# Few shot learning for small lesion detection

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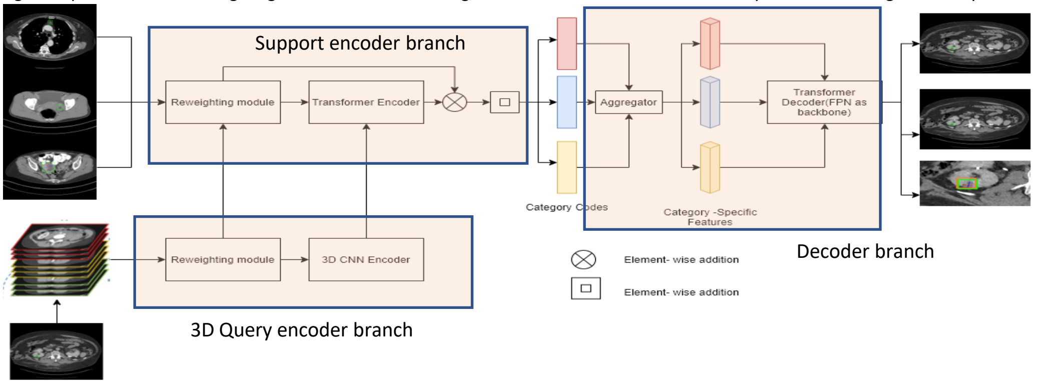
## Introduction

Small lesion detection is a challenging task in medical image analysis because apart from the small representations of objects, the diversity of input images also make the task more difficult [1]. Deep learning can increase the accuracy of lesion detection than other traditional computer vision algorithm. However, most of the state-of-the-art detectors, both in one-stage and two-stage approaches, have struggled with detecting small lesions. Moreover, to train the supervised networks for small lesions detection on medical images, very large training sets are needed with thousands of labeled images. However, for medical images, the large training data sets for small target area are normally not publicly available and difficult to label and collect. For instance, high-quality annotations by radiology experts are often costly and not manageable at large scales [2]. Therefore, this project aims to develop a deep learning model for small lesion detection on large-scale medical images, which can improve the accuracy of lesion awareness and diagnosis for diseases. Moreover, considering the limitation of labeling and collecting the small objects data-set, the model will be improved by few-shot learning approaches for limited data training.

## Method

- Data- preprocessing for CT image dataset: Analyzing the characteristics of small objects and applying the traditional computer vision approaches to enhance the appearance information of small objects against the background or similar categories.
- Model Design: Adapt 3D CNN and reweighting module to meta learning, which can localize the small lesion by few shot training accurately.




- Loss function Design:GIOU Loss [3] for bounding box regression (Solve the problem of unbalanced positive and negative samples):

$$L(y',\hat{y}) = \sum_{i=1}^{N} -L_{IOU}\,(b_i',\hat{b}_{\delta(i)}) - ln\frac{|A_c - union(b_i',\hat{b}_{\delta(i)})|}{A_c}\ (A_c \text{ is the min}|intersection(b_i',\hat{b}_{\delta(i)})|)$$

## Results

- Experiment dataset (DeepLesion): Training on the big lesion sub-dataset + 80% small lesion sub-dataset; Testing on 20% small lesion sub-dataset
- Training device: Ubuntu 16.04 with GeForce RTX 2080 Ti/PCIe/SSE2
- Evaluation criteria: accuracy, Dice score, and running time
- Testing method: normal test and patch test which cropping CT image into 9 parts as different test images (so called patches)
- Comparing the testing results produced by the trained model with the state-of-the-art models: Ours has the best detection accuracy and Dice score when the running time is acceptable (showed as table 1)
- Detecting examples are shown in figure 1: the bounding box predicted by the trained model is approximate to the ground truth

| Detection model | Accuracy | Run time (ms) | Dice overlap |
|---|---|---|---|
| Faster RCNN | 87.2% | 67 | 0.59 |
| Faster RCNN Patch test | 91.12% | 129 | 0.64 |
| Few shot learning – supporting label | 81.12% | 32 | 0.41 |
| Meta learning | 85.92% | 22 | 0.54 |
| Meta learning with reweighting module | 89.21% | 36 | 0.62 |
| Reweighted Meta learning +3D CNN | 92.21% | 47 | 0.71 |

**Table 1 –** Lesion detection performance comparison on Deep lesion Dataset

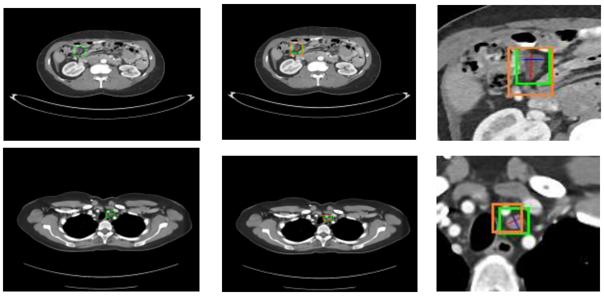


**Figure 1 –** Left: Original image with lesion ground truth (green); Middle: Detecting results of the trained model (orange); Right: Cropped results focusing on the lesion area

## Discussion

- The query encoder branch emerged 3D volume information of CT image, which increase the context features to small lesion
- The reweighting module increase difference of lesion against to the background by pre-learning more useful features from supporting images (big lesion image with sufficient samples)
- GIOU loss function balanced the positive and negative samples in the CT image, thereby improved the small lesion localization
- For future work, more experiments and ablation studies should be done to explain the model structure and provide more evidence for model effectiveness.

## References

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