Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation

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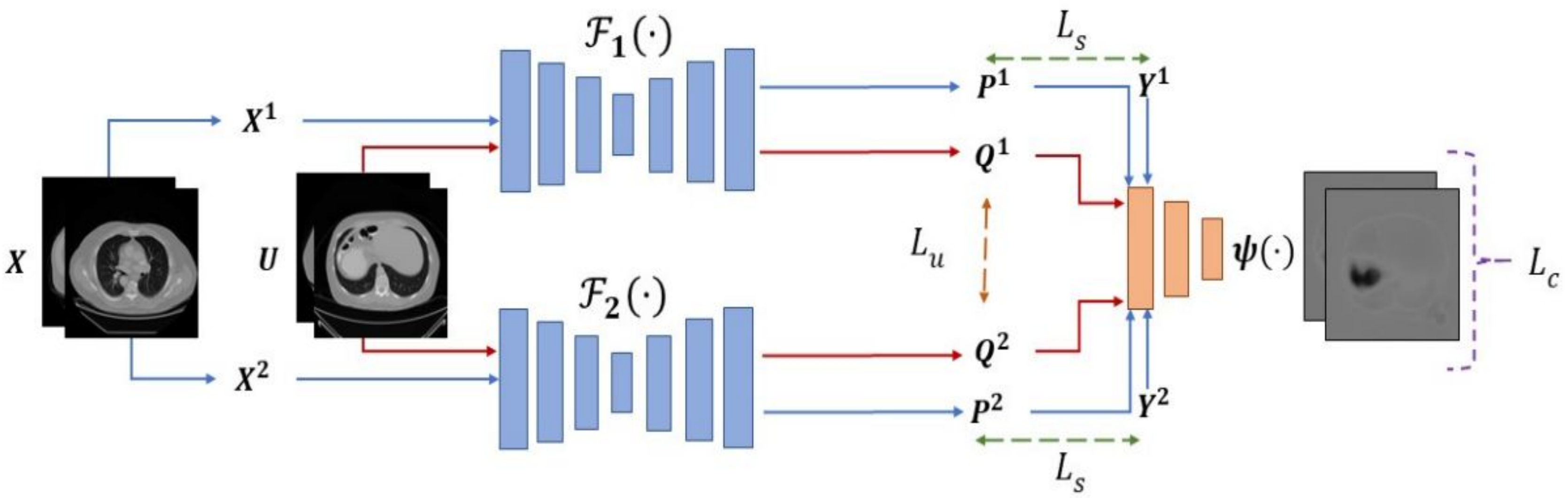
Summary of Presentation1



Multitask loss function

$$\min_{\boldsymbol{\Theta}} \max_{\theta_C} \mathcal{L}(\boldsymbol{\Theta}; \mathcal{D}) \ .$$

$$\mathcal{L}(\boldsymbol{\Theta}; \mathcal{D}) := \lambda_s \, \mathcal{L}_{\mathrm{s}}(\boldsymbol{\Theta}; \mathcal{X}) + \lambda_u \, \mathcal{L}_{\mathrm{u}}(\boldsymbol{\Theta}; \mathcal{U}) + \lambda_c \, \mathcal{L}_{\mathrm{c}}(\boldsymbol{\Theta}; \theta_C; \mathcal{D})$$

Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

Supervised Loss and Unsupervised loss

$$\mathcal{L}_{\mathrm{ce}}(\theta_i; \mathcal{X}) = \mathbb{E}_{(\mathbf{X},\mathbf{Y})\sim\mathcal{X}}\left[\left\langle \mathbf{Y}, \log\left(\mathcal{F}_i(\mathbf{X})\right)\right\rangle\right]$$

$$\mathcal{L}_{\mathrm{u}}(\boldsymbol{\Theta}; \mathcal{U}) \coloneqq \mathbb{E}_{\mathbf{U}\sim\mathcal{U}}\left[\left\langle \mathcal{F}_1(\mathbf{U}), \log\left(\mathcal{F}_2(\mathbf{U})\right)\right\rangle + \left\langle \mathcal{F}_2(\mathbf{U}), \log\left(\mathcal{F}_1(\mathbf{U})\right)\right\rangle\right]$$

