Pneumonia detection and classification using Mask R-CNN and CheXNet

Anders Stevnhoved Olsen (s154043), Caroline Dam Hieu (s182120) & Cecilie Dura André (s153316)

Introduction

The **goal** of this project is to perform **detection and classification** of **Pneumonia**, a vicious lung infection that accounts for 15% of all deaths of children under 5 years old internationally [**1**], on chest X-ray images. In this case, detection means providing bounding boxes for so-called lung opacities if evident. To fulfill this purpose, two different **state-of-the-art neural networks** have been examined and implemented: **Mask R-CNN** [**2**] and **CheXNet** [**3**].

The two networks were tested on a data set provided by Radiological Society of North America (RSNA) originally intended to be part of a Kaggle competition with the aim of improving the efficiency and diagnostic reach of Pneumonia diagnosis. **Unumed** is a Danish company whose **mission** statement is to **provide health software systems** to African, Middle Eastern and Asian health care facilities. In other words, to countries where availability of skilled radiologists is lessened.

Thus, this project serves the **purpose**:

- To **investigate networks** that may be implemented in software for Pneumonia diagnosis in third-world countries.

Pneumonia

Pneumonia is an infection that causes the alveoli of the lungs to be filled with **fluid or pus** [**1**]. These are called **lung opacities**. Diagnosis of lung opacities is usually performed using X-ray images of the lung. The attenuation of X-rays is higher in fluid than in air, and thus, an X-ray image of a patient with **lung opacities** will potentially be **brighter** than one of a normal patient. An example is shown in Figure 1. Here, haziness is visible at the locations of labeled boxes in the lung opacity image. However, it is also clear that even skilled radiologists can have difficulties classifying and locating these areas.

