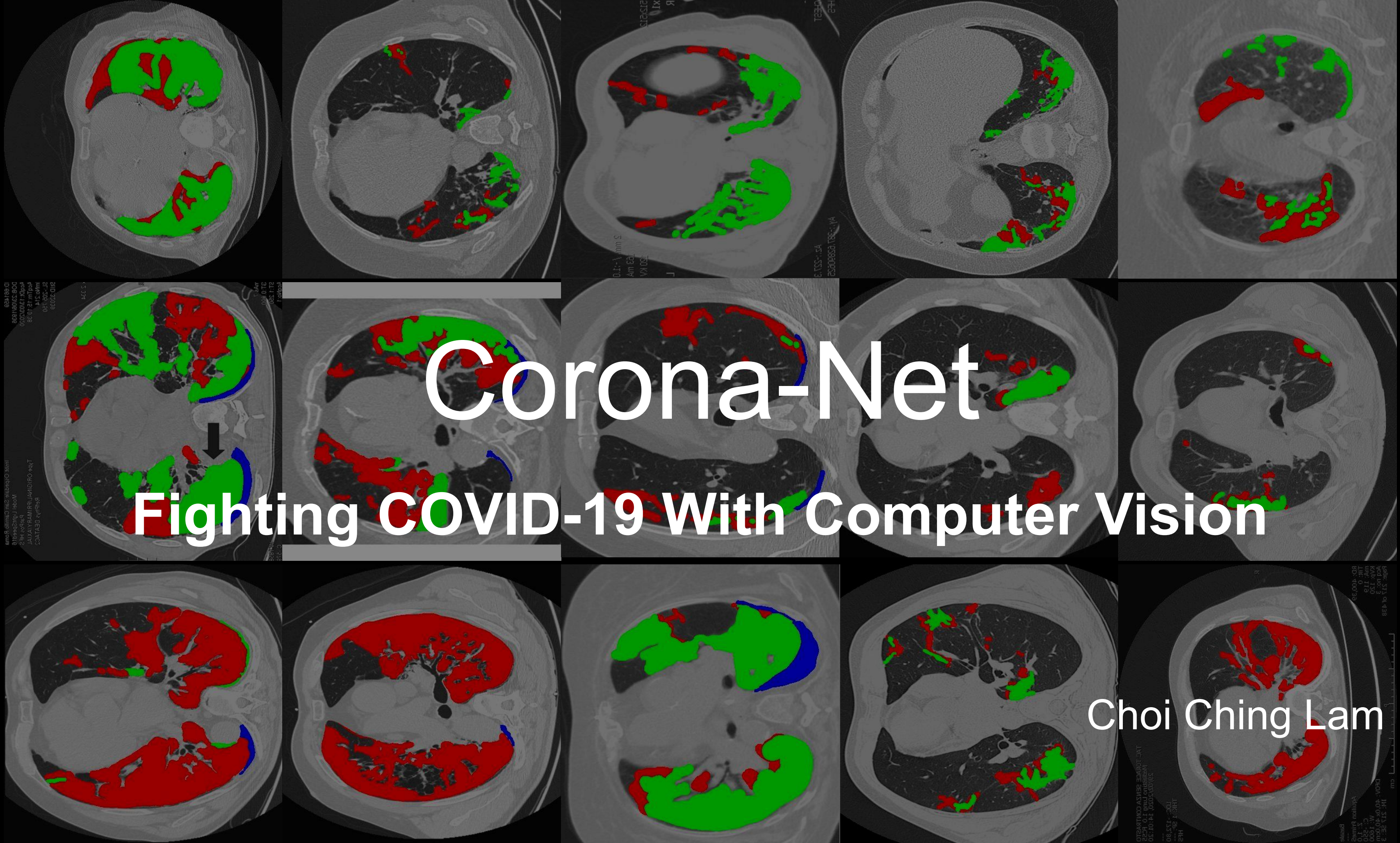


Corona-Net

Fighting COVID-19 With Computer Vision

Choi Ching Lam

Self Intro

- Choi Ching Lam
- 17 year old, Form 5 student from Hong Kong
- Favourite languages: Python, Julia
- Currently interning at NVIDIA’s AI Tech Center
- Into Computer Vision, aspires to become a researcher
- https://github.com/chinglamchoi
- https://www.linkedin.com/in/ching-lam-choi-7609541a0/
- https://medium.com/@cchoi314

