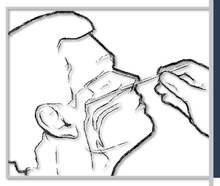
Improving Computer Tomography COVID-19 Lesion Segmentation Using Reproducible Pathways and Data Augmentation Techniques

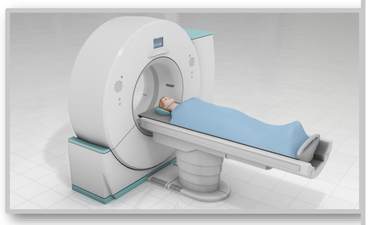
Introduction

The COVID-19 pandemic has put an immense pressure on the medical system. Testing for COVID-19 is thus crucial for early detection and prevention of future infections.



The current gold standard of **RT-PCR** has a **low sensitivity** and a **high processing** time. RT-PCR testing kits, laboratory personnel and equipment are often not available in large enough quantities.

Alternative: Medical imaging in the form of lung computer tomography (CT) **Lesion Segmentation** and Classification



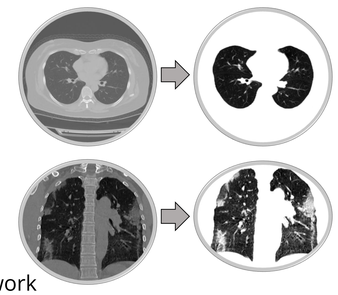
However, CT scans require professional radiologists to manually annotate each lesion which is **time consuming**.

Solution: employ machine learning techniques such as Deep Learning to **automatically annotate lesions**

Methodology

Data: 329 lung CT scans from 3 different sources (250 of which are from a single source), verified by professional radiologists