Pneumonia example

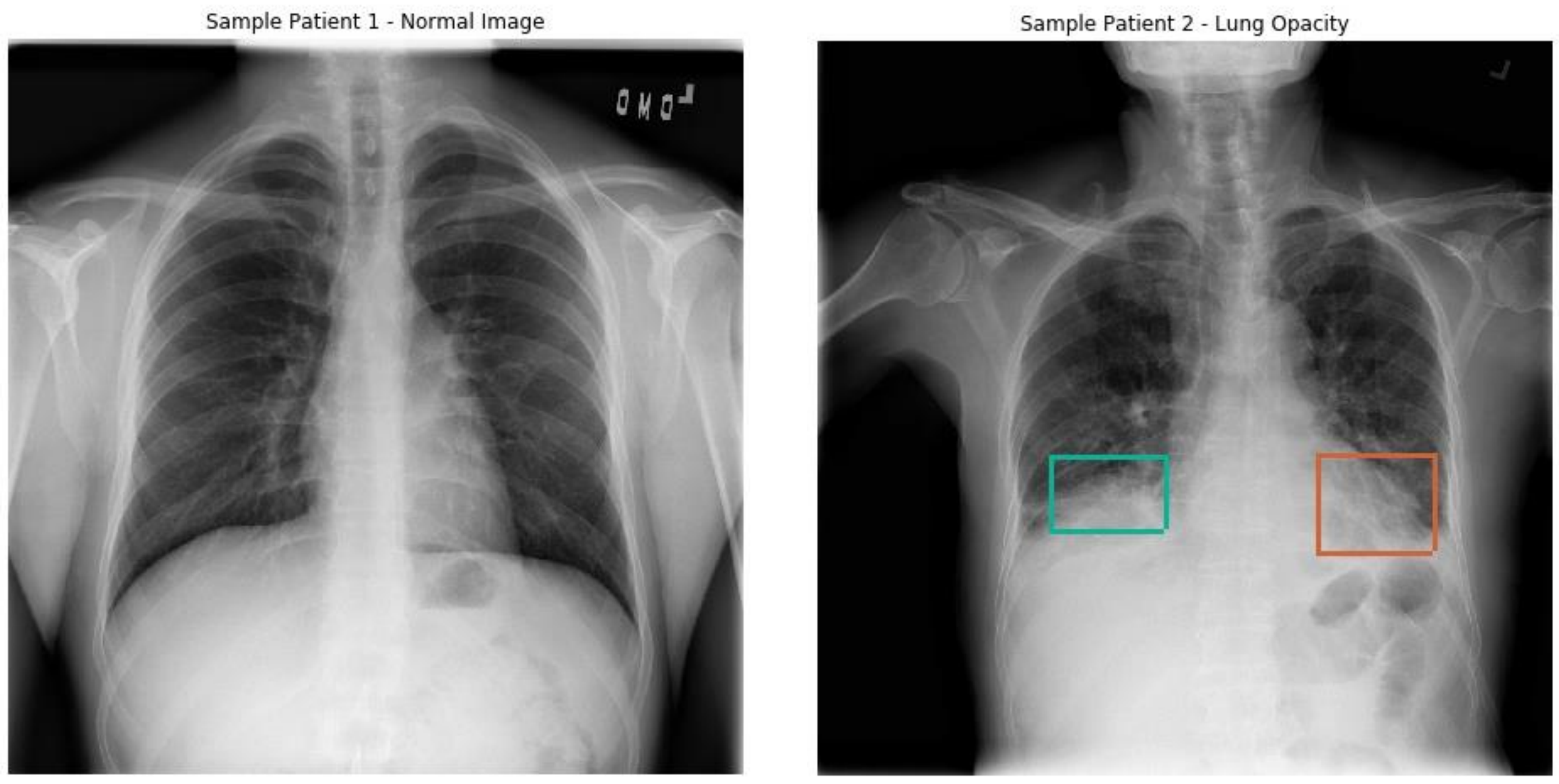


Figure 1: Two sample patients from the RSNA data set. (Left): Patient with normal lungs. (Right): Patient with lung opacity areas in both lungs.

Mask R-CNN

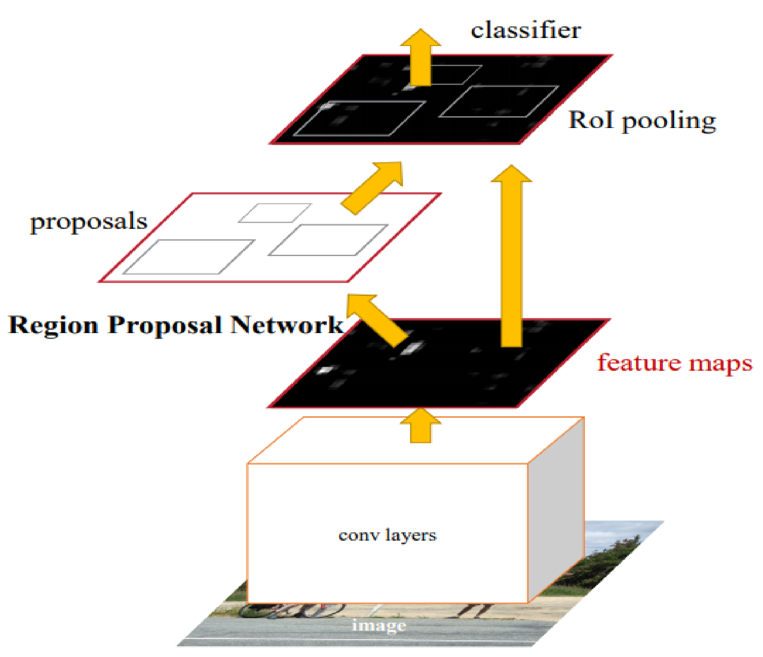


*Figure 2: The Faster R-CNN framework. Borrowed from [**4**]*

Models

Originally developed as an extension to Faster R-CNN [**4**] (see Figure 2) to perform instance segmentation, **Mask R-CNN** has been praised for its high accuracies. Mask R-CNN computes **region proposals** based on a feature map from a CNN. The proposed regions then go through a **binary softmax classifier** and a **bounding box regressor**.

CheXNet is a 121-layer CNN; a DenseNet [**5**] with multiple **residual connections** (see Figure 3) improving the flow of information and gradients through the network. The use of dense connections significantly improves optimization in very deep networks and lessens the number of parameters to train. The original CheXNet gives a heat map of class probabilities as output. A **probability threshold** is chosen and bounding boxes are placed around connected components.

