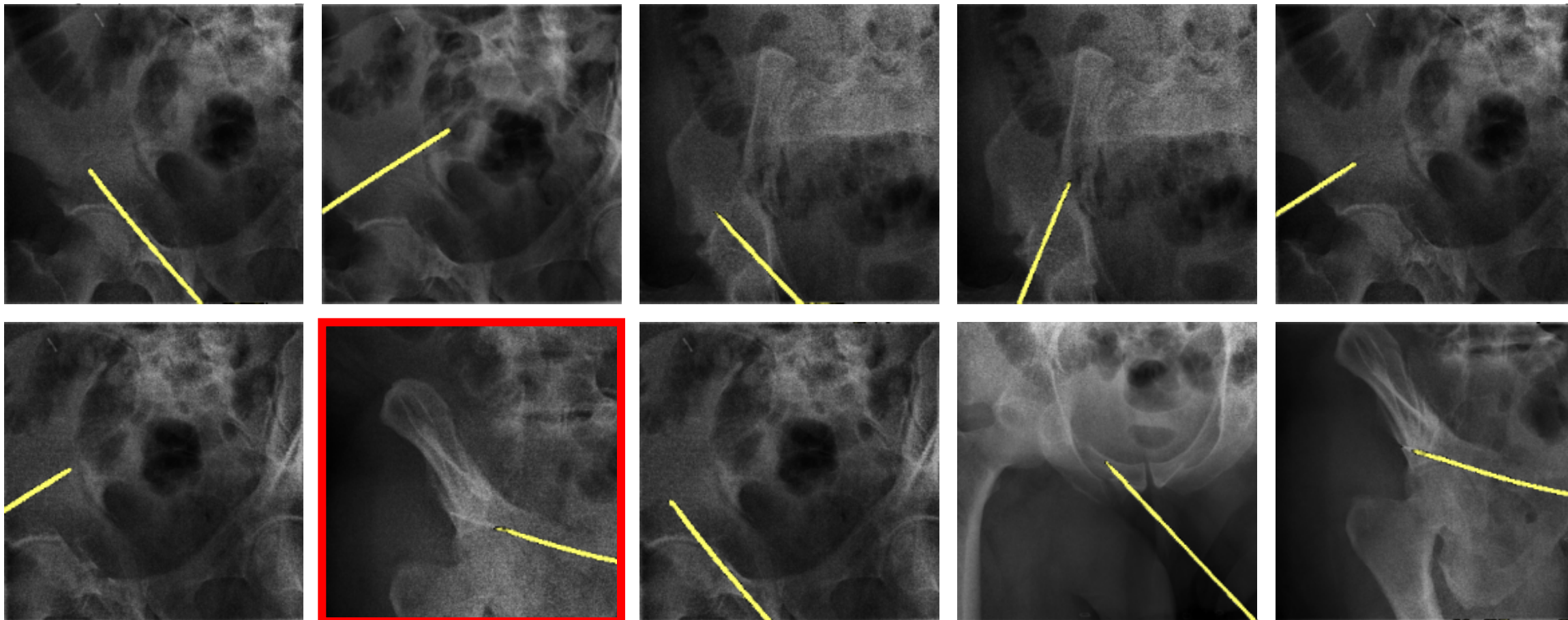
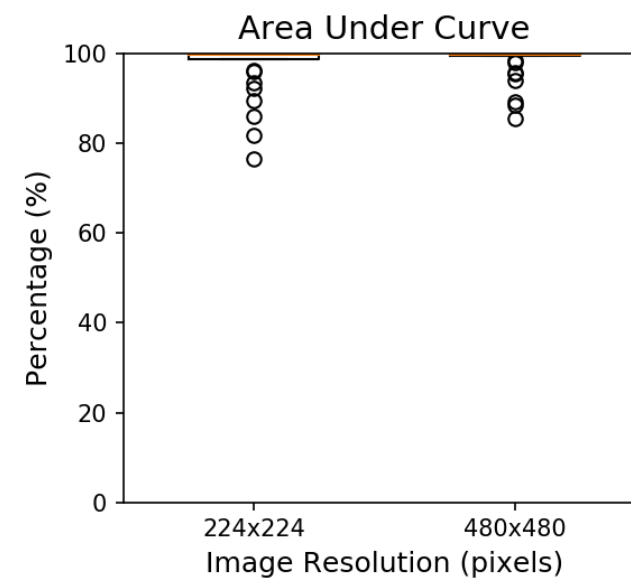
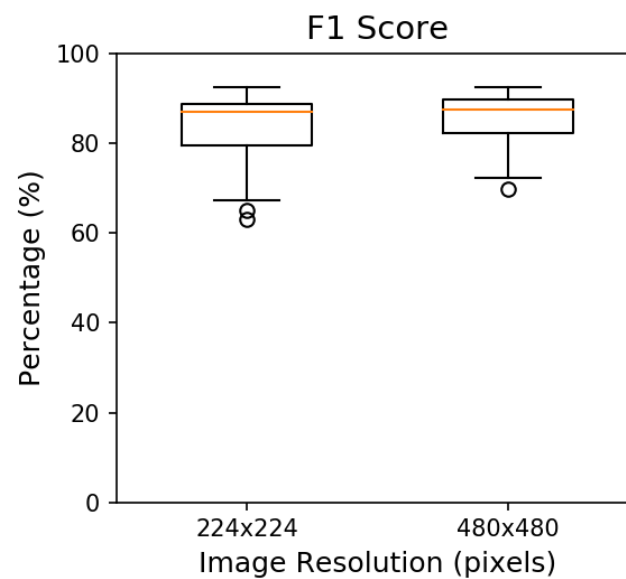