Critic Loss

$$\Psi : [0,1]^{H\times W} \to [0,1]^{H\times W}$$

$$\mathcal{L}_{adv1}(\mathbf{\Theta};\theta_C;\mathcal{X}) := \mathbb{E}_{(\mathbf{X},\mathbf{Y})\sim\mathcal{X}}\Big[-\sum_{a\in H}\sum_{b\in W}\Big\{(1-\eta)\log\Big(\psi(\mathbf{Y})[a,b]\Big) + \eta\log\Big(1-\psi(\mathcal{F}_i(\mathbf{X}))[a,b]\Big)\Big\}\Big],$$

$$\mathcal{L}_{adv2}(\mathbf{\Theta};\theta_C;\mathcal{U}) := \mathbb{E}_{\mathbf{U}\sim\mathcal{U}}\Big[-\sum_{a\in H}\sum_{b\in W}\Big\{\log\Big(1-\psi(\mathcal{F}_i(\mathbf{U}))[a,b]\Big)\Big\}\Big]$$

$$\mathcal{L}_{\mathrm{c}}(\mathbf{\Theta};\theta_C;\mathcal{D}) = \mathcal{L}_{\mathrm{adv1}}(\mathbf{\Theta};\theta_C;\mathcal{X}) + \mathcal{L}_{\mathrm{adv2}}(\mathbf{\Theta};\theta_C;\mathcal{U}).$$

Implementation Details

- The proposed model is developed in PyTorch
- Training was done from scratch without using any pre-trained model weights.
- For training of segmentation network and critic, we use SGD optimizer and RMSProp optimizer
- Dataset is divided into training (80%) and test set (20%).
- Experiments were conducted for 5%, 20% and 50% of labeled training sets.

Pseudo Code

Input: Define Segmentation networks $\{\mathcal{F}_i(\cdot)\}_{i=1}^2$, critic $\psi(\cdot)$, batch size $\mathcal{B}$, maximum epoch E_{max}, number of steps k_s and k_c for segmentation networks and critic, Labeled images $\mathcal{X} = \{(X_1, Y_1), ..., (X_m, Y_m)\}$, Unlabeled images $\mathcal{U} = \{U_1, ..., U_n\}$ and two labeled sets $\mathcal{X}^1; \mathcal{X}^2 \subset \mathcal{X}$;

Output: Network Parameters $\{\theta_i\}_{i=1}^2$ and θ_C;
Initialize Network Parameters $\{\theta_i\}_{i=1}^2$ and θ_C;

```
for epoch = 1, ··· , E_max do
    for batch = 1, ··· , B do
        for k_s steps do
            Generate predictions for labeled data F_1(x) for all X_i ∈ X^1, F_2(x) for
              all X_i ∈ X^2 and for unlabeled data F_1(x) and F_2(x) for all U_i ∈ U;
            Generate confidence maps for all predictions using ψ(·);
            Let L = L_s + L_u + L_c, as defined in Equations. (2) - (8);
            Update {θ_i}_{i=1}^2 by descending its stochastic gradient on L;
        end
        for k_c steps do
            Generate confidence maps for all labeled predictions and ground
              truth masks using ψ(·);
            Let L_c = L_adv1, as defined in 6;
            Update θ_C by ascending its stochastic gradient on L_c;
        end
    end
end
```

Reproduce Results

DSC

Dataset	5%	20%	50%
Nuclei	87.14	87.83	89.28
Heart	86.79	93.21	95.56
Spleen	88.02	92.19	96.03