Background

- Inspired by doctors from Wuhan on TV
- Inspired by Johns Hopkins University's (Center for Systems Science and Engineering (CSSE)) COVID-19 Dashboard
- Relevant to previous work on brain tumour boundary resection for lower grade glioma

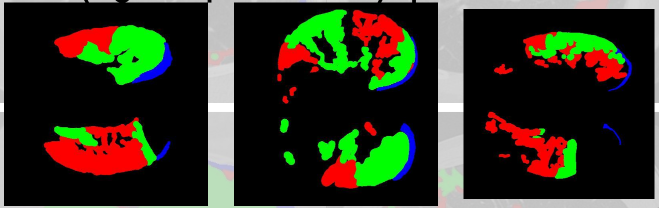
Problem Statement

- Hospitals are overwhelmed with COVID-19 patients
  - Manpower shortage → Doctors (esp radiologists), etc
  - Supplies shortage → ventilators, masks, etc
- **Solution**: **Automate CT diagnosis confirmation with AI**
  - Determine severity → Triage patients, allocate supplies
  - Gauge mortality probability
  - (Future) Design personalised treatment

Corona-Net

1. **Binary Classification**
    a. Infected (1) / not-infected (0) with COVID-19
2. **Binary Segmentation:**

    a. Predict all infected (symptoms) pixels of COVID-19 in CT
3. **3-Class Segmentation:**



    a. Predict all infected pixels & type (1 in 3) of symptoms:
    ground glass, consolidation, pleural effusion

Technologies Used

- Language: Python with NumPy library
- AI library: PyTorch
- Image processing libraries: Albumentations, Torchvision, Scikit-image, Matplotlib

Python with NumPy

- NumPy: parallelism & vectorisation
- NumPy: better support for matrices & tensors & operations
- Easy to prototype with, elegant syntax
- Powerful libraries

What to use for Image Processing?

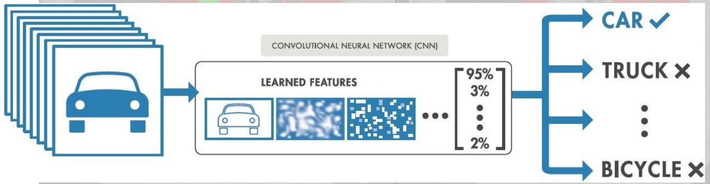
- Matplotlib vs. Scikit-image vs. Torchvision vs. Albumentations
- Matplotlib: General purpose
- Scikit-image: Advanced algorithms
- Torchvision: Tight integration with PyTorch
- Albumentations: Biomedical Imaging

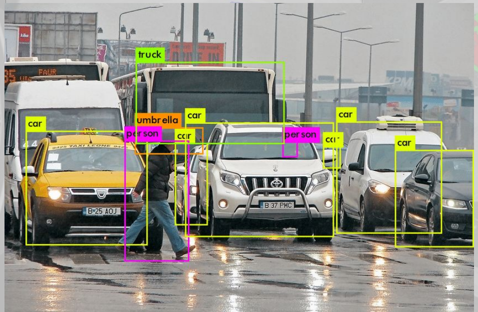
Why PyTorch?

