A Robust Ensemble-Learning Model for Covid-19 Diagnosis on CT Images

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Research Motivation

- Coronavirus 2019 (COVID-19) is an infectious disease spreading globally.

- Computed tomography (CT) is preferred COVID-19 diagnosis imaging option.
- Because of the consequent depletion of hospital resources, the use of efficient computer-aided medical diagnosis has become more critical.
- Artificial intelligence (AI) powered COVID-19 detection can facilitate an early diagnosis and further reduce the infectivity and mortality rates.

Dataset

- Images are extracted from 760 medRxiv and bioRxiv papers.

- Images containing clinical findings of COVD-19 based on their captions are manually selected.

Chest Computed tomography (CT) images of patients infected with 2019-nCoV on admission to hospital. A, Chest CT scan obtained on February 2, 2020, from a 39-year-old man, showing bilateral ground glass opacities. B, Chest CT scan obtained on February 6, 2020, from a 45-year-old man, showing bilateral ground glass opacities. C, Chest CT scan taken on January 27, 2020, from a 48-year-old man (discharged after treatment on day 9), showing patchy shadows. D, Chest CT scan taken on January 23, 2020, from a 34-year-old man (discharged after treatment on day 11), showing patchy shadows.

- **Dataset Challenges**
  - Degraded quality
  - Some lesions are market
  - High variability (size, intensity, etc.)

COVID-19   COVID-19   COVID-19   COVID-19
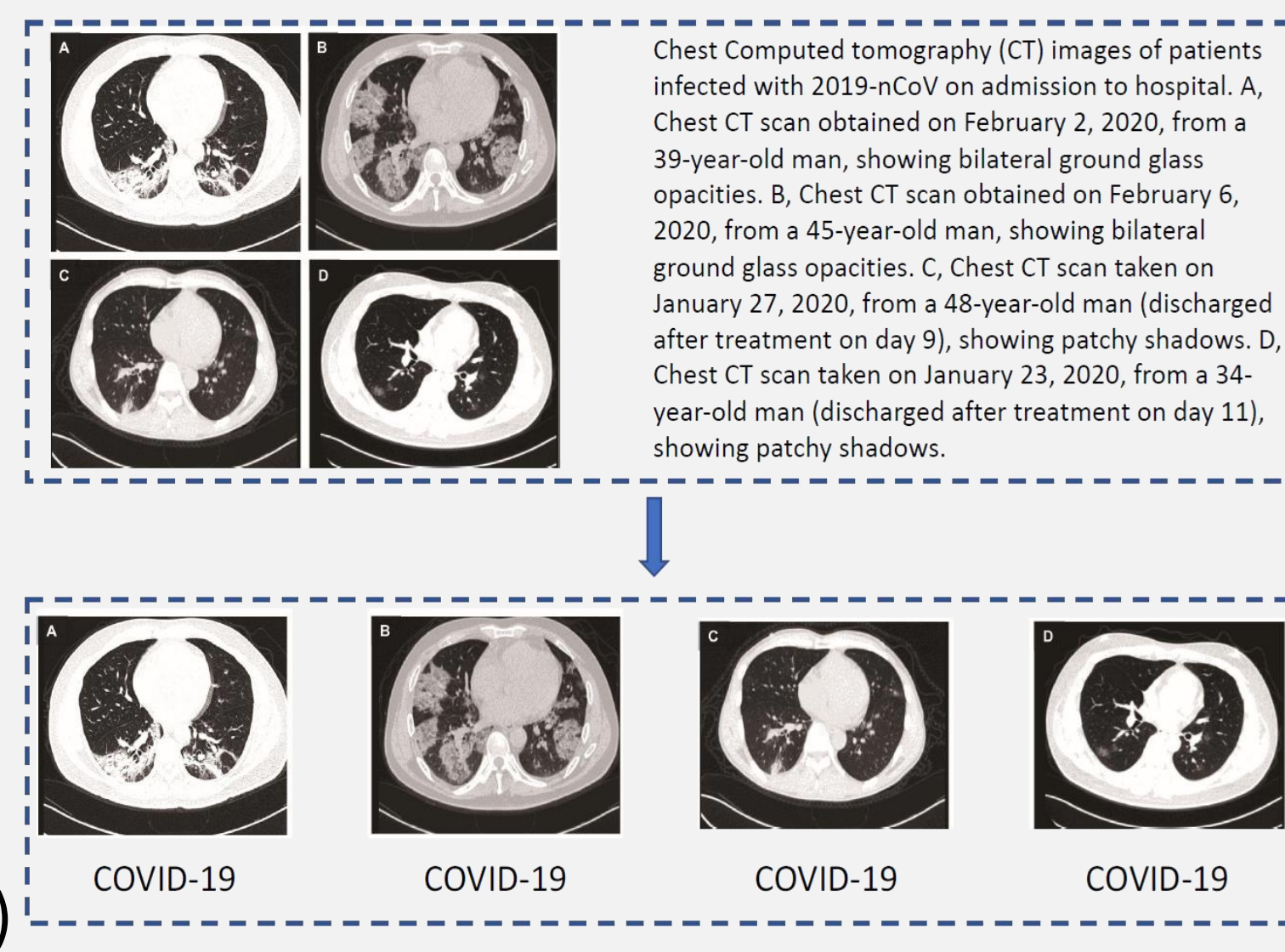
Research Gap

