CT Liver Lesion Localization using Deep CNNs

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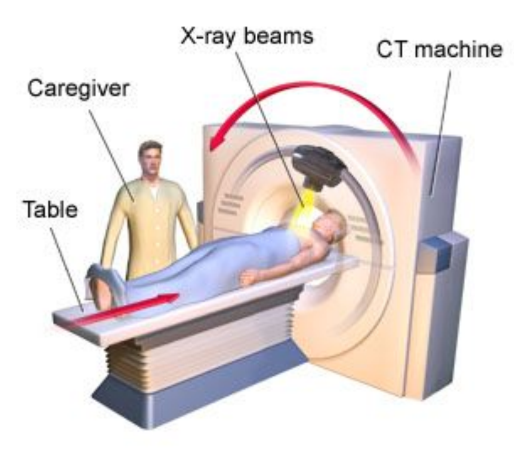
Motivation

- **Automated Lesion Localization in Computed Tomography (CT) scans** is poised to revolutionize the practice of radiology through increased efficiency and accuracy of diagnosis.
- The use of medical imaging is increasing in the United States.
- We want to apply state-of-the-art detection techniques to the **problem of liver lesion localization in CT scans**..



Computerized Axial Tomography Scan

Technical Setup and Data

- Data: We used a subset of the **DeepLesion dataset** comprised of **2369 512x512x1 pictures** of CT scans each labeled with a bounding box for the main lesion present.
- Pre-processing involved slice extraction, windowing, and pixel normalization
- **Our baseline** consists of 4 convolutional layers, 2 maxpool layers and a **4x1 output layer of bounding box coordinates.**

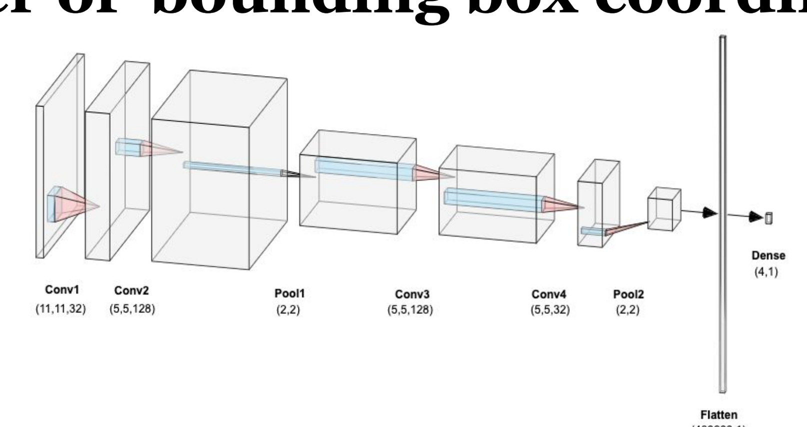
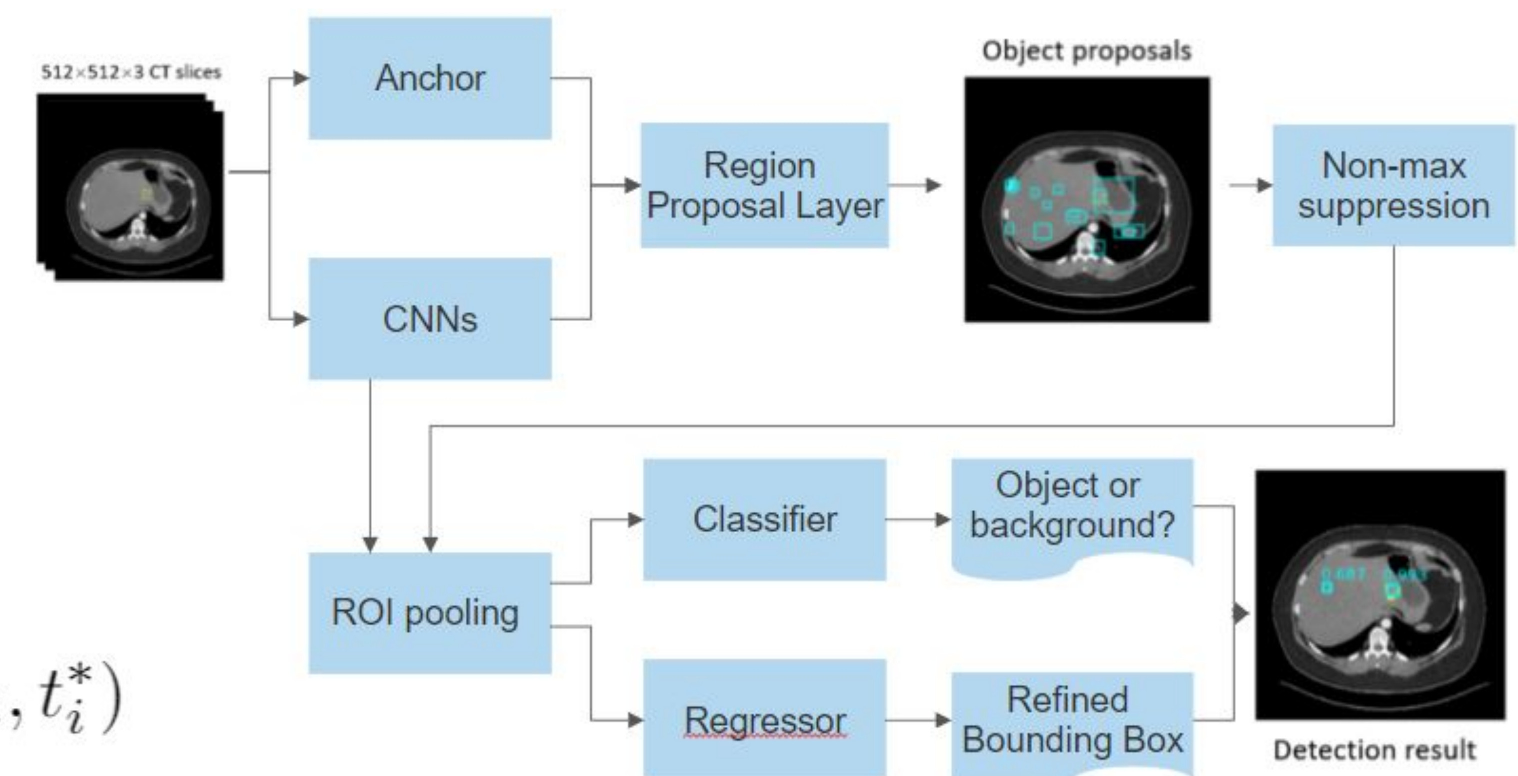