- More research / academia support
- Better customisation ability
- Similar to NumPy
- Dynamism e.g. Dynamic computation graphs

Model Architecture

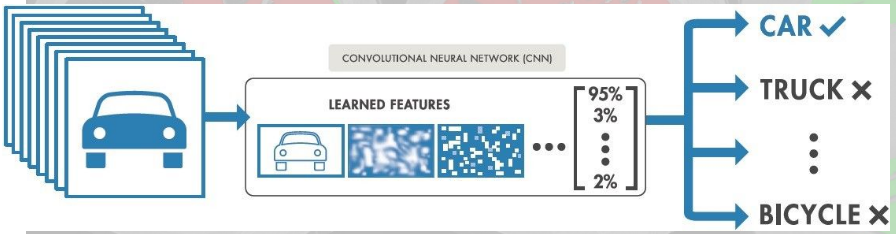
- For multi-label segmentation
- Classification vs. detection vs. segmentation
- Classification: Input image → output class label
- Detection: Input image → output bounding box & class label
- Segmentation: Input image → output image mask

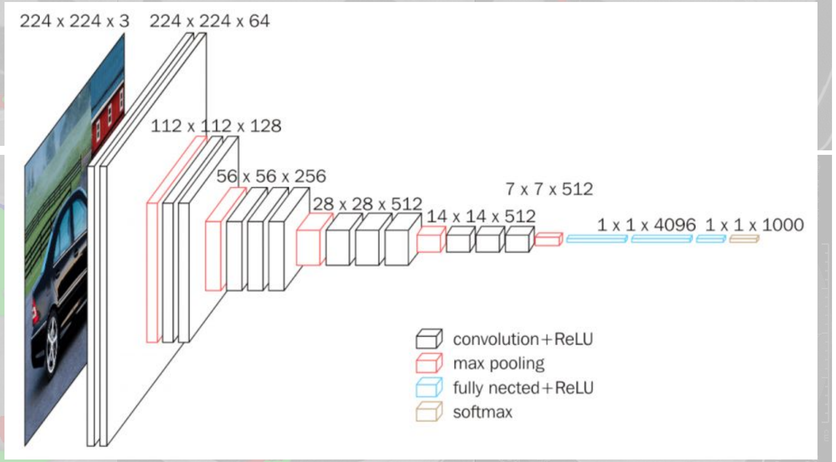




Classification

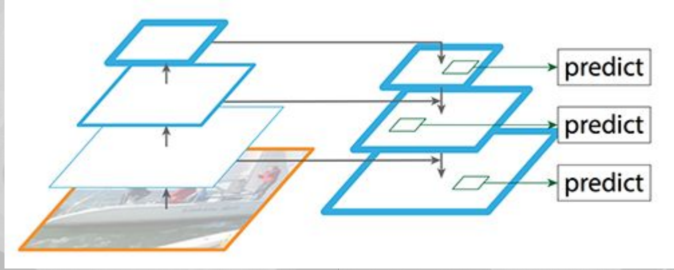
- Input image → output class label (FC layer)
- Can use vanilla Convolutional Neural Networks
- Deep CNNs: accuracy saturation & degradation problem
    - Residual Networks
    - Feature Pyramid Networks





Classification

- ResNets: Shortcut connections
    - Relieves pressure from added deep layers when identity mapping
- FPNs: lateral, top-down connections
    - Fuses feature maps at different scales
    - Each feature map retains local & global information

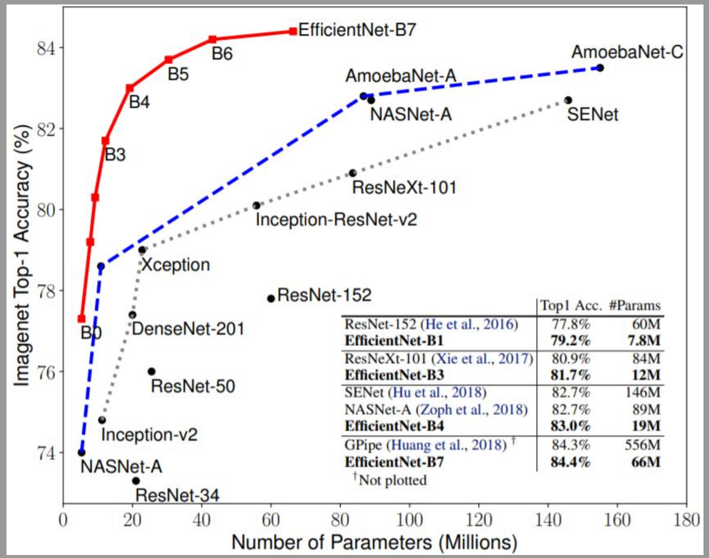


Efficient-Net

- Introduce novel Compound Scaling Method
  - Joint scaling of network 1) depth, 2) width, 3) input resolution

