Deep Learning-Based Automatic Tumour Segmentation in Breast-Conserving Surgery Navigation Systems

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Breast-Conserving Surgery

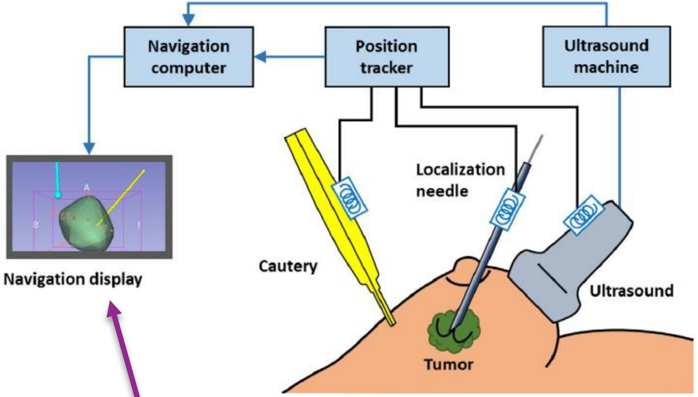
Healthy Tissue Retention

Complete Tumour Excision

30% of patients undergoing BCS will have positive margins on post-op pathology analysis

NaviKnife

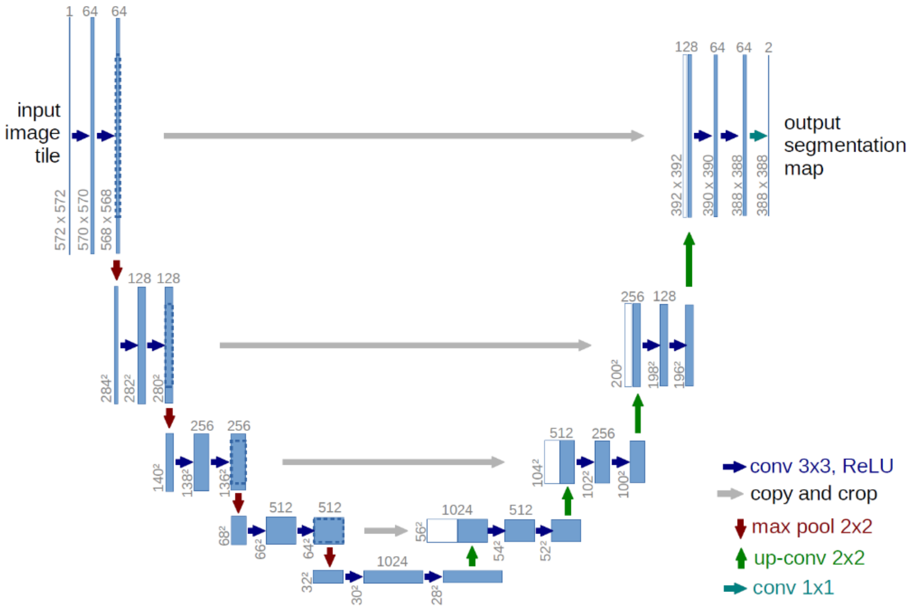

Navigation display
Cautery
Localization needle


Navigation computer
Position tracker
Ultrasound machine
Navigation display
Localization needle
Cautery
Ultrasound
Tumor

Objective

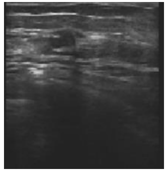
Develop **intraoperative automatic segmentation** of the breast tumour on 3D ultrasound imaging to **replace manual contouring** by a radiologist.

U-Net



1 64 64
input
image
tile
572 x 572
570 x 570
568 x 568
128 128
284²
282²
280²
256 256
140²
138²
136²
512 512
68²
66²
64²
1024
32²
30²
28²
1024 512
56²
54²
52²
512 256
104²
102²
100²
256 128
200²
198²
196²
128 64 64 2
392 x 392
390 x 390
388 x 388
388 x 388
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

U-Net Training



- 33 patients
- 7218 images

Input:
128x128x1

Encoder
(Downsampling)

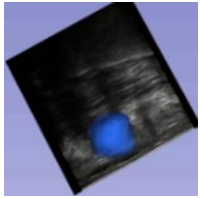
- Regular convolutions and max pooling layers applied
- Learns **WHAT** information

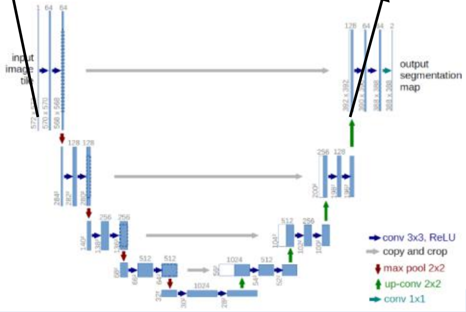
- Transposed convolutions along with regular convolutions applied
- Recovers **WHERE** information