- Deep learning has enabled breakthrough in a variety of computer vision tasks.

- Exhibit comparable performance with radiologist (Maghdid et al. 2020)

- Limitations of deep learning are the reliability concerns about the generalizability to all cases and the blackbox nature, hindering interpretability.

Research gap is to improve generalizability and interpretability of deep learning.

Contributions

- We propose a **robust ensemble deep learning model** for Covid-19 Diagnosis on Lung CT Scan Images.
- The two **base-learners**, **Residual Attention92** and **Densenet121** networks, are chosen as they consolidate each other by focusing on complementary features.
- We compared different **meta-learner**s and found **SVM with radial basis function kernel** to give the best performance.
- Our experimental results demonstrate our proposed method's robustness with **an average 4% accuracy improvement** over each individual base-learner.
- Our code and results are available open source on Github: https://github.com/maftouni/Corona_CT_Classification.git
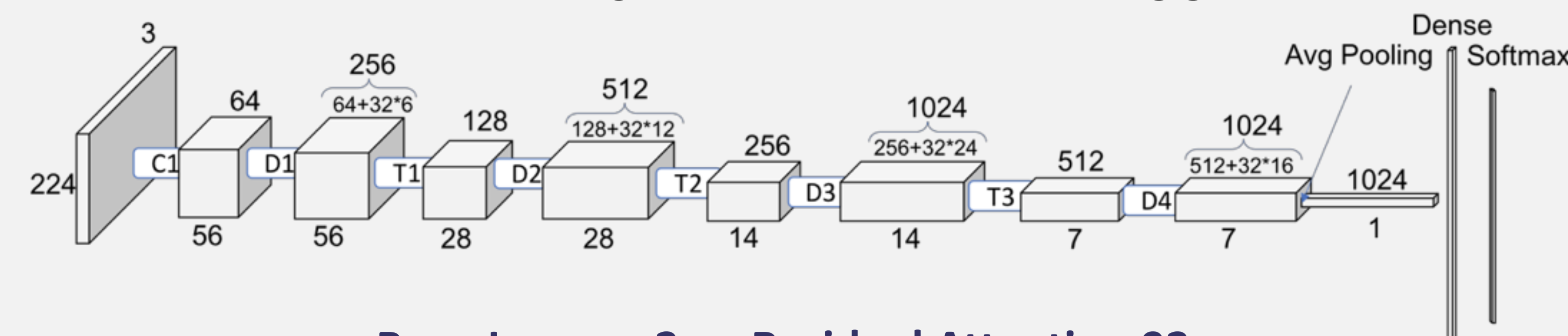
Proposed Methodology