$$
\begin{aligned}
\text{depth: } & d = \alpha^{\phi} \\
\text{width: } & w = \beta^{\phi} \\
\text{resolution: } & r = \gamma^{\phi} \\
\text{s.t. } & \alpha \cdot \beta^{2} \cdot \gamma^{2} \approx 2 \\
& \alpha \geq 1, \beta \geq 1, \gamma \geq 1
\end{aligned}
$$

Upscale computational resources & FLOPS by 2^{ϕ}



SOTA on ImageNet with fewer parameters (less complexity) → more computationally efficient

Segmentation

- Image Segmentation (binary, multi-class), semantic segmentation

Binary Segmentation

Algorithm 1 Binary Segmentation

Result: Binary image mask $M \in \mathbb{R}^{H \times W}$

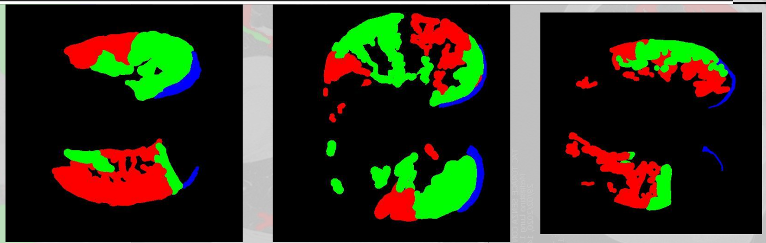
for *pixel in CT_scan_slice* **do**
  if *pixel == infected with COVID-19* **then**
    pixel $\leftarrow 1$
  else
    pixel $\leftarrow 0$
  end
end

Multi-class Segmentation

Algorithm 1 Multi-Class Segmentation

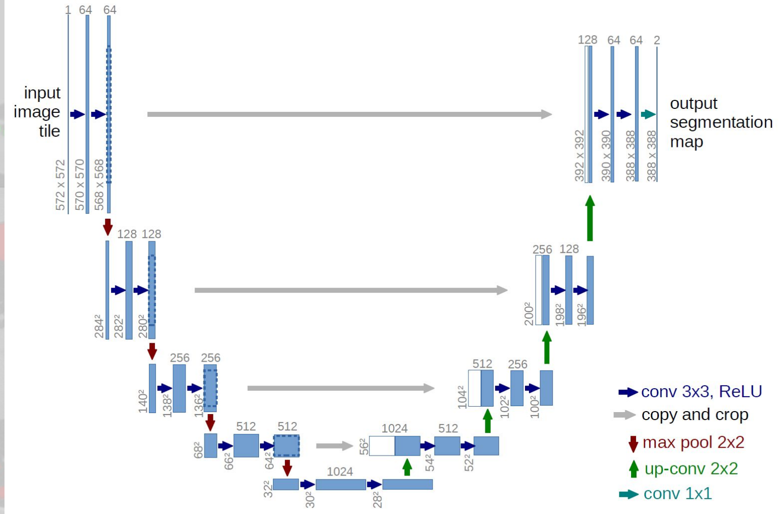
Result: 3D image mask $M \in \mathbb{R}^{3 \times H \times W}$

for *pixel in CT_scan_slice* **do**
  if *pixel == infected with Ground_glass* **then**
    pixel $\leftarrow 1$
  else if *pixel == infected with Consolidation* **then**
    pixel $\leftarrow 2$;
  else if *pixel == infected with Pleural_effusion* **then**
    pixel $\leftarrow 3$;
  else
    pixel $\leftarrow 0$;
  end
end