Decoder
(Upsampling)

Output:
128x128x1

- 3D ultrasound with segmented breast tumour





CAR 2021

Canadian Association of Radiologists
L'Association canadienne des radiologistes

Implementation Strategies

- Hyperparameter Optimization
  - Random search → Baseline
  - Trial and error → Model parameters

(Model Design + Hyperparameters) ⟶ Model Parameters

The building blocks:

- # Layers
- Activations
- Optimizers

...

The knobs that you can turn:

- Learning Rate
- Dropout

...

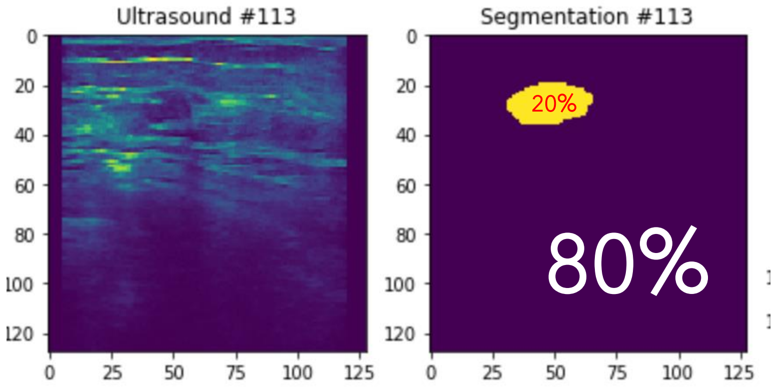
The variables learned from the data:

- weights

...

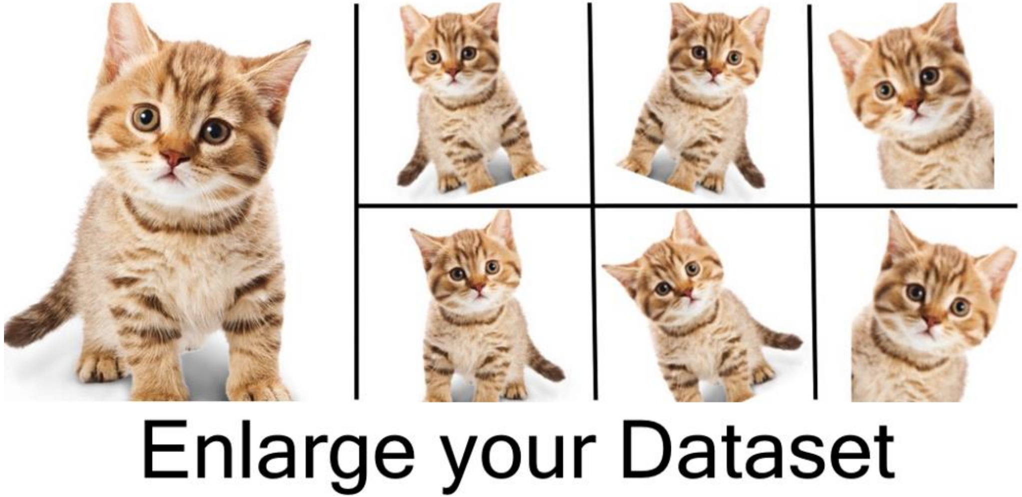
Implementation Strategies

- Weighted categorical loss function
  - Healthy adipose tissue >> Tumour tissue
  - Predict only healthy tissue → Specificity 80%
  - Ideal ratio = **85:15**



Implementation Strategies

- Data augmentation
  - Translation, zoom, shift, rotation, flip



Model

Model Parameter	Value
Layers	7
Kernels	3x3 downsampling 4x4 upsampling
Learning rate	1e-4
Loss function	Weighted categorical loss fxn
Activation function	Softmax
Batch size	32
Epochs	200

