Convolutional Networks for Biomedical Image Segmentation

CS/IT 308 - Machine Learning Project Presentation

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- U-Net:Convolutional Networks for Biomedical Image Segmentation
- **Significance:** Highly influential (109,163+ citations), seminal work.

2. Problem Statement

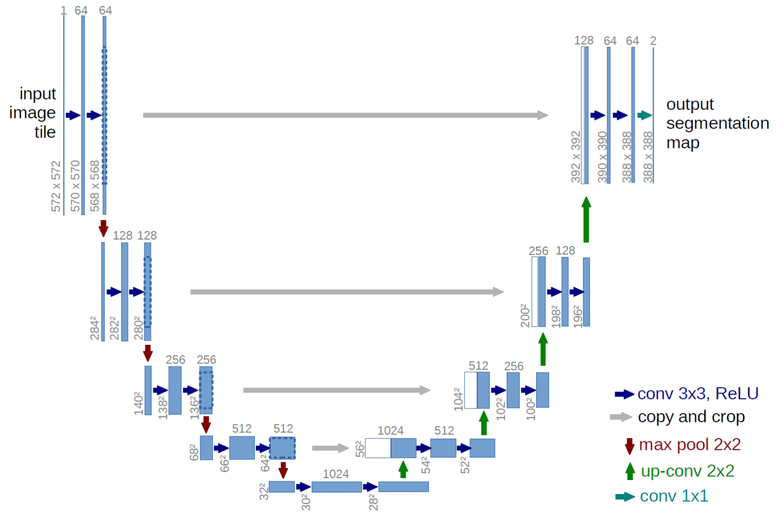
- **Given:** Limited labeled biomedical images; Need for precise segmentation.
- **Input:** $X \in \mathbb{R}^{512\times512\times1}$ — a single-channel grayscale image.
- **Approach:** U-Net architecture, data augmentation, optimized loss.
- **Output:** $Y \in \mathbb{R}^{388\times388\times2}$ — a pixel-wise segmentation mask (2 classes per pixel).
- **Objective:** Develop a CNN for accurate biomedical image segmentation.
- **Constraints:** Limited data, class imbalance, high precision needed.
- **Motivation:** To achieve high-accuracy results while ensuring faster training on a small image dataset.
- **Application:** Tumor detection, organ delineation, disease monitoring.

3. Dataset and Environment

Type: 2D grayscale biomedical images
Description: Set of 30 images (512x512 pixels) from serial section transmission electron microscopy of the Drosophila first instar larva ventral nerve cord (VNC).

- **Split:**
  - Training Set: 930 augmented & annotated MRI images
  - Validation Set: 30 images
  - Test Set: 30 images
- **Environment:**
  - Hardware: NVIDIA Quadro GP100 (16GB VRAM, 34% Util)
  - Language: Python 3.9
  - Platform: PyTorch

U-Net Architecture



U-Net: Encoder-decoder architecture with skip connections for biomedical image segmentation

4. Neural Architecture and Training

Architecture (U-Net based):

- Encoder-decoder structure using 5 levels of convolution + pooling / upsampling.
- Skip connections: Center cropping applied before concatenation for size alignment.
- Custom upsampling implemented using ‘Upsample‘ + ‘Conv2d‘.
- Custom weight initialization: Kaiming normal for conv layers, uniform for final layer.

Training Details:

- Optimizer: Stochastic Gradient Descent (SGD) with learning rate 2×10^{-5} and momentum 0.99.
- Batch Size: 8 (Train), 4 (Validation). Total Train Batches/Epoch: 117.
- Epochs: 50.
- Gradient Accumulation: Applied every 4 steps (simulates effective batch size 32).
- Validation: Performed after each epoch, computing average loss and IoU.

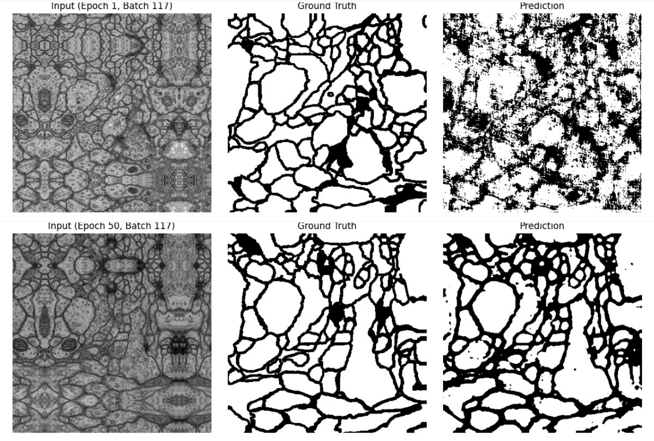
Loss Function:

- Custom weighted Binary Cross-Entropy (BCE) loss.
- Employs pixel-wise class balancing using inverse frequency weighting.
- Particularly useful for datasets with significant background-foreground imbalance.

Key Implementation Notes:

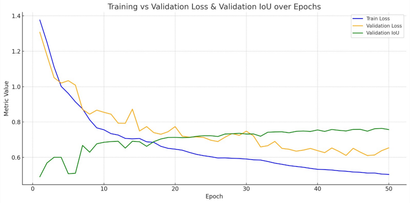
- Input images were mirror-padded to handle spatial dimension reduction during convolutions.
- Intersection over Union (IoU / Jaccard Score) used as the primary validation metric.
- Qualitative visualization samples saved at intervals to monitor prediction quality.

5. Result 1: Qualitative Segmentation Examples



Qualitative Segmentation Examples

6. Result 2: Training Progress (Loss IoU)



Training Insights (Epochs 1–50):

- Train Loss consistently decreased (1.38 $\rightarrow$ 0.50), showing stable learning.
- Validation IoU improved significantly (0.49 $\rightarrow$ 0.76), 55% relative increase.
- IoU shows stable growth after epoch 25, peaks at epochs 42–49 (IoU $>$ 0.75).
- Best balance around epoch 48: Val Loss: 0.614, Val IoU: 0.762

7. Result 3: Quantitative Test Set Evaluation

Final Test Set Performance

- Average Intersection over Union (IoU / Jaccard): **0.7576**
- Average Pixel Accuracy: **0.8765**
- Average Loss (Weighted BCE): 0.6544

(Metrics computed on the held-out test set of 30 images)

8. Conclusion and Future Work

Conclusion:

- Implemented U-Net provides robust performance.
- Achieved high accuracy on unseen data.
- Combination of U-Net, mirror padding, and weighted BCE loss effective.

Key Reference:

- Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: MICCAI 2015. LNCS, vol 9351. Springer.