Fully Convolutional Networks

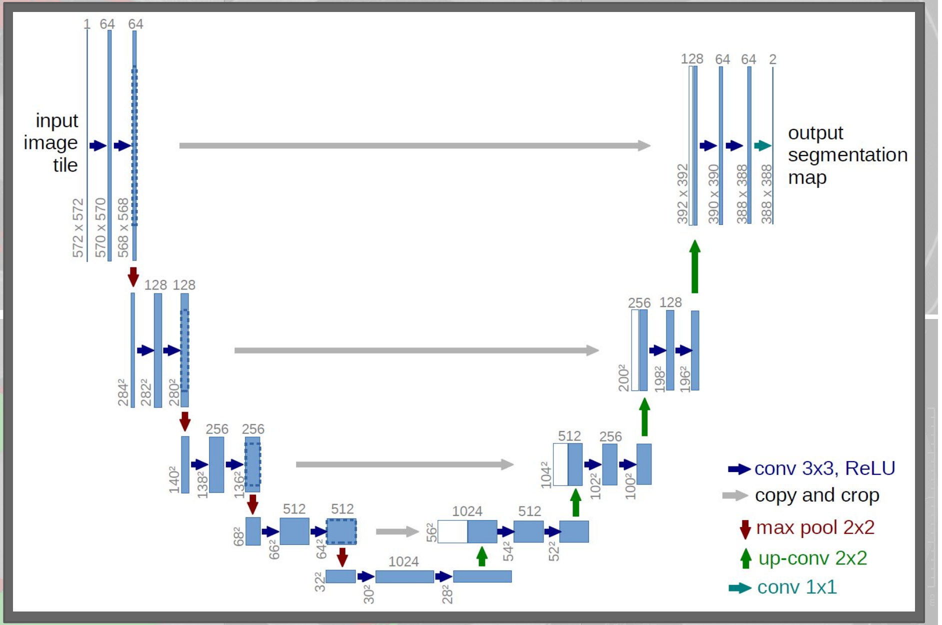
- Used in Corona-Net
- Encoder-decoder network



- Learns convolutional filter directly not function
- U-Net: FCN for biomedical imaging with symmetrical upsampling & downsampling paths, SOTA

U-Net

- Introduce symmetrical contracting & expansive path
- A Fully-Convolutional Network → Computes convolutional filter instead of function
- SOTA in ISBI Challenges
- Tailored to biomedical imaging
- Successful fusion of local to global, spatial-semantic features



Data & Augmentation

- COVID-19 CT segmentation dataset
  - http://medicalsegmentation.com/covid19/
- Augmentation for better generalisation to latent data:
  - Elastic Transformations & Scale Shift ➜ simulate natural deformations of human biological tissue
  - Random cropping ➜ shift invariance
  - Normalisation ➜ grey value invariance
  - Random rotations ➜ rotational invariance

Segmentation Evaluation

Evaluation Metrics	**Accuracies & Losses** (1: binary, 2: multi-class)
1. Dice Coefficient {[0, 1] with 1 best} $$Dice = \frac{2\,\lvert A \cap B \rvert}{\lvert A \rvert + \lvert B \rvert}$$	see table 1
2. Rand Loss {[0, 1] with 0 best} $$RI = \frac{a+d}{\binom{n}{2}},\ RE = 1 - RI$$	see table 2

Dice Coefficient	Rand Loss	Optimiser	Learning Rate
0.5641	0.2167	Adam	1e-02
0.7374	0.1031	Adam	1e-03
0.7965	0.0766	Adam	1e-04
0.4745	0.1591	Adam	1e-05

Dice Coefficient	Rand Loss	Optimiser	Learning Rate
0.5160	0.2490	Adam	1e-02
0.5900	0.2114	Adam	1e-03
0.6160	0.1985	Adam	1e-04
0.5001	0.2565	Adam	1e-05

Future Development

- Recommend Personalised Medicine / Treatment
  - Based on extent (area) and occurrence of particular symptoms of each COVID-19 patient
- Weakly-supervised segmentation
  - Using Global Average Pooling & Object Region Mining
  - No need for labour-intensive mask annotations