Method: Cross-Validation

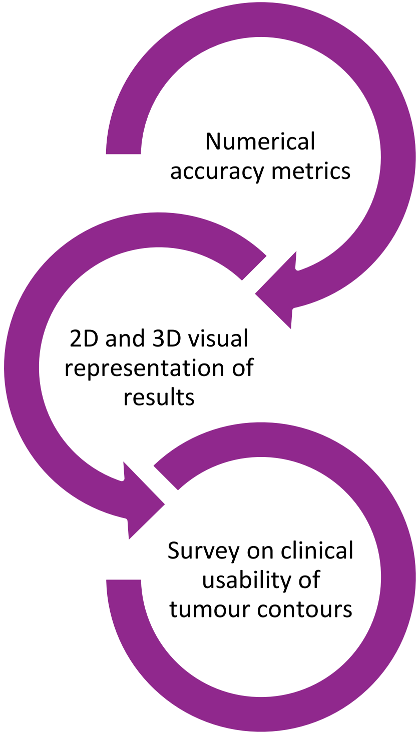
80% for training, 20% for testing

→ Prevents Overfitting

1.	Train	Train	Train	Train	Test
2.	Train	Train	Train	Train	Test
3.	Train	Train	Train	Train	Test
4.	Train	Train	Train	Train	Test
5.	Train	Train	Train	Train	Test

Model “blinded” to test set

Method: Evaluation



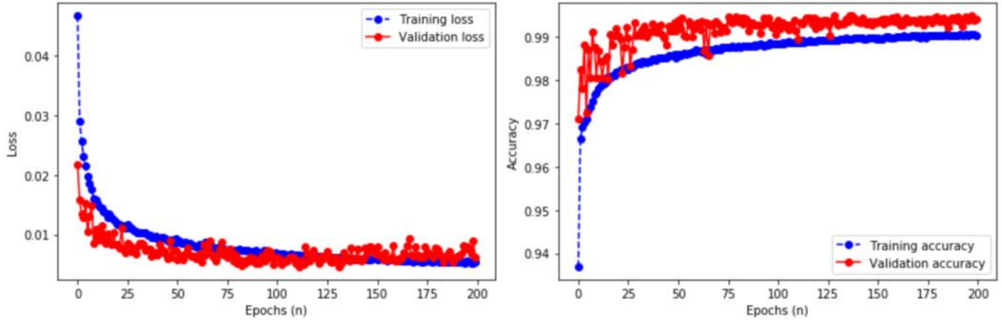
Results

Capability of the model in distinguishing the classes

Harmonic mean of sensitivity and specificity

Accuracy Metric	Value
Area under the ROC curve (AUC)	0.94
Dice similarity coefficient (DSC)	0.70
Sensitivity	92%
Specificity	65%

Total training time: 19:25:10.582479

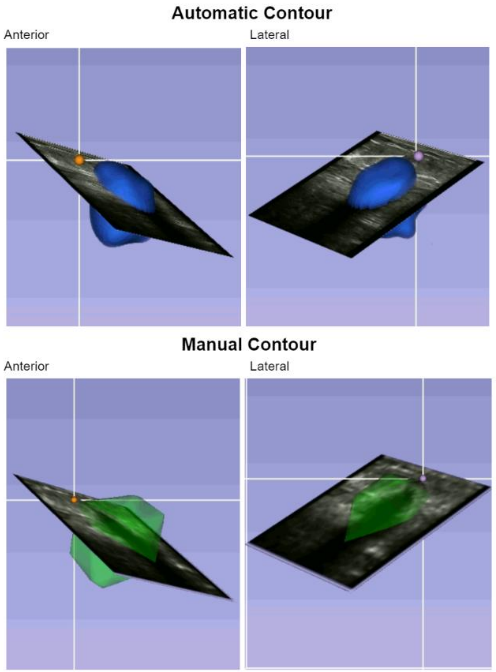


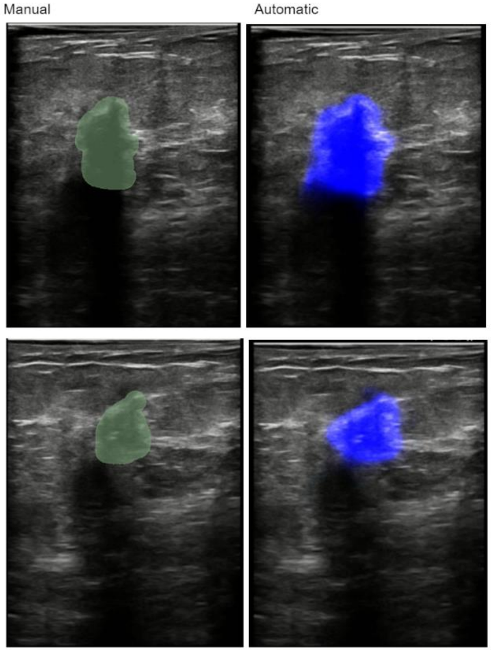
Existing Work

Comparisons to similar studies:

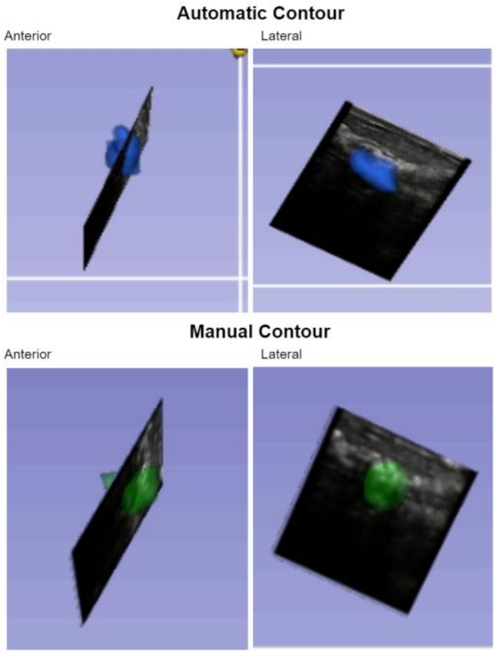
Model	AUC
Zhuang et al.	0.92
Byra et al.	0.95
Almajalid et al.	0.82
Wang et al.	0.92
Our model	0.94

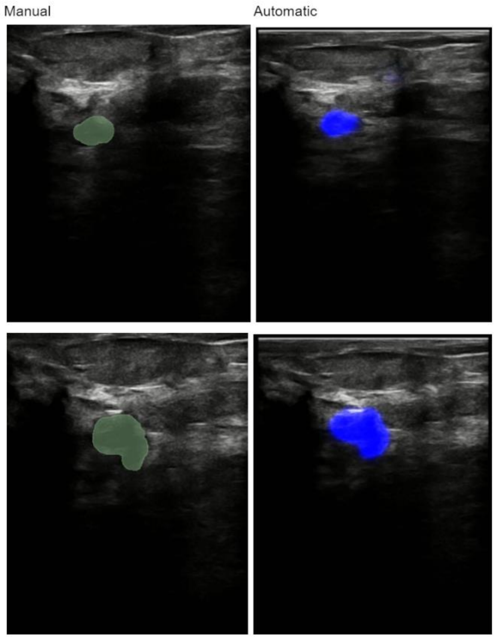
Example 1


Automatic Contour
Anterior
Lateral
Manual Contour
Anterior
Lateral


Manual
Automatic

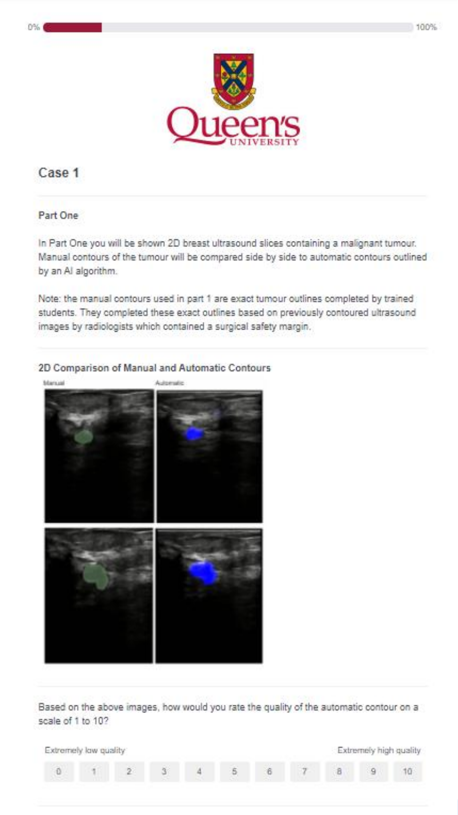
Example 2


Automatic Contour
Anterior
Lateral
Manual Contour
Anterior
Lateral


Manual
Automatic

Clinical Relevance

- Survey results:
  - **100%** of responses rated tumour contour **quality** in 2D and 3D above 70%
  - **78%** of responses rated tumour contour **quality** in 2D and 3D above 80%
  - **56%** of responders stated that they would be **comfortable** using the automatic tumour contours in **breast conserving surgery**

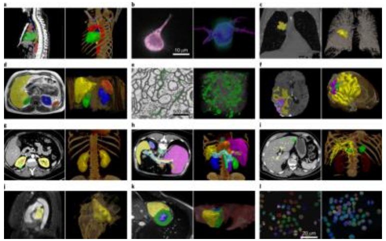


Conclusion

- High sensitivity and AUC values
- Good visual representation and robust 3D reconstruction pipeline
- Survey results positive for contour quality

Next Steps

nnU-Net



Thank You

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  Dr. Jay Engel
  Dr. Doris Jabs

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