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

- **Input:**
  - 33 patients
  - 7218 images
  - 128x128x1
  - Regular convolutions and max pooling layers applied
  - Learns WHAT information

- **Encoder (Downsampling):**
  - Transposed convolutions along with regular convolutions applied
  - Recovers WHERE information

- **Decoder (Upsampling):**
  - 3D ultrasound with segmented breast tumour
  - Output: 128x128x1

- **Output:**
  - 3D ultrasound with segmented breast tumour
Implementation Strategies

• Hyperparameter Optimization
  – Random search → Baseline
  – Trial and error → Model parameters
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

Enlarge your Dataset
## Model

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layers</td>
<td>7</td>
</tr>
<tr>
<td>Kernels</td>
<td>3x3 downsampling</td>
</tr>
<tr>
<td></td>
<td>4x4 upsampling</td>
</tr>
<tr>
<td>Learning rate</td>
<td>1e-4</td>
</tr>
<tr>
<td>Loss function</td>
<td>Weighted categorical loss fxn</td>
</tr>
<tr>
<td>Activation function</td>
<td>Softmax</td>
</tr>
<tr>
<td>Batch size</td>
<td>32</td>
</tr>
<tr>
<td>Epochs</td>
<td>200</td>
</tr>
</tbody>
</table>
Method: Cross-Validation

80% for training, 20% for testing

→ Prevents Overfitting

<table>
<thead>
<tr>
<th></th>
<th>Train</th>
<th>Train</th>
<th>Train</th>
<th>Train</th>
<th>Test</th>
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</thead>
<tbody>
<tr>
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<td>5</td>
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</tbody>
</table>

Model “blinded” to test set
Method: Evaluation

- Numerical accuracy metrics
- 2D and 3D visual representation of results
- Survey on clinical usability of tumour contours
Results

<table>
<thead>
<tr>
<th>Accuracy Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area under the ROC curve (AUC)</td>
<td>0.94</td>
</tr>
<tr>
<td>Dice similarity coefficient (DSC)</td>
<td>0.70</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>92%</td>
</tr>
<tr>
<td>Specificity</td>
<td>65%</td>
</tr>
</tbody>
</table>

Harmonic mean of sensitivity and specificity

Capability of the model in distinguishing the classes

Total training time: 19:25:10.582479
Existing Work

Comparisons to similar studies:

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhuang et al.</td>
<td>0.92</td>
</tr>
<tr>
<td>Byra et al.</td>
<td>0.95</td>
</tr>
<tr>
<td>Almajalid et al.</td>
<td>0.82</td>
</tr>
<tr>
<td>Wang et al.</td>
<td>0.92</td>
</tr>
<tr>
<td>Our model</td>
<td>0.94</td>
</tr>
</tbody>
</table>
Example 1
Example 2
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

• Queen’s Perk Lab:
  Dr. Tamas Ungi
  Dr. Gabor Fichtinger

• Kingston Health Sciences Center:
  Dr. Jay Engel
  Dr. Doris Jabs
References