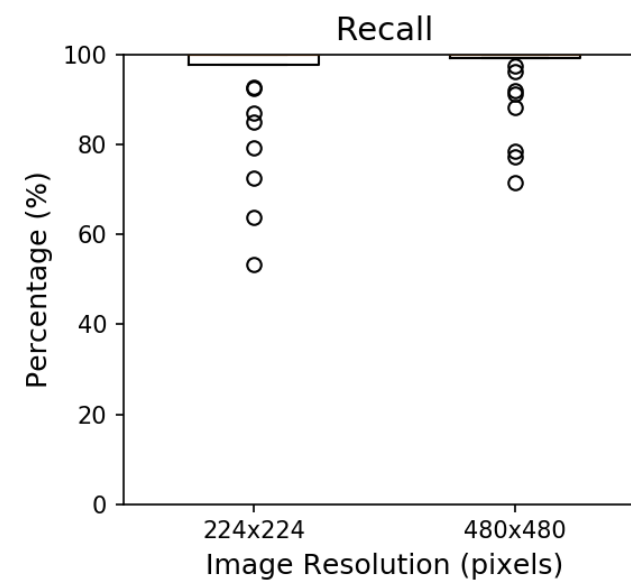
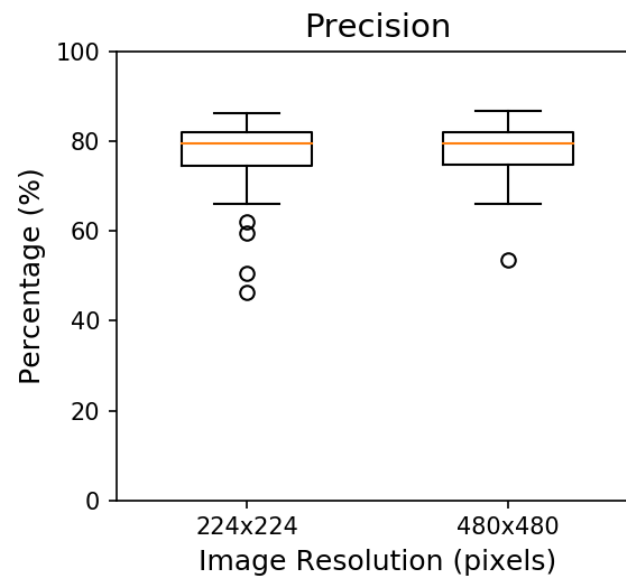


