Politecnico di Torino
Dipartimento di Automatica e Informatica

PhD in Computer and Control Engineering
34th cycle

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Machine learning methods for the analysis and interpretation of images and other multi-dimensional data

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1. Introduction

Computer aided detection (CAD) for medical images is considered as a fine-grained task. CAD systems help doctors in diagnosis. Therefore, this area has been the center of attention for many deep learning practitioners. However, acquiring datasets for supervised learning requires the consensus opinion of several radiologists which makes data preparation costly and time-intensive. As a result, the typical size of datasets is rather small with respect to natural RGB images. Moreover, even with large scale datasets, only a small portion is annotated. A possible solution for retrieving annotations is to automatically mine reports collected in clinical practice, which however may introduce noise in the reference standard.

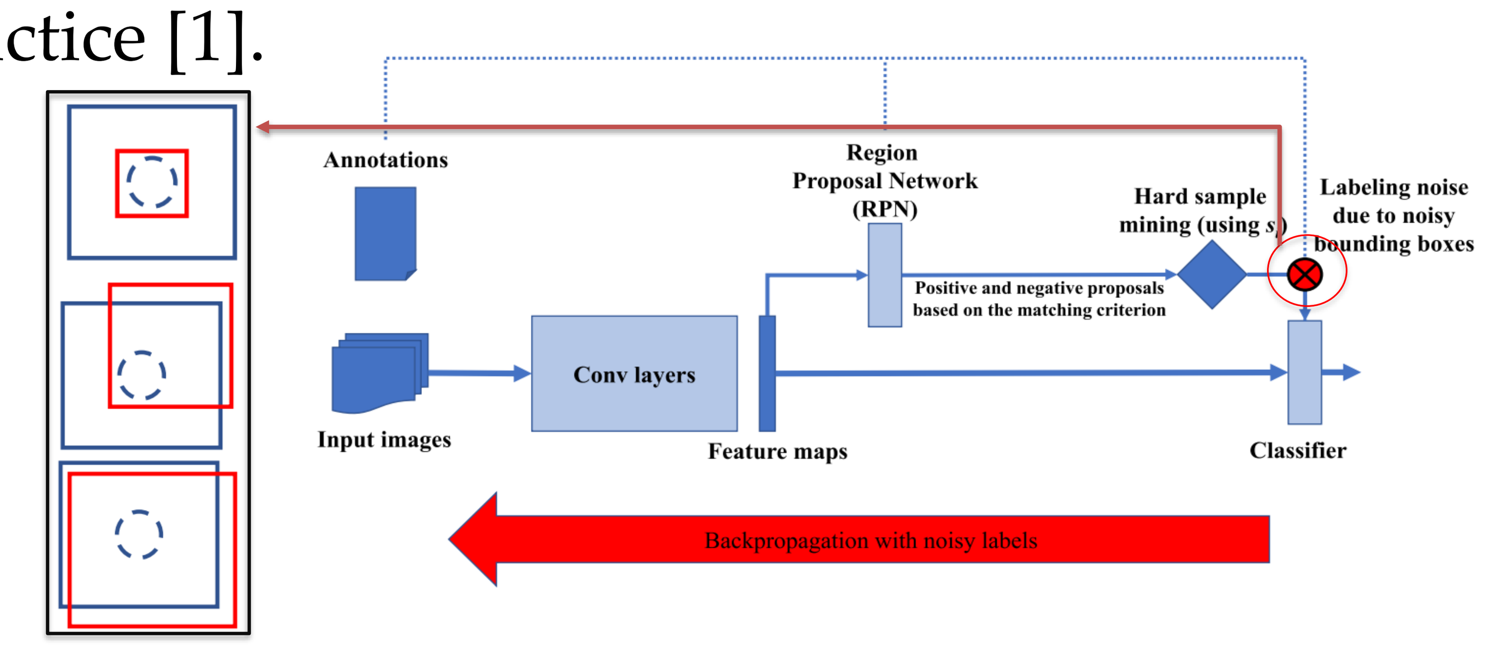
2. Objectives

The objectives of this research focus on two main pillars: (1) Studying methods that makes training robust against noise, (2) Developing and studying multi-task, cross-domain training pipelines with less reliance on annotations.