Both models are trained on 24186 images annotated with classes "*normal*" or "*lung opacity*" and validated on 1500 images.

CheXNet

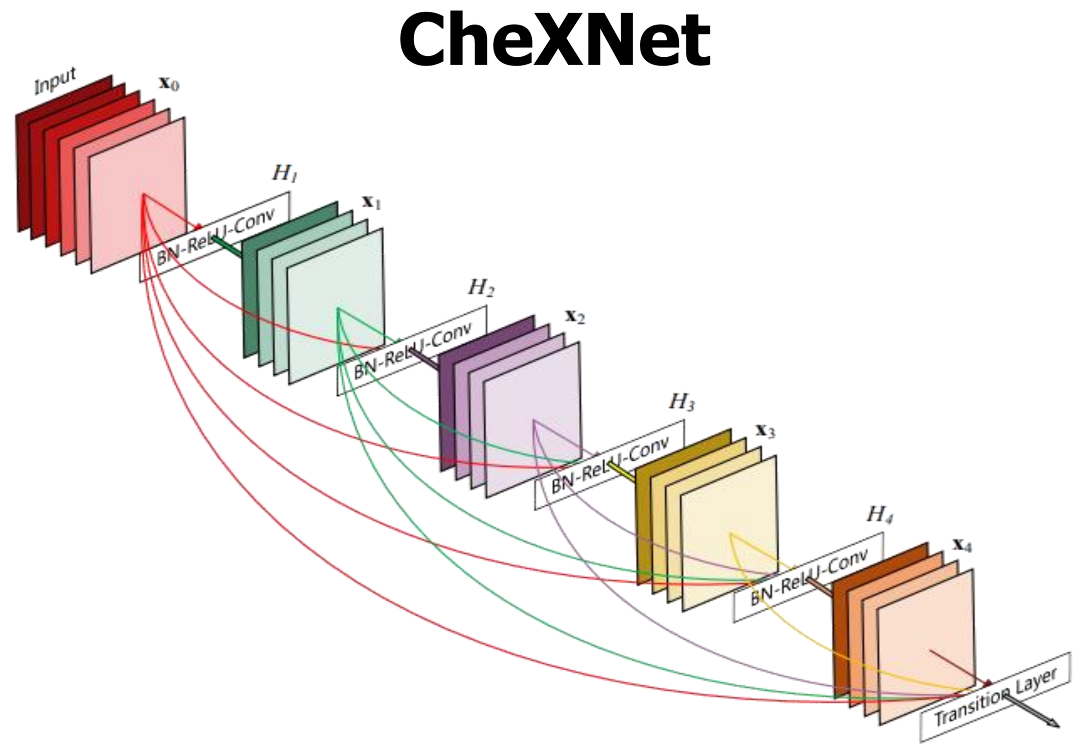


*Figure 3: A dense block with residual connections in CheXNet. Borrowed from [**5**]*

Results

Mask R-CNN

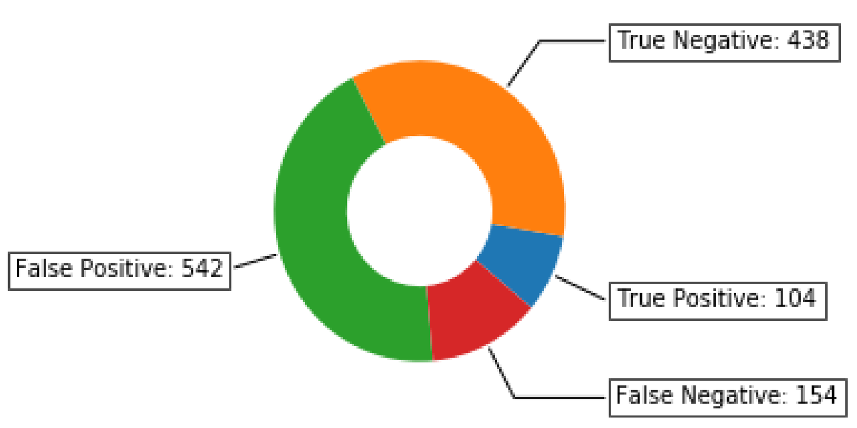


Figure 4: Confusion diagram of bounding box detection on 1000 test images with confidence threshold 0.95 and IoU threshold 0.5. Accuracy: 45%