Figure1: Baseline CNN architecture

Models and Architecture

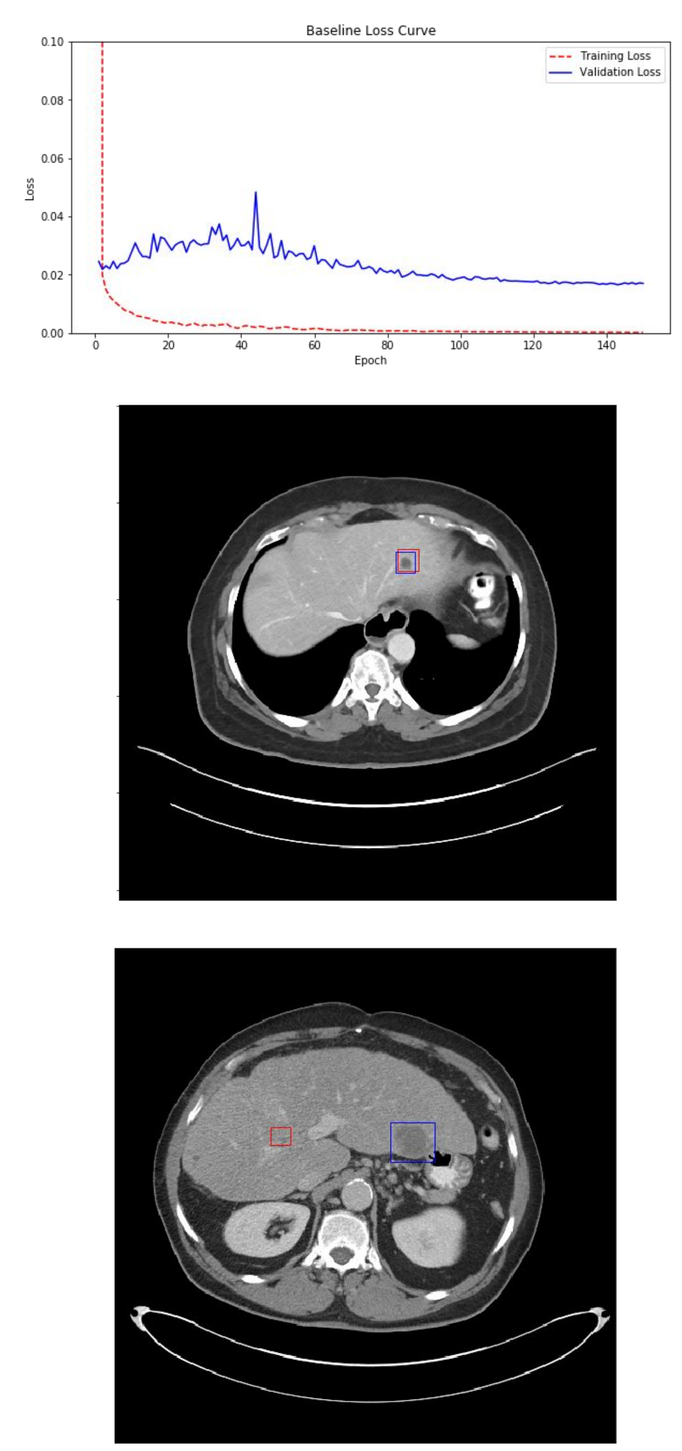
- **Transfer learning:** We experimented with transferring different trained **VGG-16 layers** to our baseline as well as making them **fixed or trainable.** We also used **ResNet-50** for Faster-RCNN
- We used **Faster R-CNN** as our main detection model.
- This architecture uses a **trainable region proposal network.**
- We customized **anchor boxes** based on results from the literature.