3. Methods

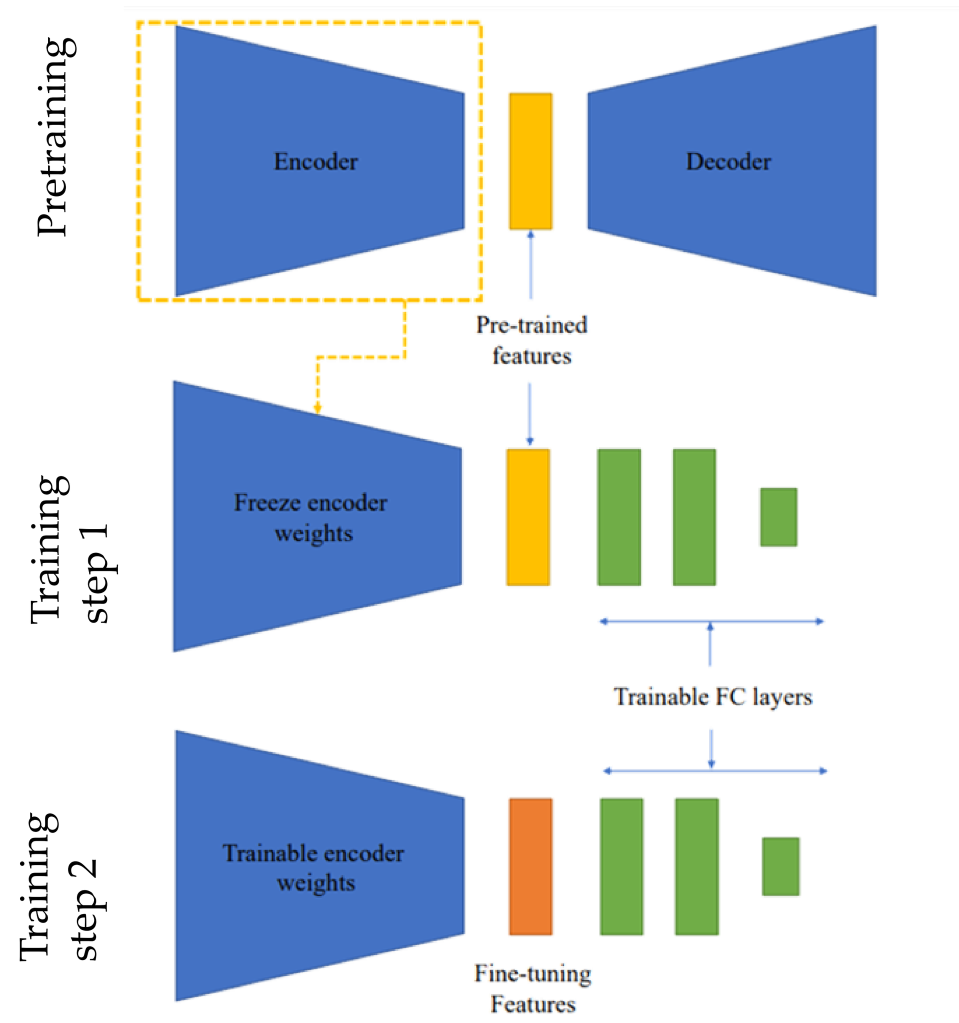
3.1 Learning from noisy annotations

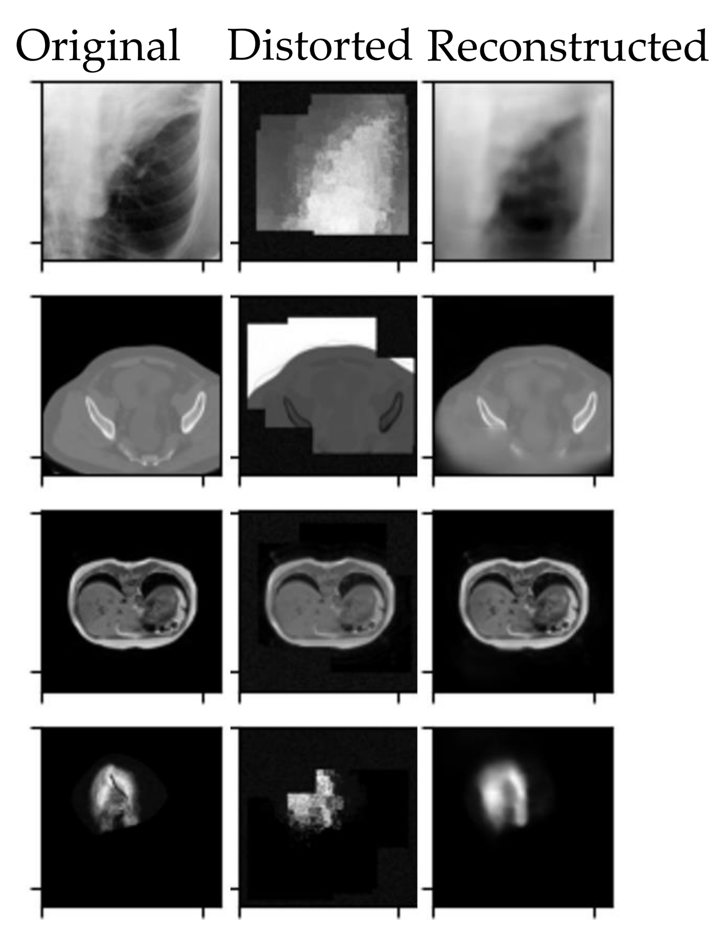
A quantitative approach has been provided for the evaluation of noisy annotations in object detection by injecting varying degrees of noise in images, enlarging bounding boxes surrounding masses. It has been shown that labeling noise propagates through the training procedure due to imperfect matching. A novel matching criterion has been proposed to counter this effect. This activity opens new opportunities to use bookmarks that are collected routinely in clinical practice [1].



3.2 Self-supervised representation learning

Self-supervision is a method of pretraining on unlabeled dataset a deep neural network by a self-generated pretext task. In this research, a self-supervised pretraining framework has been applied to half a million images collected from publicly available datasets covering various medical imaging modalities and body parts. The extracted features can discriminate better than ImageNet, which is now the de-facto standard for transfer learning in the medical domain.