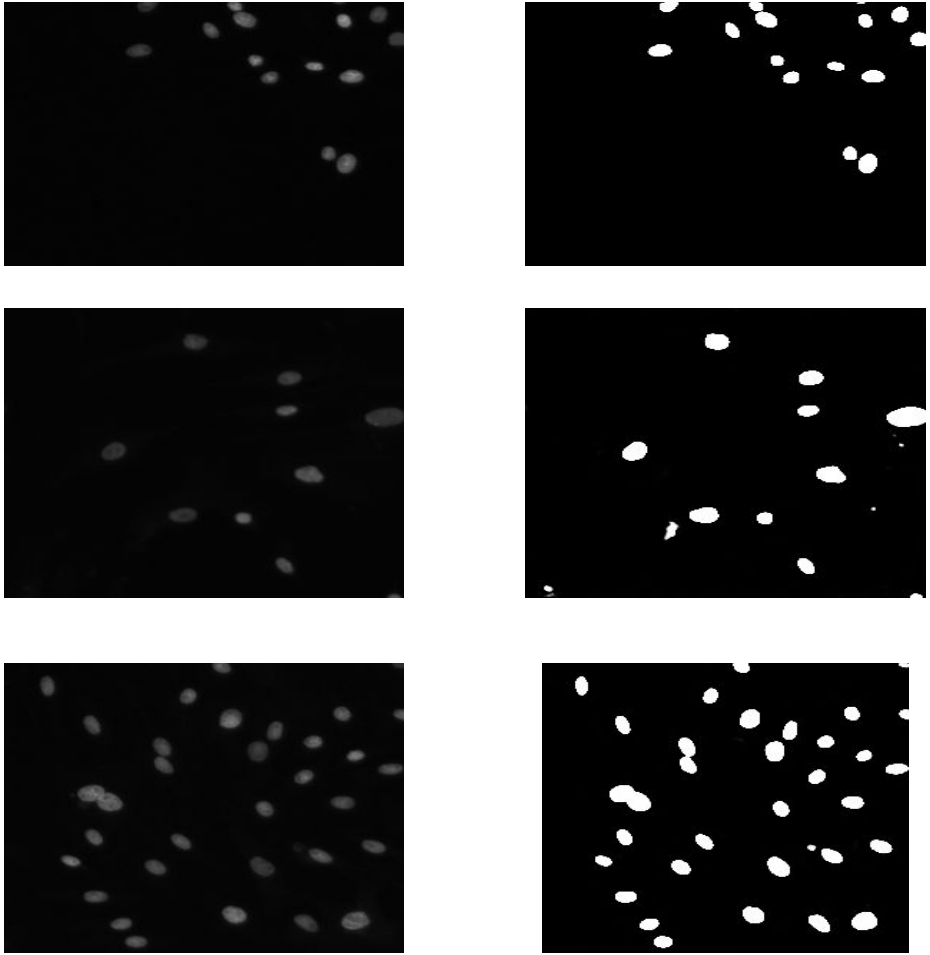
Dataset	5%	20%	50%
Nuclei	**73.3552**	**79.0114**	**87.9831**
Heart	-	-	-
Spleen	-	-	-

MAE

Dataset	5%	20%	50%
Nuclei	3.57	3.43	3.03
Heart	0.10	0.05	0.03
Spleen	0.10	0.07	0.03

Dataset	5%	20%	50%
Nuclei	**4.0**	**3.14**	**1.906**
Heart	-	-	-
Spleen	-	-	-

Visual Results



Ground Truth **Predictions**

Future Work

- We can also make use of 3D-Unet instead of Unet

- We can further improve dual view training by self-tuning mechanisms.

Conclusion

- Duo-Seg net efficiently uses the Unlabelled data for medical image segmentation

- Unet3D can further improve the model and will make the model easy to use.

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References

- Yi, Xin, Ekta Walia, and Paul Babyn. "Generative adversarial network in medical imaging: A review." Medical image analysis 58 (2019): 101552.

- Zhao, Jing, et al. "Multi-view learning overview: Recent progress and new challenges." Information Fusion 38 (2017): 43-54.

- Sivagami, S., et al. "Unet architecture based dental panoramic image segmentation." 2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET). IEEE, 2020.

- Miyato, Takeru, et al. "Virtual adversarial training: a regularization method for supervised and semi-supervised learning." IEEE transactions on pattern analysis and machine intelligence

Thank You

DuoSegnet Colab