- The two **base-learners** are fine-tuned on CT images. The features extracted from base-learners are stacked together and processed by a **meta learner** for the final prediction.
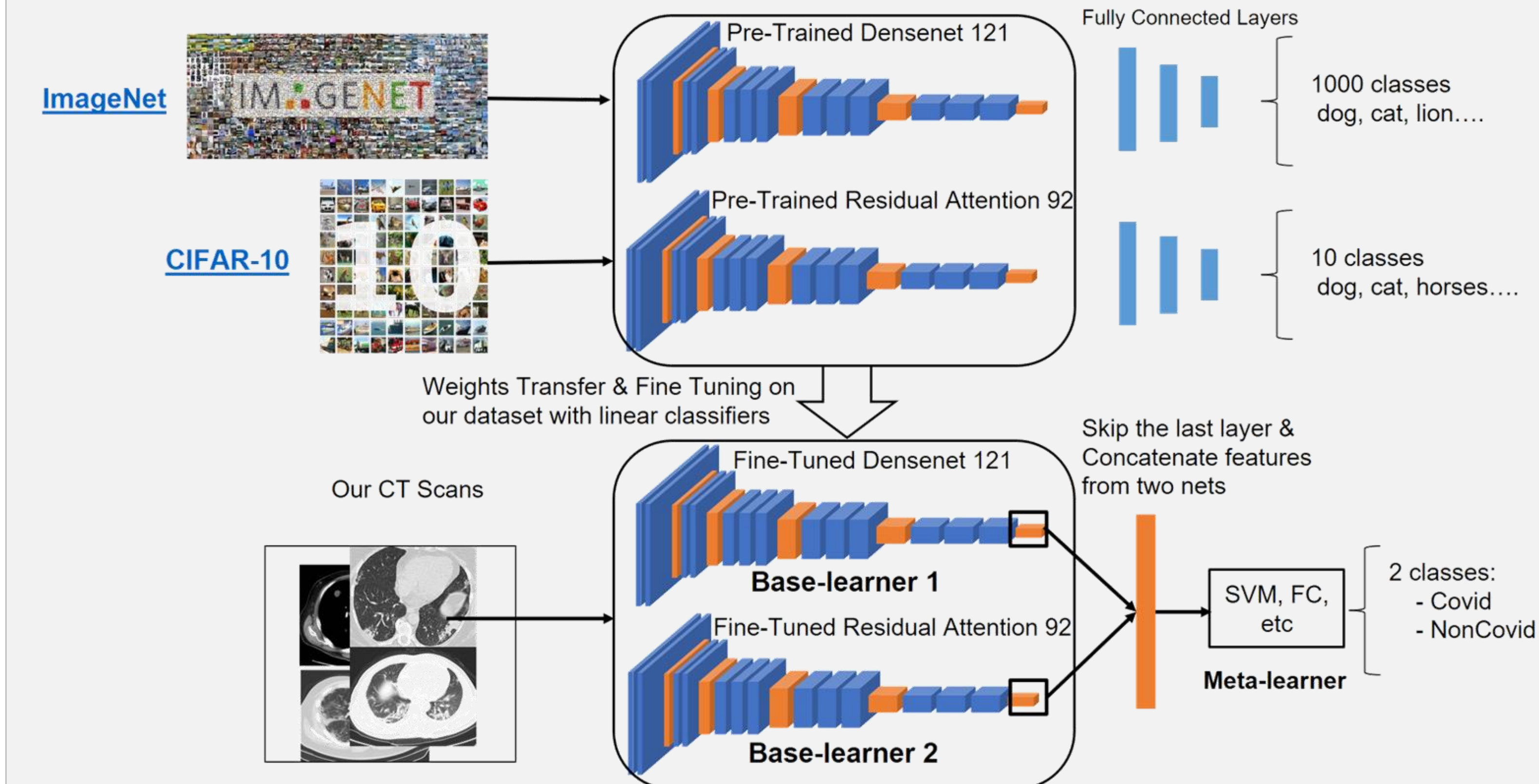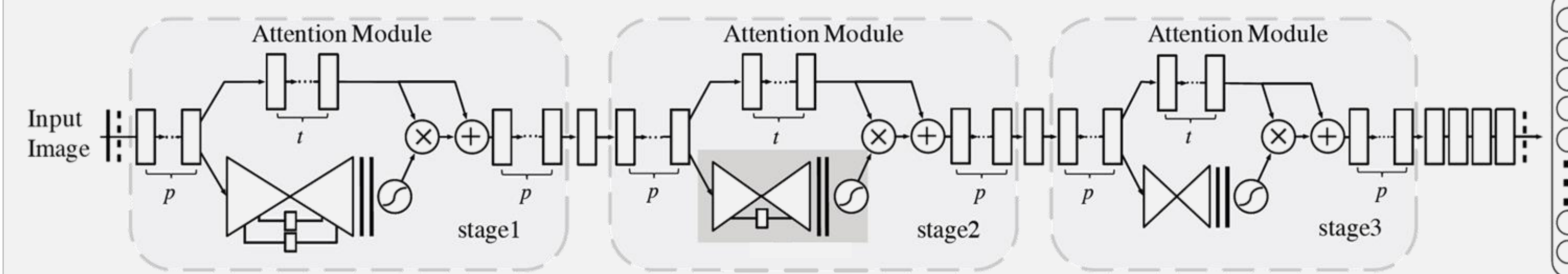

Base-Learner 1 : DenseNet121

- Utilizes **dense connections** to regularize and **alleviate vanishing-gradient**.