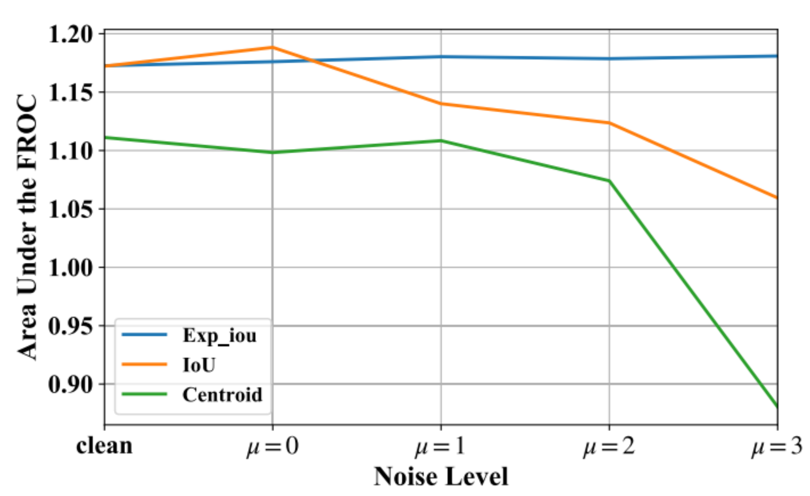




Pretext task example

4. Results and conclusion

The proposed methods open new opportunities to train on real-world datasets by relaxing the requirements for annotation and requiring less data for training.



Faster RCNN becomes robust in presence of noise using proposed method that is described in Section 3.1.

Task	ImageNet	Our method
LUNA16	0.548	0.826
Chest X-Ray	0.580	0.764
MURA	0.568	0.646

The representations provided by the self-supervised training in Section 3.2 outperforms ImageNet for classification.

5. References

1. Famouri, Sina, et al. "*Breast Mass Detection With Faster R-CNN: On the Feasibility of Learning From Noisy Annotations.*" IEEE Access 9 (2021): 66163-66175.

2. Famouri, S., Morra, L., & Lamberti, F. (2020, September). *A Deep Learning Approach for Efficient Registration of Dual View Mammography*. In *IAPR Workshop on Artificial Neural Networks in Pattern Recognition* (pp. 162-172). Springer, Cham.