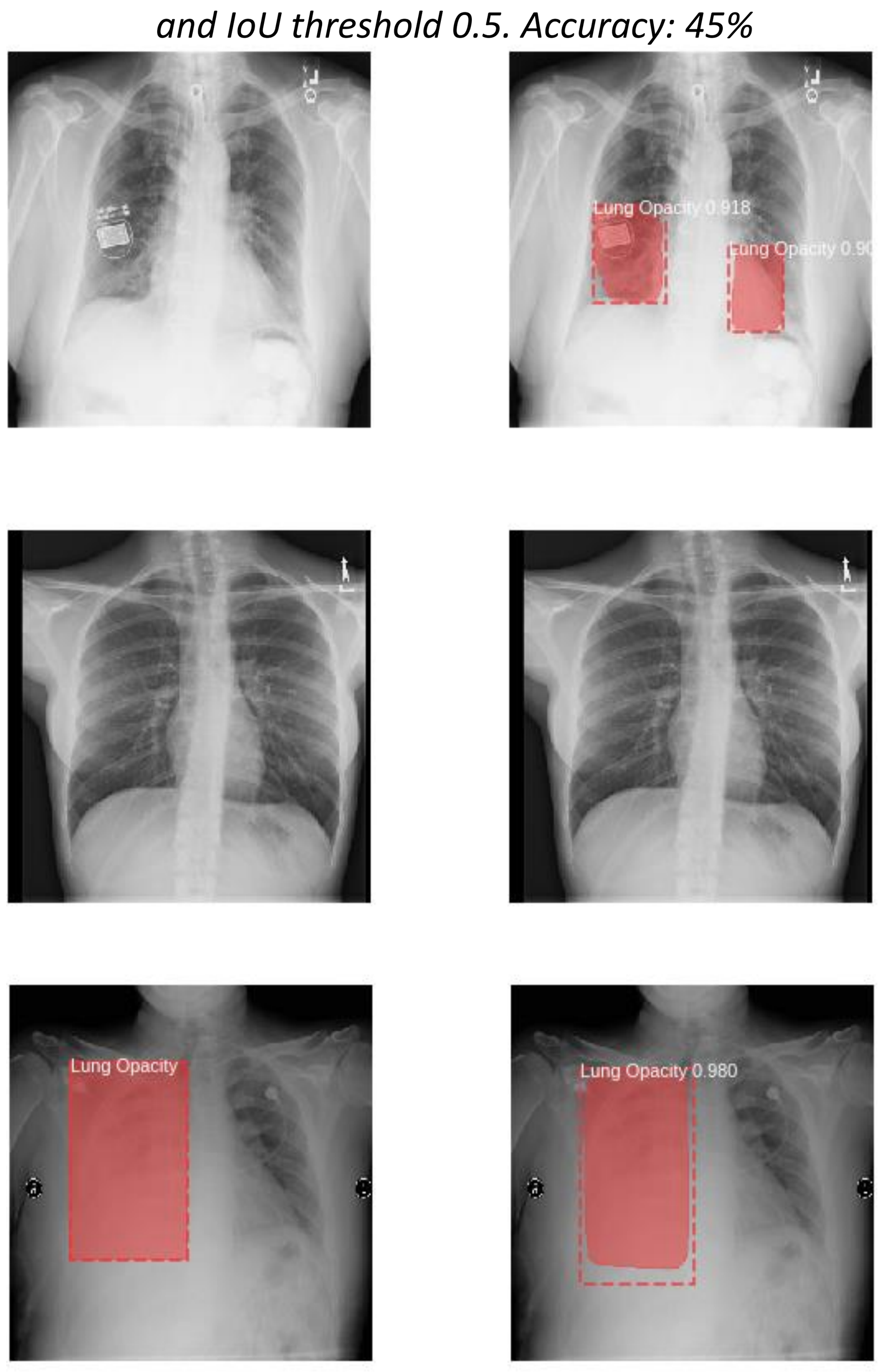


Figure 5: Ground truth vs predicted objects using Mask R-CNN with confidence threshold 0.75