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*)$$

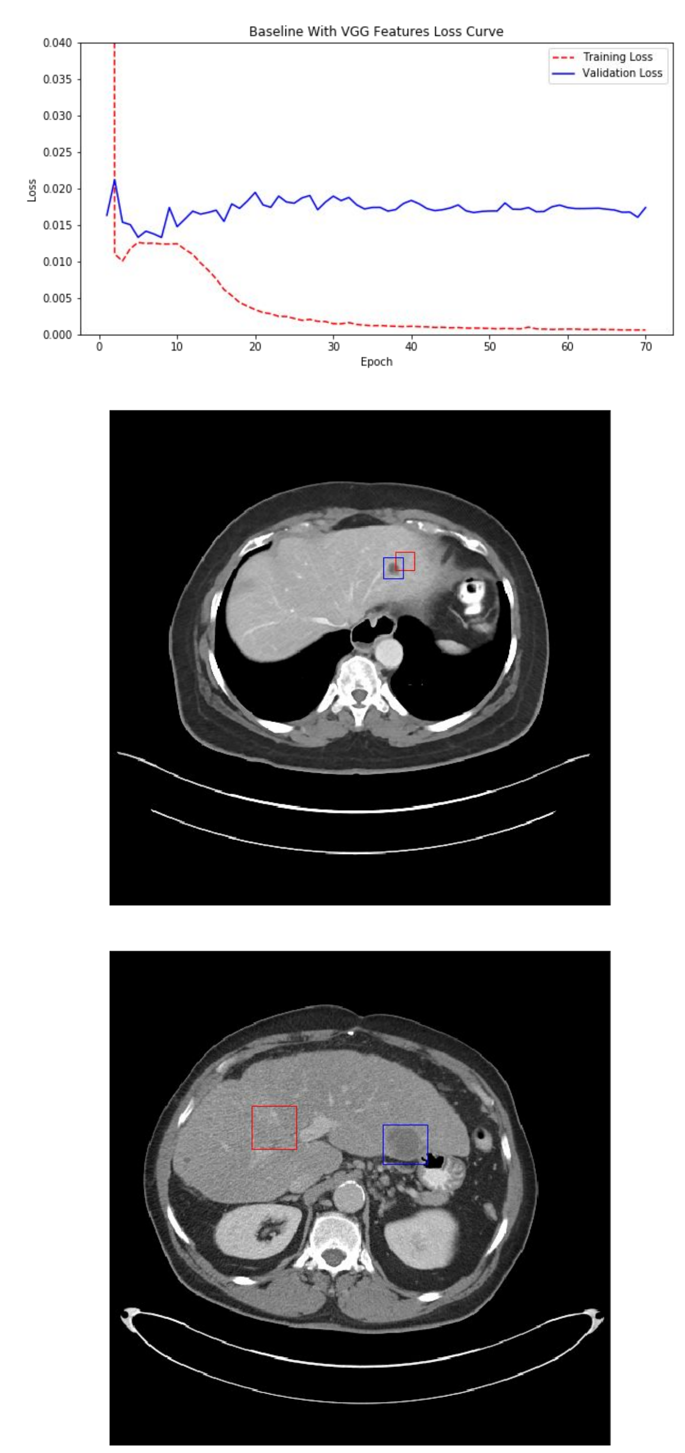


Experiments & Results

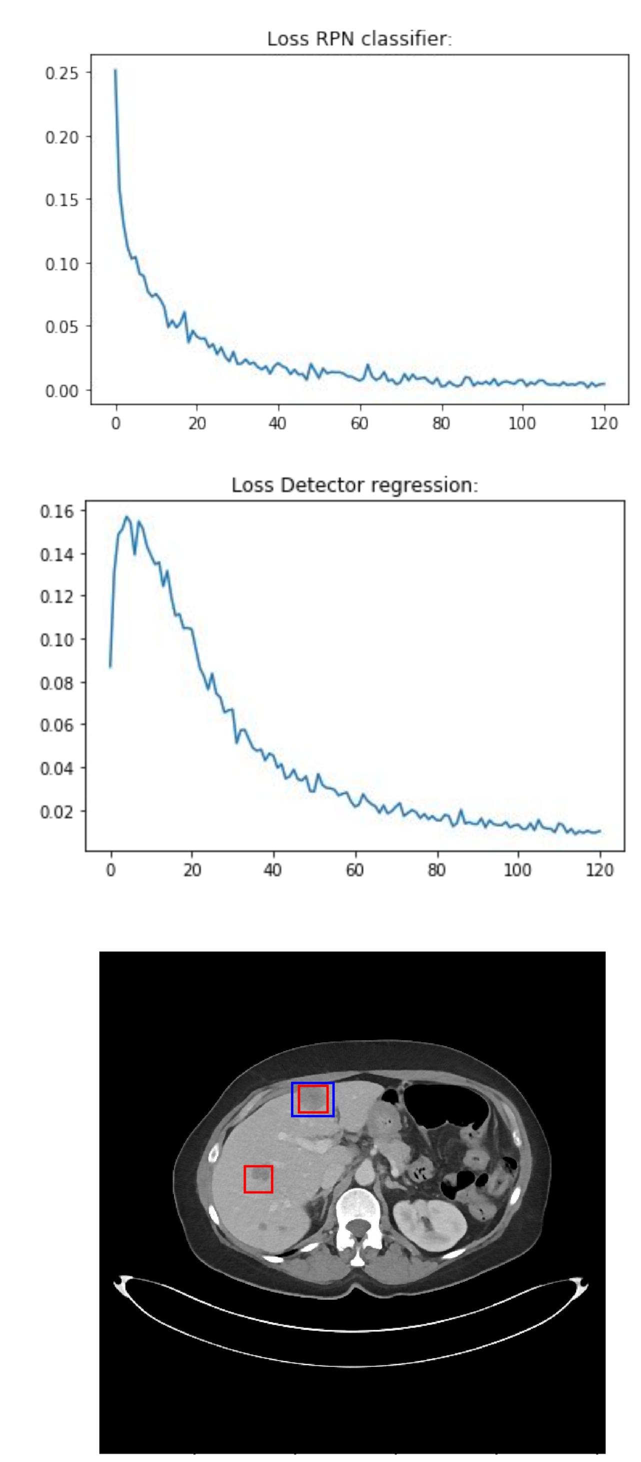
Baseline model



Baseline model + Fixed VGG



Faster R-CNN



- **Baseline model:** We tuned and ran the baseline on 150 epochs, learning rate of 0.003 and no dropout.
- **Baseline model +Fixed VGG + Skip**: We ran the model for 70 epochs, 0.0001 learning rate and dropout of 0.05.
- **Faster RCNN:** We trained Faster RCNN on the liver data for 120 epochs.

Results: Sensitivity

Baseline	Baseline + VGG-16	Faster R-CNN
0.069	0.079	0.5

Challenges & Future Work

- **Noisy labels** are a challenge.
- It would be interesting to see how other architectures, such as **YOLO** perform on the same task.
- We would like to explore how the model performs on other types of lesions, such as **lung**, **kidney** etc.