Deep Vein Thrombosis Detection From CT Scans

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Motivation

- Deep vein thrombosis (DVT) is a blood clot commonly found in deep veins of the lower extremities
- Every year, 60,000-100,000 Americans die of complications arising from DVT
- Patients who get CT scans are frequently discharged before a radiologist looks at the scan
- Early and automated detection is critical for lowering fatalities and in regions with few radiologists

Data and Features

- We use the VITAL dataset curated by Dr. Lawrence Hofmann's team at Stanford
- The images are grayscale of size 512x512

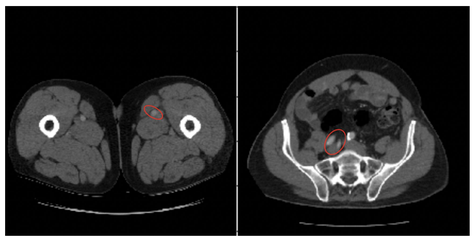


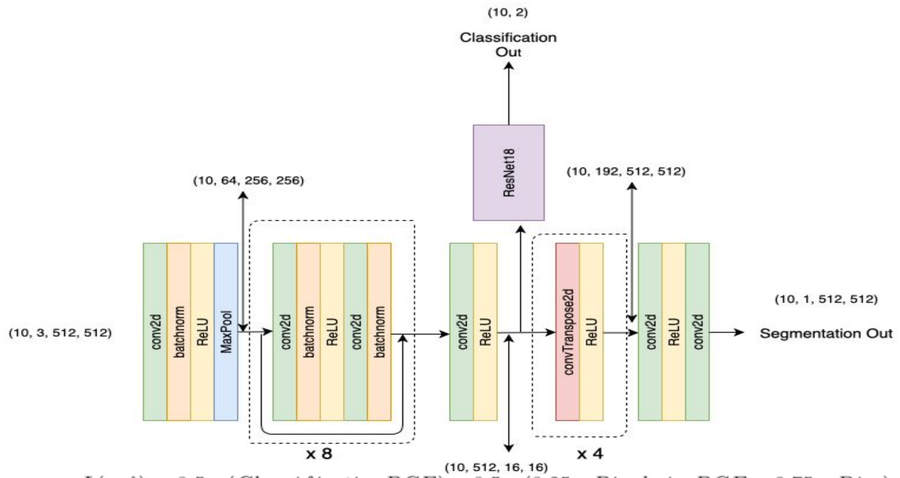
Fig. 1. Presence of DVT in Femoral (Left) and Iliac veins (Right)

- 33% of 460 CT scans in validation & test sets, 2D slices split 84%-8%-8%
- Two distinct anatomies: Femoral (below the groin) and Iliac (above the groin) - focused solely on femoral scans
- Radiologist-Labeled vein locations and "DVT or No DVT" label given per scan
- Image split into 16x16 "patches" and labeled for vein detection

Models

- Baseline (non-deep-learning) Model
  - Get SIFT encoded image features and use K-Means and SVM classifier to classify images
- Classification Models
  - DenseNet-161
  - VGG-16

  Final classification layers were replaced to reflect the correct number of classes.
- Multitask Model



$$L(y, \hat{y}) = 0.5 * (ClassificationBCE) + 0.5 * (0.25 * PixelwiseBCE + 0.75 * Dice)$$

Results

Experiment	AUC	Precision	Recall
SIFT Baseline	0.55	0.56	0.72
VGG-16	0.50	0.54	0.40
DenseNet-161 (train)	0.78	0.72	0.94
DenseNet-161 (test)	0.51	0.6	0.6
DenseNet-161 (test) with dropout	0.66	0.63	0.88
Multitask ResNetUNet	**0.69**	**0.68**	**0.73**

Table 1: Classification performance across models

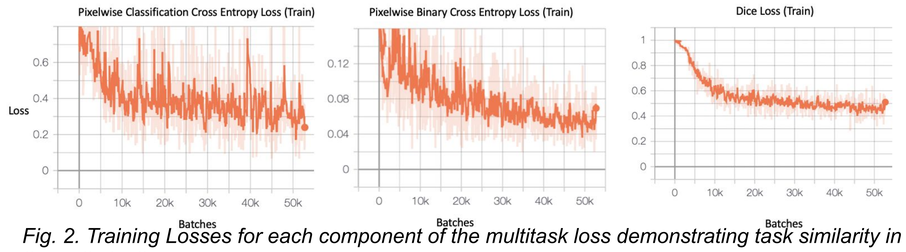


Fig. 2. Training Losses for each component of the multitask loss demonstrating task similarity in the optimization process

Analysis

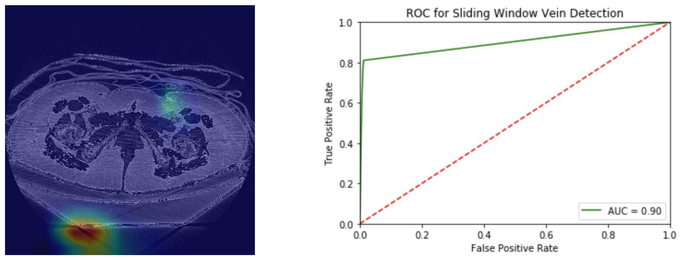


Fig. 3. Error Analysis of the Classification Models. (Left) CAMs for incorrectly classified images.(Right) ROC Curve for Patchwise Sliding Window Vein Detection

- CAMs indicate that in images the model misclassifies, it is unable to localize the veins
- We trained a fully convolutional sliding window model to locate veins in the images regardless of thrombosis. The model hits AUC of 0.9 indicating that it can identify the region of the vein.

Key Findings

- Highly localized information is needed for detection of thrombosis from CT scans.
- Deep Neural Networks are capable of locating regions in CT scans where veins are present.
- Anatomy matters and including scans from above the groin degrades network performance.

Conclusions and Future Work

- Deep learning is effective in DVT detection and can perform better with more local information.
- Future modeling: Cascaded model structures with vein localization followed by thrombosis classification.
- Future datasets: A more comprehensive dataset including normal cases is needed with consistency in quality of scans between patients.

References: [1] M. G. Beckman, W. C. Hooper, S. E. Critchley, and T. L. Ortel, "Venous thromboembolism: A publichealth concern,"American journal of preventive medicine, Apr. 2010. [Online]. Available:https://www.ncbi.nlm.nih.gov/pubmed/20331949
[2]O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation,"CoRR, vol. abs/1505.04597, 2015. arXiv:1505.04597. [Online]. Available:http://arxiv.org/abs/1505.04597.