Image Resolution

Marginal improvement in performance

*need larger test set and statistical analysis to assess

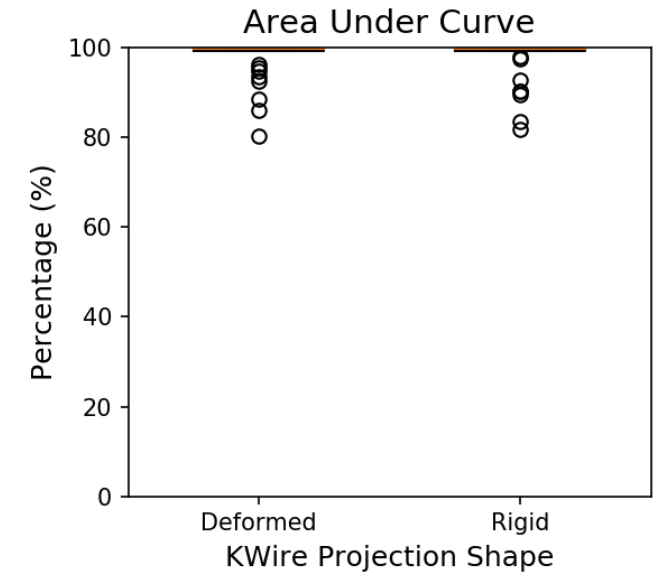
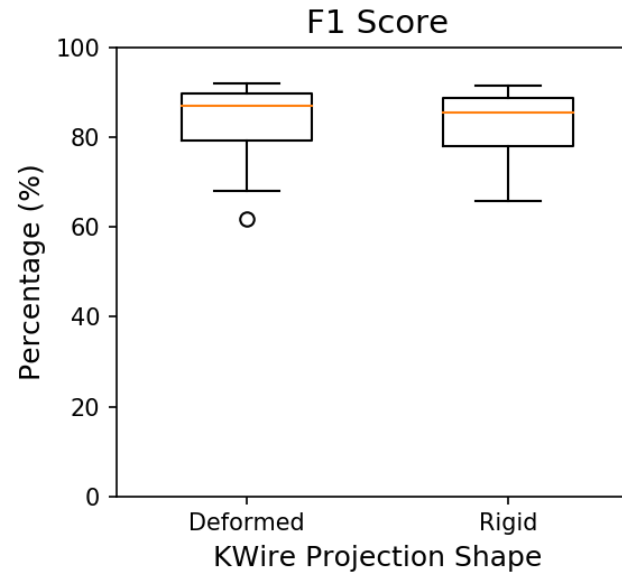
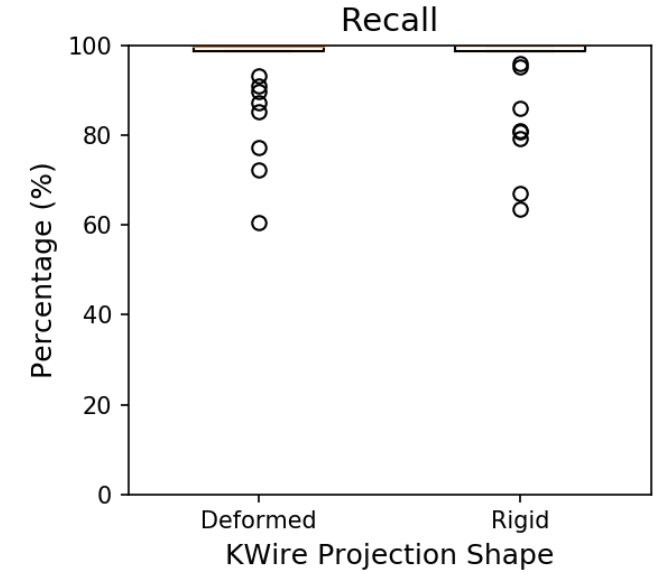
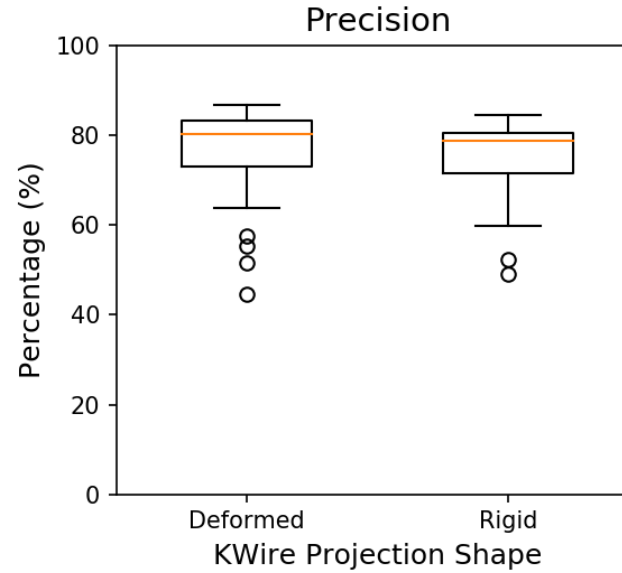
Training Dataset Size: 2000
Batch Size: 4
Epoch: 80
Image Size: 224 vs. 480 px