CheXNet

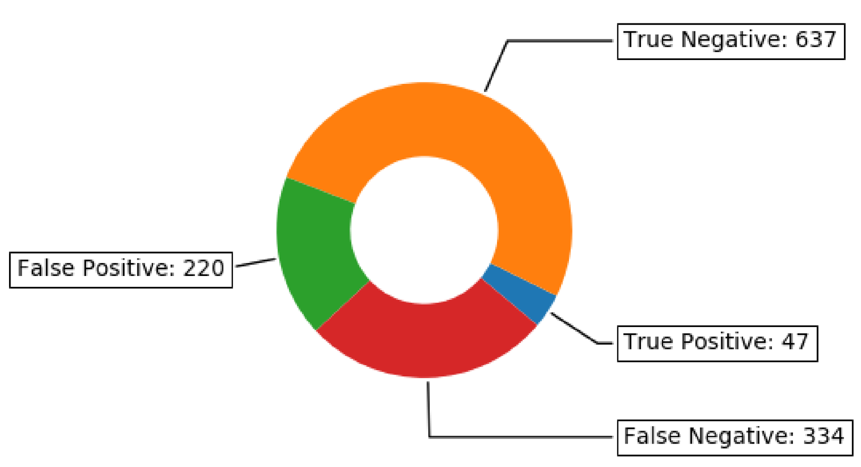


Figure 6: Confusion diagram of bounding box detection on 1000 test images with confidence threshold 0.5 and IoU threshold 0.5. Accuracy: 55%