Base-Learner 2 : Residual Attention 92

- Utilizes **mixed attention** to capture different types of attention for feature learning.


Data Preprocessing & Model Training

- Used **6-fold cross-validation**, giving 452 training and 91 validation images.
- Used **Bayesian Optimization** to tune the hyperparameter of the model.
- Applied the following **transformations** and **augmentations** on training and only transformations on validation set:

| Types	Parameters
Resize	Training: [256 , 256] Validation: [224 , 224]
Random Resized Crop *	Scale = (0.5, 1) Size = 224
Random Horizontal Flip *	Probability = 0.5
Random Rotation *	max left rotation=10 max right rotation=10
Normalize Each Channel	Mean = [0.485, 0.456, 0.406], Standard Deviation = [0.229, 0.224, 0.225]

Experimental Results

Structure	Training Accuracy	Training F1 score	Cross-Validation Accuracy
DenseNet121	94.12%	93.49%	90.81%
Residual Attention	94.50%	94.99%	91.34%
Proposed Method	98.89%	98.79%	95.68%
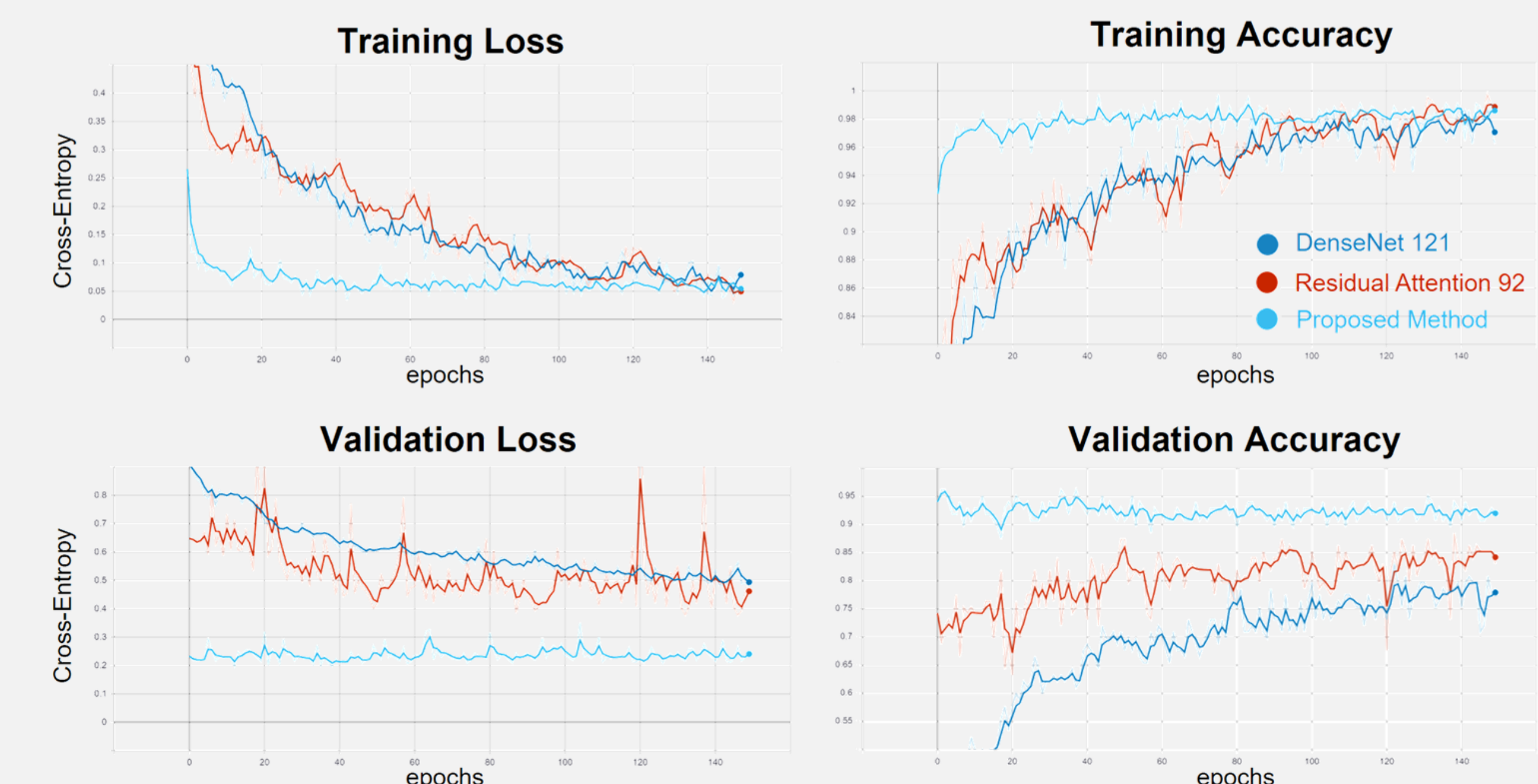
Visualization: Grad-cam Activation Maps
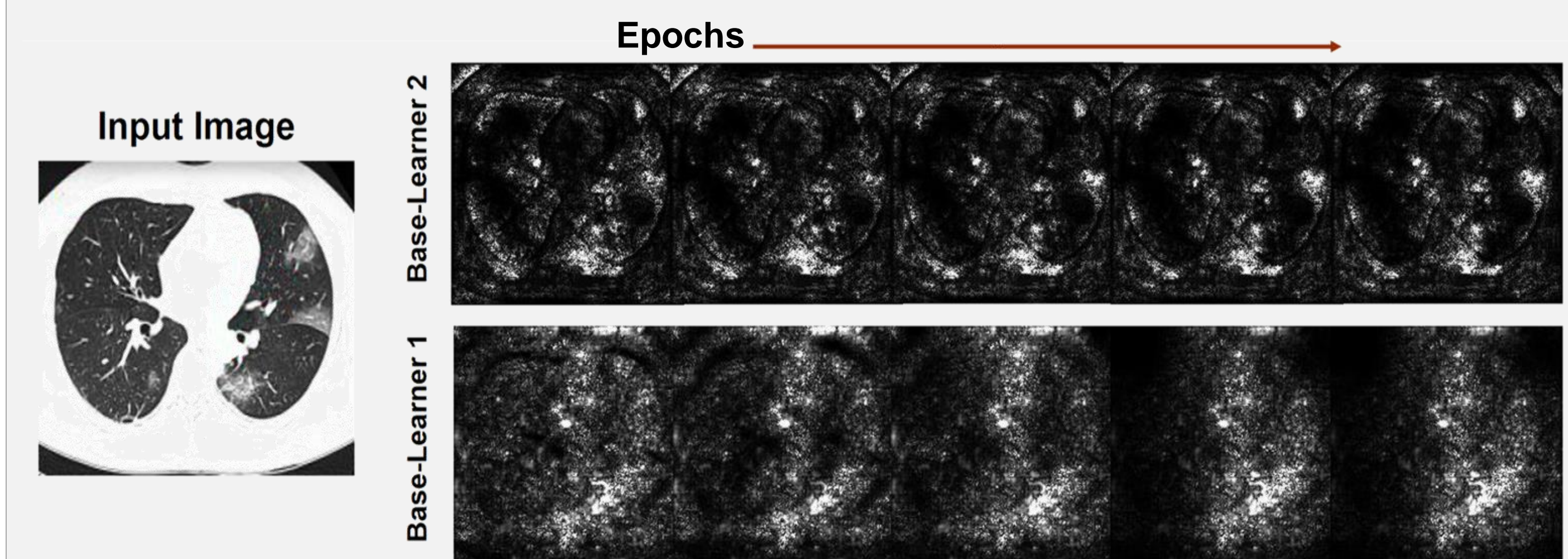
- The more epochs we run, the **more focus** is given to **covid-19 manifestations**.
- This focus is more evident in the **second base-learner** as it uses **attention modules**.
- Base-learners focus on **complementary, attention-aware,** and **global features**.
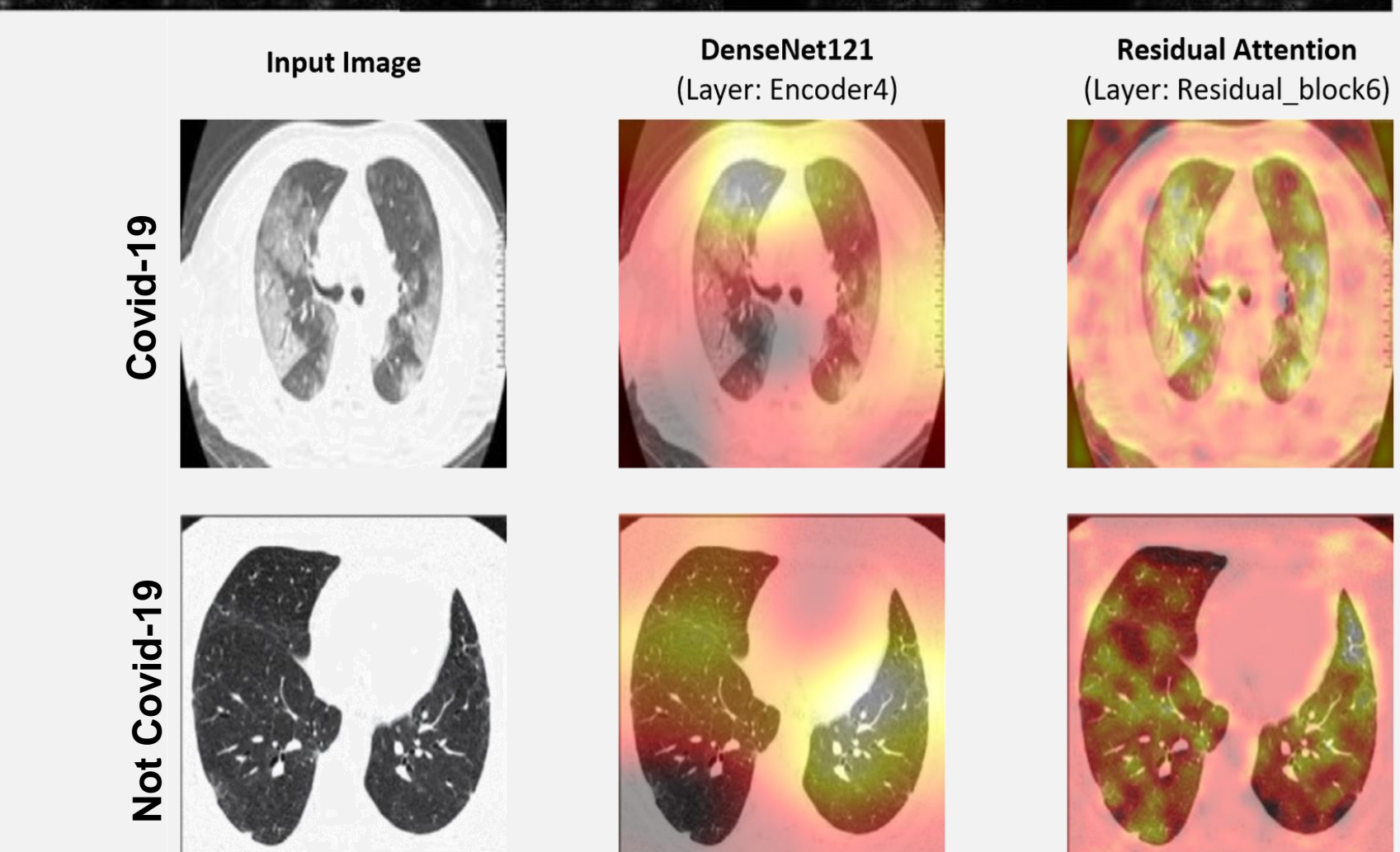
References

1. Zhao, Jinyu, et al. "COVID-CT-Dataset: a CT scan dataset about COVID-19." arXiv preprint arXiv:2003.13865 (2020).
2. Girshick, Ross. "Fast r-cnn." Proceedings of the IEEE international conference on computer vision. (2015).
3. Maghdid, Halgurd S., et al. "Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms." arXiv preprint arXiv:2004.00038 (2020).
4. Divina, Federico, et al. "Stacking ensemble learning for short-term electricity consumption forecasting." Energies 11.4 (2018).
5. Wang, Fei, et al. "Residual attention network for image classification." Proceedings of the IEEE conference on computer vision and pattern recognition. (2017).
6. Huang, Gao, et al. "Densely connected convolutional networks." Proceedings of the IEEE conference on computer vision and pattern recognition. (2017).
7. Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. (2017).

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