Training Dataset Simulated K-Wire Shape

Performance is essentially
equivalent

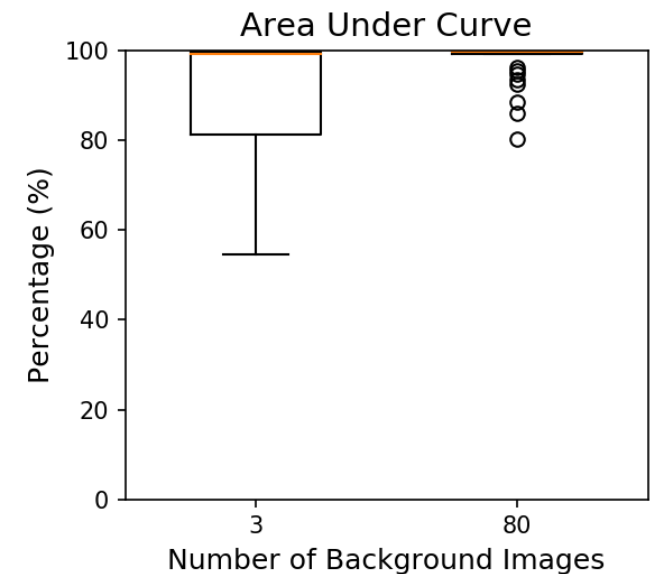
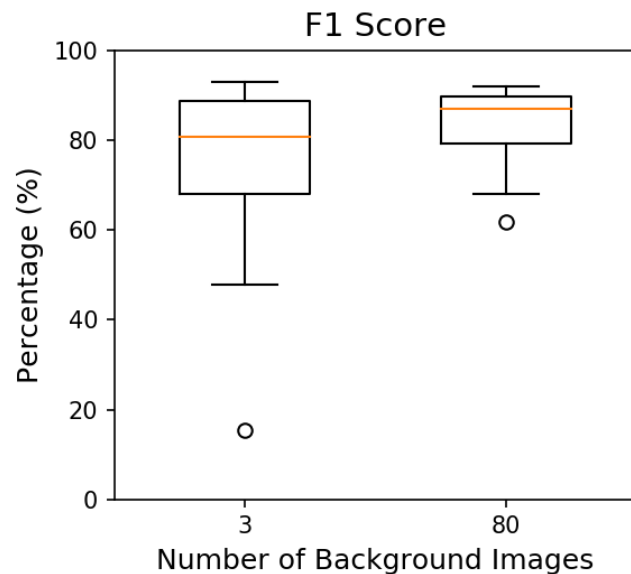
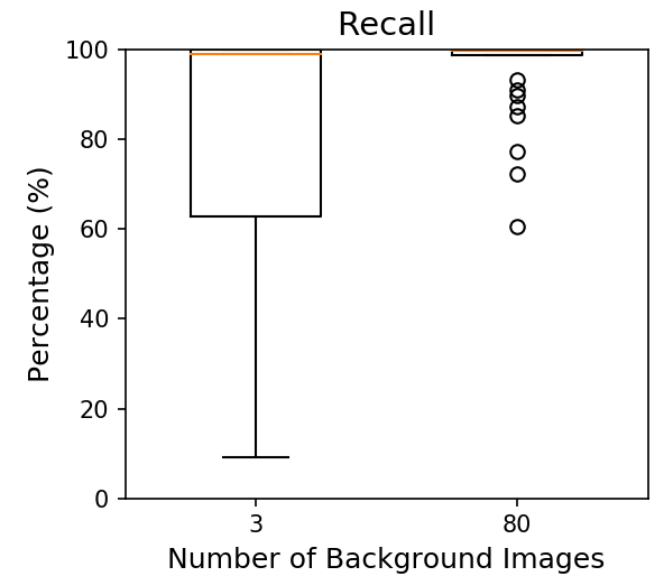
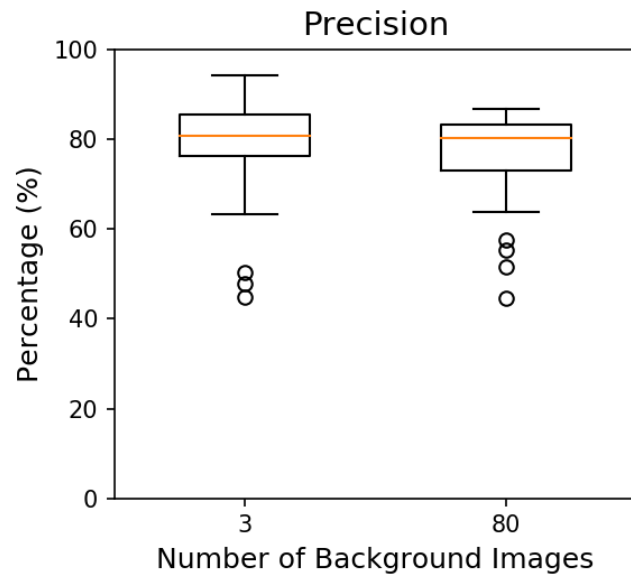
Training Dataset Size: 2000
Batch Size: 10
Epoch: 80
Image Size: 224x224