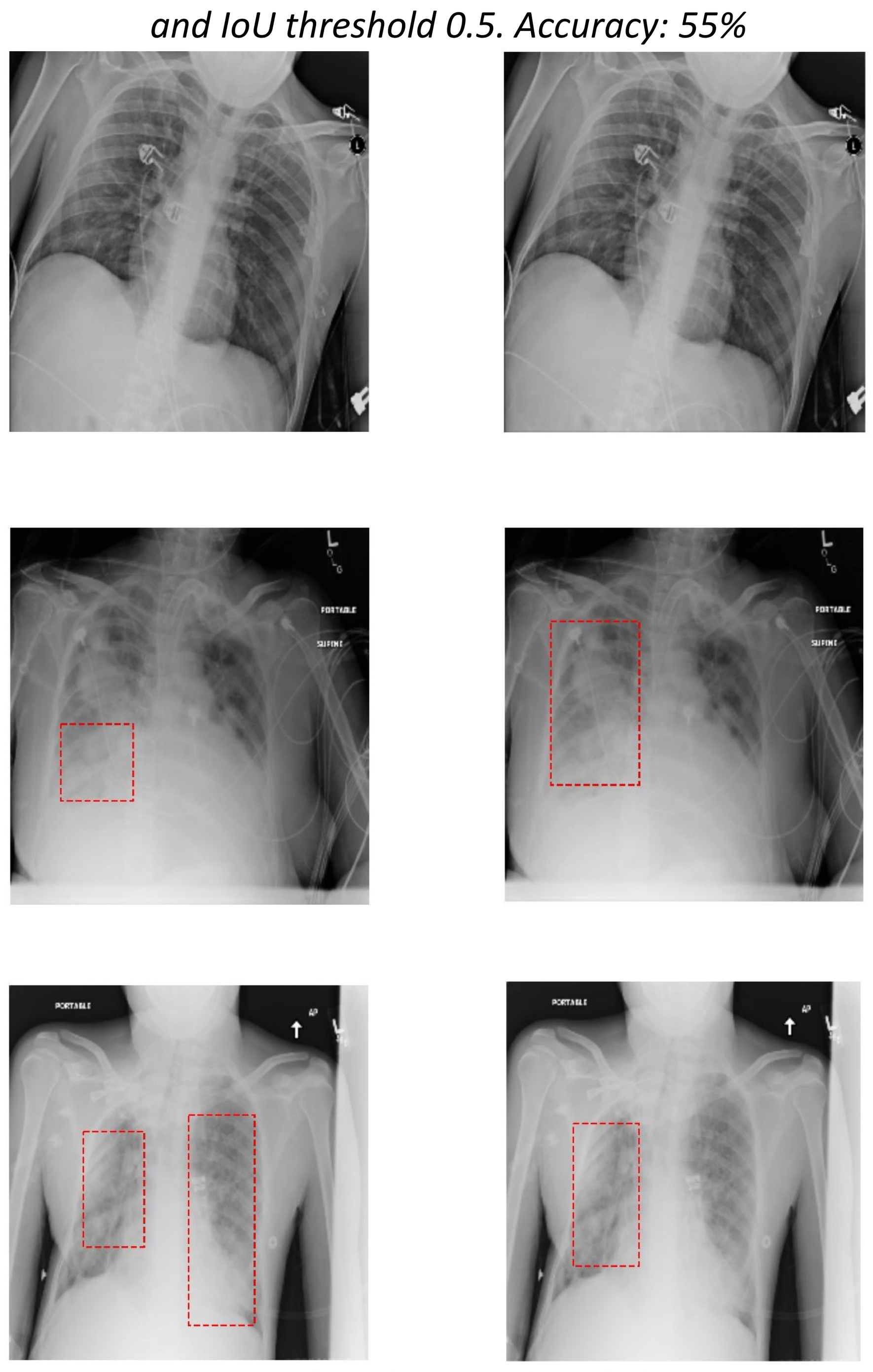
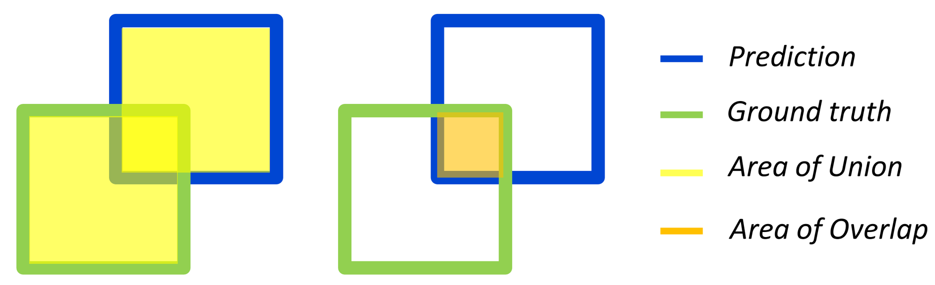


Figure 7: Ground truth vs predicted objects using CheXNet with confidence threshold 0.5

Evaluation

Intersection over Union: $IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$



Discussion

Several possibilities for extending the proposed models exist. The provided dataset also includes images of **other lung diseases**, annotated "*No pneumonia/not normal*", such as long nodules, pleural effusion or enlarged heart**. Knowledge** of these other diseases may serve to **improve** Pneumonia **classification** accuracies by ruling out the disease before performing the binary classification. **Further, experiments** could be done using:

- **Data augmentation**
- **Data quality** assurance
- **Other** state-of-the-art networks (YOLO, RetinaNet)
- Further investigate **hyperparameters**
- **What** does the **doctor need? High/low confidence?**

References

[**1**]: World Health Organization, "*Pneumonia*", 2016
URL: who.int/news-room/fact-sheets/detail/pneumonia (visited on 03/12-2018)
[**2**] Kaiming He et al., "*Mask-R-CNN*" (Proceedings of the IEEE International Conference on Computer Vision, 2017)
[**3**] P Rajpurkar, J Irvin et al., "*CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning*" (arXiv preprint, 2017)
[**4**] Ren et al., "*Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*" (Conference on Neural Information Processing Systems, 2015)
[**5**] Huang et al., "*Densely Connected Neural Networks*" (IEEE Conference on Pattern Recognition and Computer Vision, 2017)

Contact

Anders Stevnhoved Olsen	Caroline Dam Hieu	Cecilie Dura André
s154043@student.dtu.dk	s182120@student.dtu.dk	s153316@student.dtu.dk