Data preprocessing:
Lung segmentation
Extracting the lung from the CT

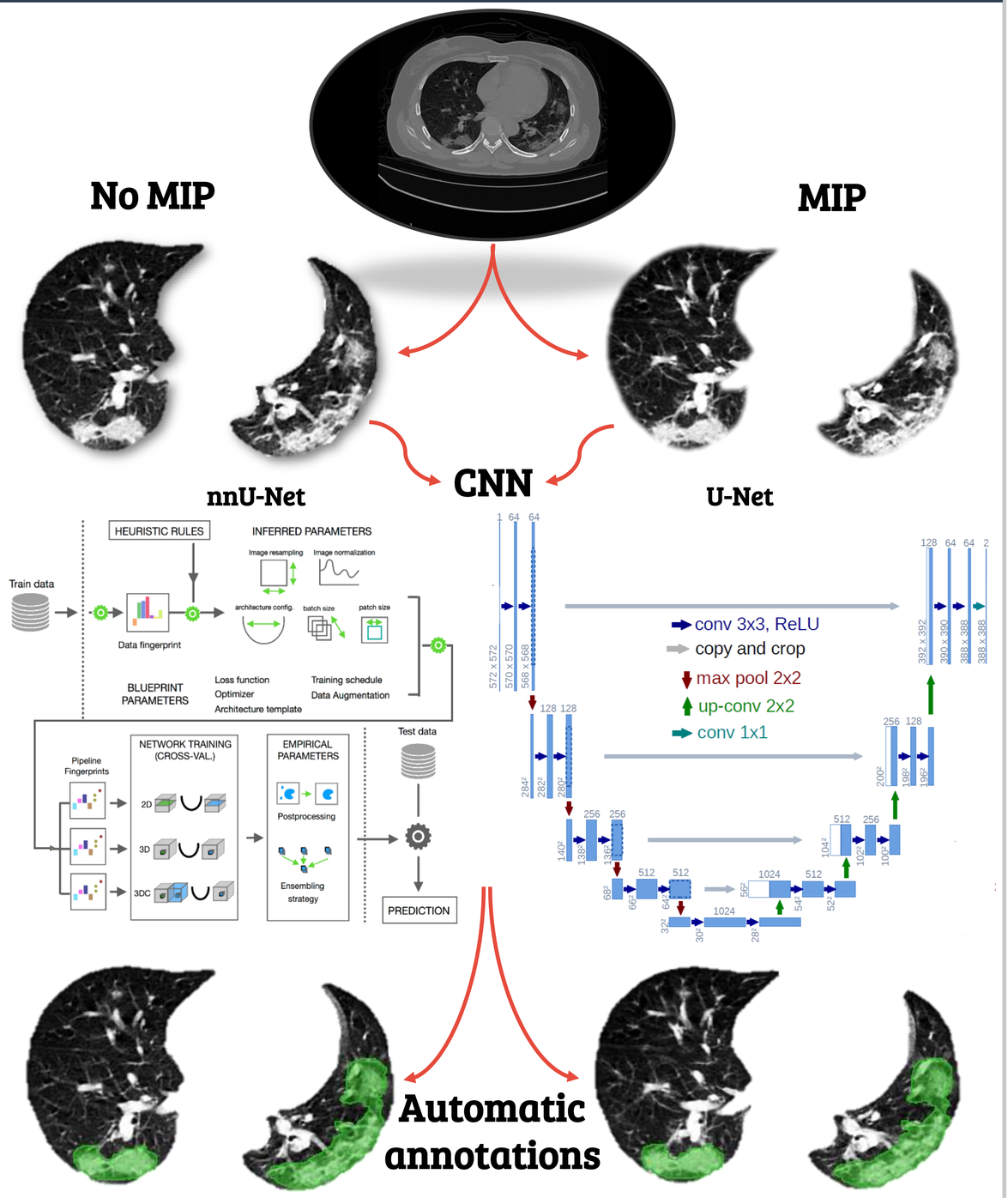


Deep Learning Models:

❖ **U-Net**
- Convolutional Neural Network
- 23 layers
- Specialized in image segmentation
- Two paths:
  - Contracting – captures the context of the image
  - Expansive – ensures precise localization

❖ **nnU-Net** (Dynamic U-Net)
- Automatically adapts to any dataset (increases generalization)
- Uses 2D, 3D and 3D-Cascade U-Net

Reproducible pathway by using open-source:
- MONAI framework
- data
- preprocessing and data augmentation techniques



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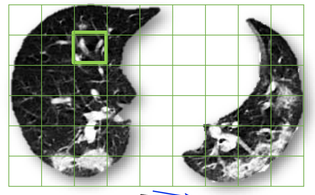
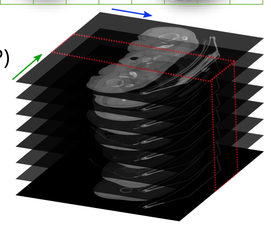
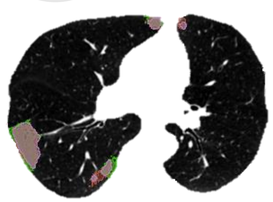
Data augmentation techniques:
- **Noise filters: 15%**
- adding random Gaussian noise
- **Sliding windows**
- only pass smaller, consecutive "windows", not the full image
- **Maximum Intensity Projection** (MIP)
- map 3 adjacent slices into one by selecting the maximum intensity



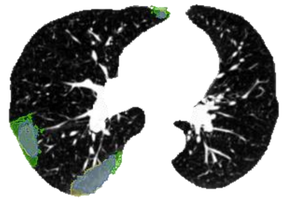


Results

- **U-Net**: sliding windows resulted in the best AUC of 0.8 (F1 = 0.51, sensitivity = 0.6, specificity = 0.99, precision = 0.44)
- **nnU-Net**: noise filters resulted in the best AUC of 0.81 (F1= 0.59, sensitivity = 0.63, specificity = 0.99, precision = 0.59)



No MIP



MIP

Predictions given by U-Net and nnU-Net

Discussions

Highest performance: **noise filters** and **sliding windows**

MIP did not aid the segmentation task

The differences between U-Net and nnU-Net are not visible in the current study. However, nnU-Net might have a higher **generalization capability**.

Predictions:
- **Overestimations** – the models might not be fully adapted to the task
- **Underestimations** – comorbidities such as interstitial lung disease or fibrosis could be visible in the lung CT

Limitations:
- Low amount of data (only 329 CT, 30-50 left for testing)
- Low quality data: open-source data often lacks the quality standards of private data, meaning blurrier CT scans and missing annotations for certain visible lesions

Future work:
- MIP for classification tasks, not just segmentation
- Minimum Intensity Projection instead of Maximum Intensity Projection
- More high quality data with the help of professional radiologists and the annotation tool MONAI Label