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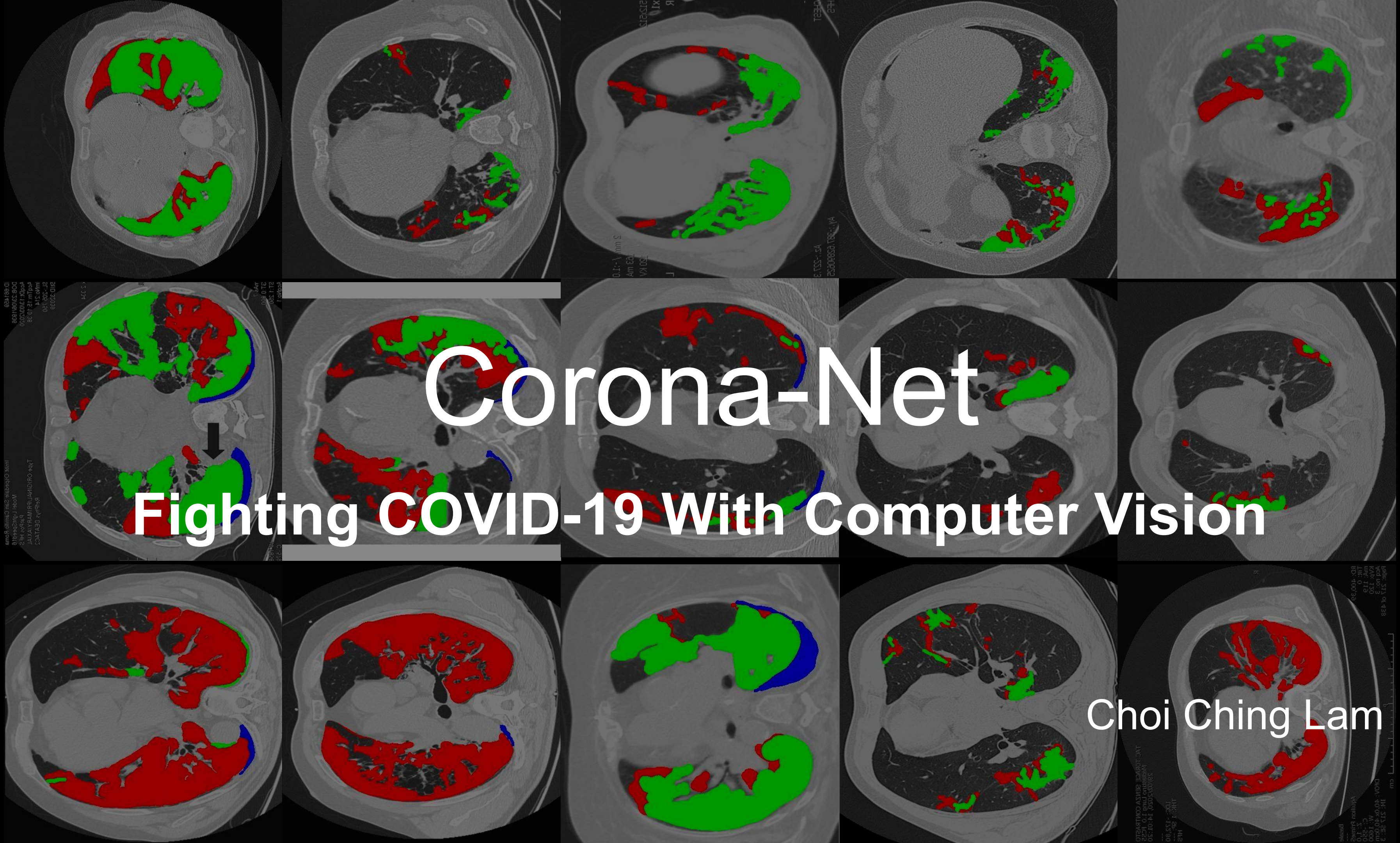
Contact Me

