Cross-domain Mitochondria Segmentation in Electron Microscopy Images

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Outline

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1. Motivation

- **Project motivation**
  - **Medical image analysis** is vital for **AI-driven disease diagnosis**.
  - Existing **deep learning models** experience a **significant performance decline** when tested on **images from unfamiliar domains.**
  - Acquiring labels for specific medical domains is **costly, time-consuming, and prone to errors.**

- **Project aim**
  - Enhance the **generalization abilities** of current AI models.
  - Develop novel frameworks for **cross-domain** medical image analysis.

2. Research Questions

- **Research questions**
  - How can we **adapt deep learning** for **consistent performance in unfamiliar imaging**, notably electron microscopy (EM)?
  - What strategies can be employed to **reduce reliance** on expensive, error-prone medical labels?
  - Is it feasible to create a **cross-domain framework** for **variability in EM images**, focusing on **mitochondria segmentation?**
- **Research scope**
  - **Addressing Label Scarcity:** Investigate strategies to tackle challenges in cross-domain imaging due to **limited label availability**.
  - **Mitochondria Segmentation:** Design a **cross-domain framework** for mitochondria segmentation in EM images.

3. Literature Review

- **Brief summary of related literature**

- **Supervised Domain Adaptation (Supervised DA)**
    - **Trains on labeled data from both domains** to reduce distribution differences and enhance target domain performance.
    - E.g. Ghafoorian *et al.* 2017, Samala *et al.* 2018, Khan *et al.* 2019, Gu et al. 2019, etc.

- **Semi-supervised Domain Adaptation (Semi-supervised DA)**
    - **Merges source domain labels with partial target labels,** utilizing unlabeled data for better target performance.
    - E.g. Roels et al. 2019, Madani et al. 2018.

- **Unsupervised Domain Adaptation (Unsupervised DA)**
    - **Relies on source domain labels and target's unlabeled data,** minimizing distribution gaps for label-free target adaptation.
    - E.g. **Peng et al. DAMT-NET 2020**, Daniel, et al. 2022, Gholami et al. 2018, Zhang et al. 2019, etc.

4. Research Method

- **Methodology**
  - **Base Model: Domain Adaptive Multi-Task Network (DAMT-NET)**
  - **Optimization Approaches**
    - **Large-scale Heterogeneous 3D EM Database**
      - Explore diverse sources, acquisition techniques, and samples
    - **Deep Utilization of Target Domain Knowledge**
      - Enhance domain adaptability through self-learning
      - Leverage structured visual information
    - **Style Transfer**
      - Separate "content" and "style" via neural networks
      - Apply specific styles to different image contents

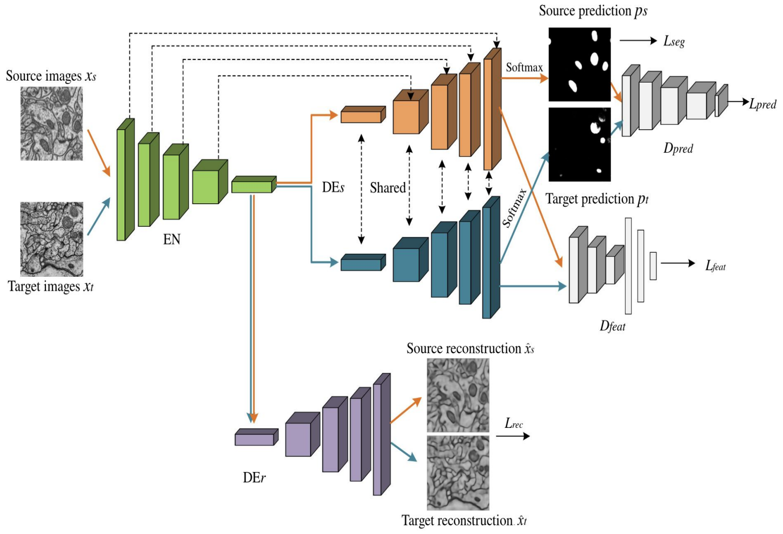

Figure 1. Architecture of DAMT-Net from Peng et al. (2020).

