# Appendix E1

### Details on Data Processing and Deep Learning Model Training

**Preprocessing:** CT images were extracted from Digital Imaging and Communications in Medicine (DICOM) files. We then followed the following steps to preprocess the CT images. First, the lung region is extracted as the region of interest (ROI) using a U-net (1) based segmentation method. Afterward, the extracted lung ROI was resampled to the same spacing (1 mm) in the z-direction. To reduce the dimensionality of the CT scan, we further down sampled the lung ROI by 5 times in the z-direction and scaled it to S × 224 × 224 pixels with S as the number of CT slices in the down sampled lung ROI. Then, the voxel intensity values were first clipped using a window/level of 1500HU/-500HU and were then normalized to the range of [0, 1]. To reduce the influence of vascular structure and boost the signals of the lesions, a maximum intensity projection (MIP) algorithm was also applied to each of the slices. Finally, the preprocessed image is then passed to the proposed COVID-19 detection neural network (COVNet) for the predictions.

**Data augmentation:** Each training example was rotated randomly between –3 and 3 degrees and flipped horizontally or vertically with 50% probability. We further add random Gaussian noise with a maximum variance of 0.015 to the image.

**Implementation details: COVNet** was implemented with Python 3.7 and PyTorch 1.4 (2) and training with an NVIDIA V100 GPU. The weights of the ResNet50 (3) backbone of the **COVNet** was first initialized to values optimized on the ImageNet database (4) and were then fine-tuned to fit our chest CT dataset. The cross-entropy loss was used to optimize the model. The model with the highest accuracy on the internal validation set was chosen for evaluation on the independent testing set. The code to reproduce the results in this study is made available via: https://github.com/bkong999/COVNet.git.

Table E1. Detailed CT imaging protocol information.

| Manufacturer | Scanner Model | Number of Exams | kVP | Exposure | Slice Thickness (mm) | Reconstruction matrix | In-plane pixel resolution ($mm^2$) |
|---|---|---|---|---|---|---|---|
| SIEMENS (Munich, Germany) | Emotion 16 | 796 | 110 ~ 130 | 12 ~ 172 | 1.5 ~ 2.0 | 512x512 | 0.34x0.34 ~ 0.97x0.97 |
| | SOMATOM Definition AS | 709 | 80 ~ 140 | 14 ~ 413 | 0.6 ~ 2.0 | 512x512 | 0.29x0.29 ~ 0.86x0.86 |
| | SOMATOM Definition Flash | 427 | 100 ~ 120 | 50 ~ 368 | 0.6 ~ 2.0 | 512x512 | 0.39x0.39 ~ 0.96x0.96 |
| | SOMATOM go.Now | 672 | 110 ~ 130 | 41 ~148 | 1.0 ~ 3.0 | 512x512 | 0.50x0.50 ~ 0.76x0.76 |
| GE MEDICAL SYSTEMS (Illinois, United States) | BrightSpeed | 580 | 80 ~ 120 | 1 ~ 10 | 1.25 | 512x512 | 0.43x0.43 ~ 0.95x0.95 |
| | Discovery CT590 RT | 229 | 100 ~ 120 | 2 ~ 10 | 1.25 | 512x512 | 0.58x0.58 ~ 0.81x0.81 |
| | Discovery CT750 HD | 156 | 100 | 2 ~ 7 | 1.25 | 512x512 | 0.60x0.60 ~ 0.93x0.93 |
| | LightSpeed16 | 20 | 120 | 3 ~ 11 | 1.25 | 512x512 | 0.78x0.78 |
| | Optima CT520 Series | 54 | 120 | 2 ~ 10 | 1.25 | 512x512 | 0.56x0.56 ~ 0.85x0.85 |
| | Optima CT660 | 141 | 100 ~ 120 | 1 ~ 5 | 0.625 ~ 1.25 | 512x512 | 0.60x0.60 ~ 0.98x0.98 |
| | Revolution EVO | 1 | 120 | 6 | 1.25 | 512x512 | 0.74x0.74 |
| | Revolution CT | 17 | 80 ~ 140 | 1 ~ 3 | 0.625 ~ 1.25 | 512x512 | 0.61x0.61 ~ 0.88x0.88 |
| Philips (Amsterdam, Netherlands) | Brilliance 64 | 220 | 120 ~ 140 | 80 ~ 375 | 1.0 ~ 3.0 | 512x512 | 0.50x0.50 – 0.98x0.98 |
| | iCT 256 | 87 | 80 ~ 140 | 58 ~ 300 | 1.0 | 512x512 | 0.38x0.38 – 0.97x0.97 |
| NMS (Shenyan, China) | NeuViz 128 | 130 | 100 ~ 120 | 180 ~ 300 | 1.0 ~ 1.25 | 512x512 | 0.44x0.44 – 0.90x0.90 |
| | NeuViz Prime | 53 | 120 | 45 ~ 353 | 1.0 | 512x512 | 0.49x0.49 – 0.87x0.87 |
| TOSHIBA (Tokyo, Japan) | Aquilion | 54 | 100 ~ 120 | 40 ~ 218 | 0.5 ~ 1.0 | 512x512 | 0.47x0.47 – 0.82x0.82 |
| Kangda Intercontinental Medical Equipment (Ningbo,China) | Apsaras | 10 | 120 | 150 | 1.25 | 512x512 | 0.68x0.68 – 0.78x0.78 |

## References


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