Training Dataset: Diversity of Background Image Selection

Increased diversity in
background images prior to
augmentation yields better
results

Training Dataset Size: 2000
Batch Size: 10
Epoch: 80
Image Size: 224x224



CNN Architectures

Displayed comparison
UNet to UNet++

UNet++: more complex network

~2x the inference time /
image

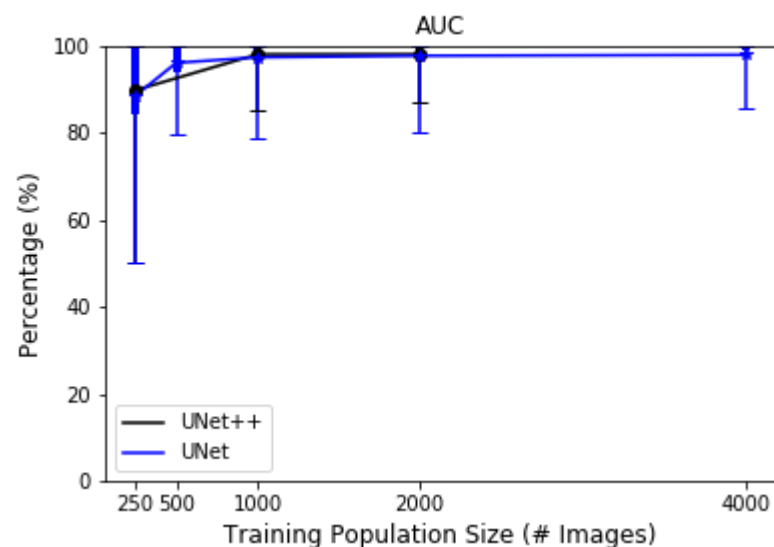