4. Research Method

- **Data Collection**

  Datasets

  - **Mouse Hippocampus**
    - Widely-used benchmark for mitochondria segmentation
    - Used as unlabeled target domain
  - **Drosophila III VNC**
    - Used as labeled source domain
  - **Drosophila I VNC**
    - Used as unlabeled target domain for testing

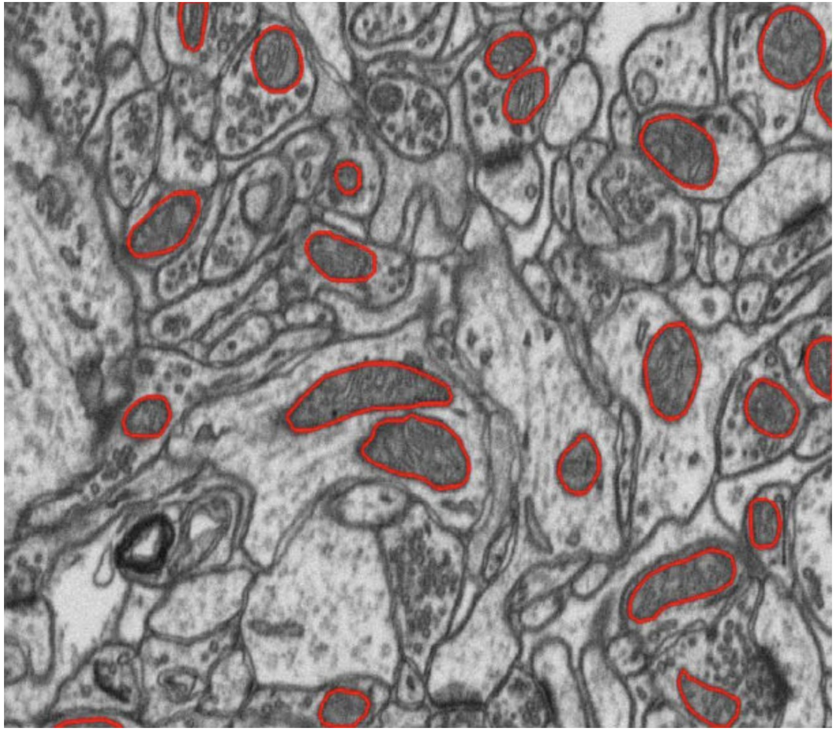

Figure 2. Mouse Hippocampus image from EPFL CVLab EM Dataset.

4. Research Method

- **Evaluation Metrics**

DSC (Dice Similarity Coefficient)

$$\mathrm{DSC} = \frac{2 \times |A \cap B|}{|A| + |B|}$$

JAC (Jaccard Index)

$$\mathrm{JAC} = \frac{|A \cap B|}{|A \cup B|}$$

- **Quantitative Analysis**
  - **Models for Comparation**
    - Our Proposed Method
    - DAMT-NET (Base Model)
    - Representative UDA Methods:
      i. Y-NET
      ii. DANN
    - NoAdapt Model
    - Supervised Method

- **Qualitative Analysis**
  - Showcase and analyze **successful and failed** segmentation cases.

5. Project Plan

Estimated Date	Tasks	Deliverables
2023-11-15	Data Preprocessing	Preprocessed Image Data
2023-11-30	Reproduce DAMT-NET Results	DAMT-NET Segmentation Results
2023-12-05	Implement Optimization 1: Dataset Exploration	New Dataset
2023-12-20	Implement Optimization 2: Self-learning Strategy	Self-learning Model
2024-01-05	Implement Optimization 3: Image Style Features	Style Feature Model
2024-01-20	Attempt Combined Optimization and other Approaches	Combined Optimization Model
2024-02-05	Comparative Experiments with Other Methods	Comparative Results and Analysis
2024-02-20	Analyze Results and Draft Paper	Initial Paper Draft
2024-03-01	Refine and Finalize Paper	Final Paper

6. References

1. Peng, J., Yi, J., & Yuan, Z. (2020). Unsupervised Mitochondria Segmentation in EM Images via Domain Adaptive Multi-Task Learning. IEEE Journal of Selected Topics in Signal Processing, 14(6), 1199-1202.
2. EPFL Computer Vision Lab. EM Datasets. EPFL CVLab. https://www.epfl.ch/labs/cvlab/data/data-em/. Accessed on October 2, 2023.