- Choi Ching Lam
- Email: ccl5a09@gmail.com
- https://github.com/chinglamchoi
- https://medium.com/@cchoi314
- https://www.linkedin.com/in/ching-lam-choi-7609541a0/
- https://twitter.com/cchoi314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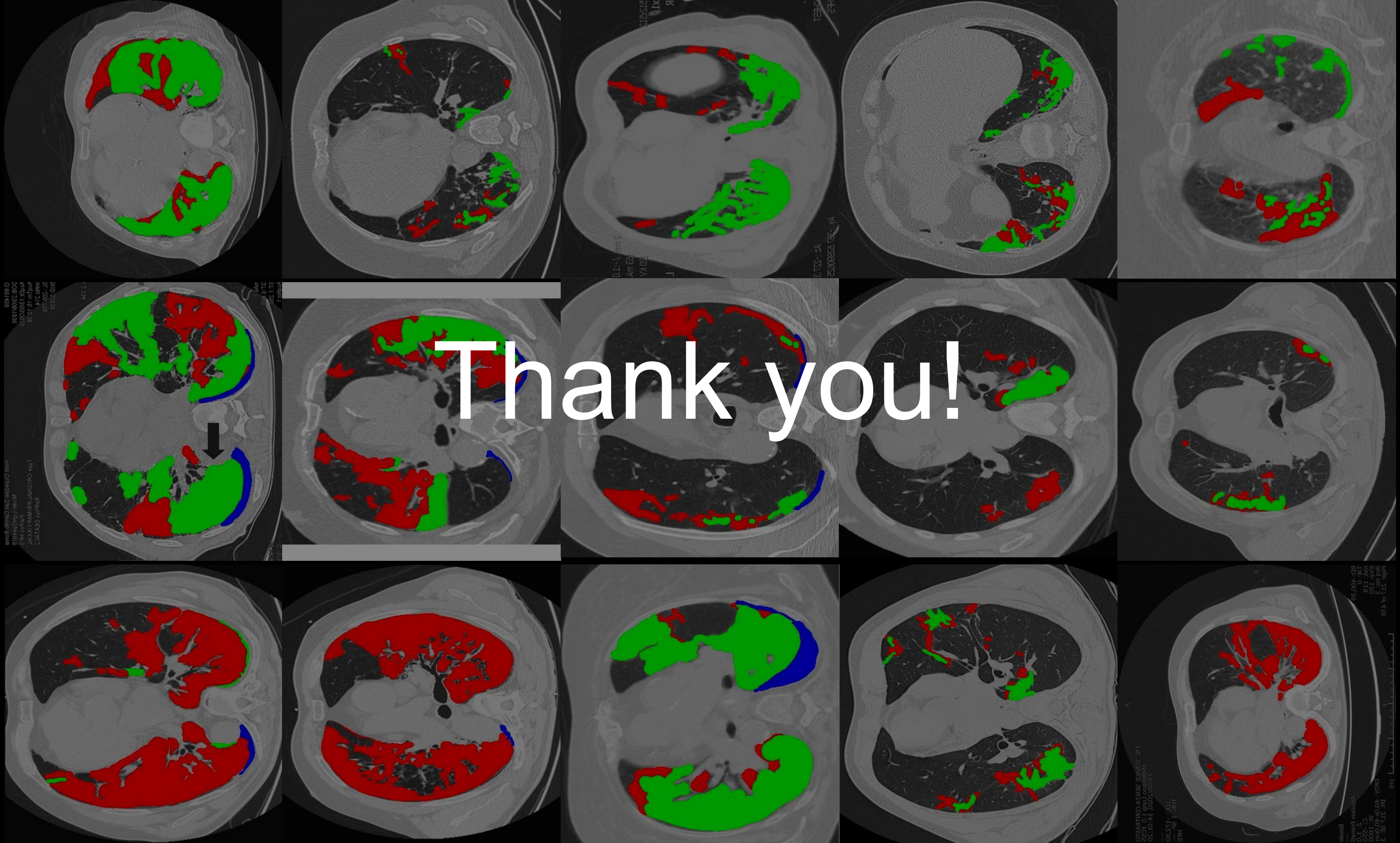
Thank you!