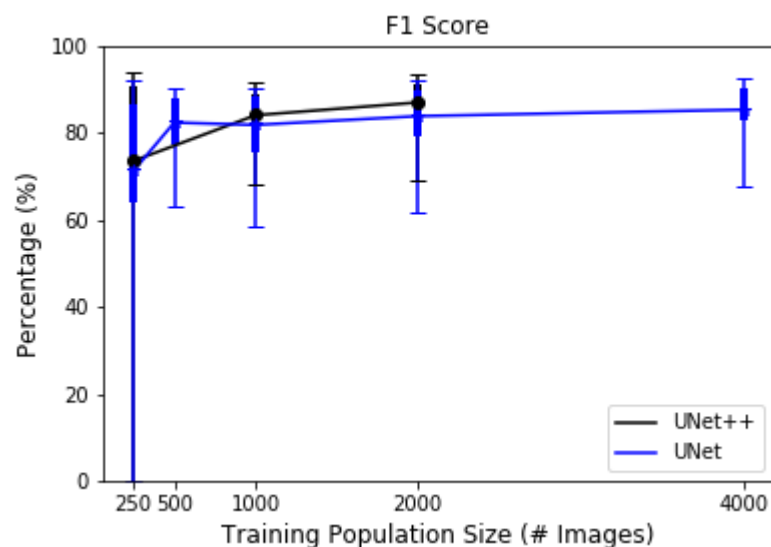
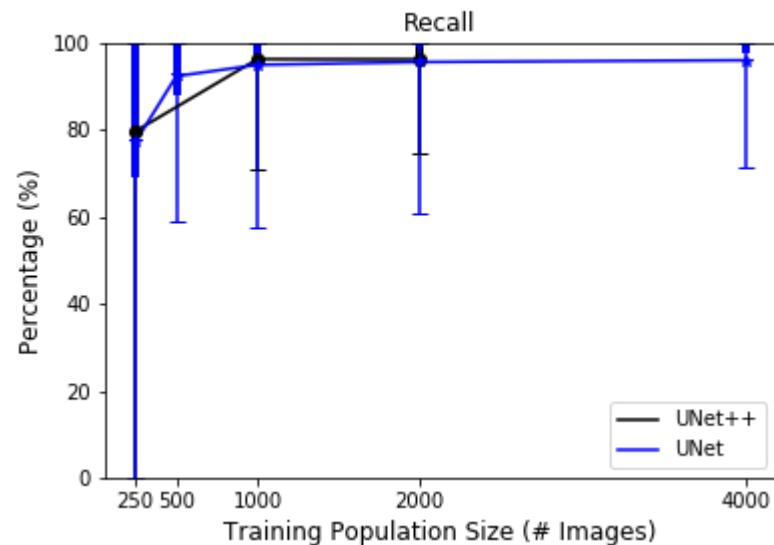
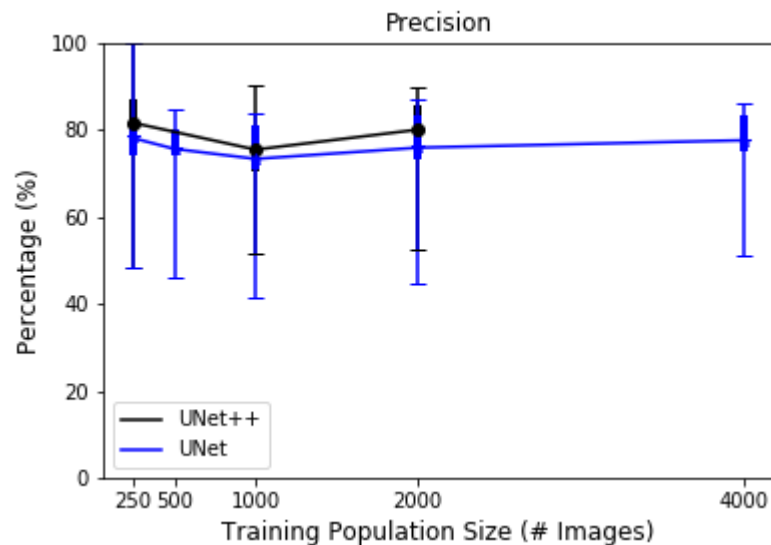
Similar performance

Training Dataset Size: 250–4000

Batch Size: 4

Epoch: 80

Image Size: 224x224



Summary

1. Generated simulated dataset
2. Trained and evaluated application of UNet for K-Wire detection
3. Achieved predictions on real pelvic images from real patient experiments



Minimum Deliverable



Expected Deliverable

Responsibility Ownership

| Irina Bataeva | Kinjal Shah |
|--|---|
| <ul style="list-style-type: none">● Training Set Generation: K-wire simulation● Test Set Segmentation● Model Evaluation: Task Specific Metrics | <ul style="list-style-type: none">● Training Set Generation: Dataset augmentation● Model Implementation● Model Evaluation: Standard CNN Metrics |

Next Steps

Improve Transfer Learning

Refine dataset generation process

Assess alternate model architectures

Multiple K-Wires

Multi-class segmentation, object detection

3D Localization

Multi-class segmentation



Questions

Thank you!

Appendix: Prediction Example



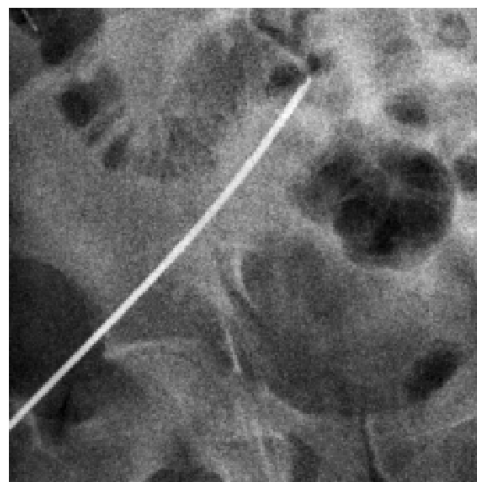
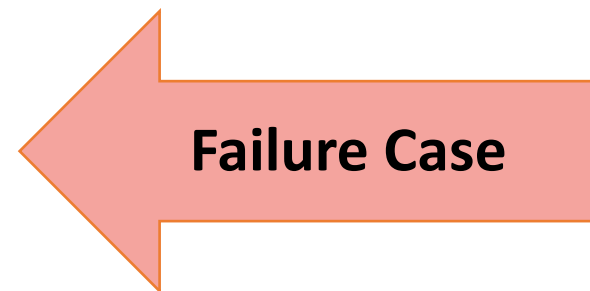
Input Image



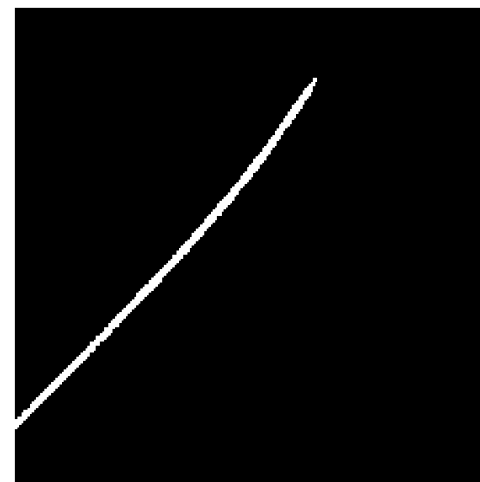
Ground Truth



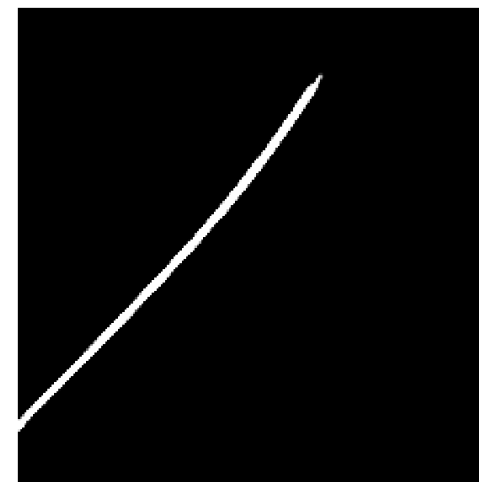
Prediction



Input Image



Ground Truth



Prediction

Appendix:

Prediction Example (4000 image training dataset) – Image crop issue



Appendix:
Prediction Example (4000 image training dataset) – Failure

