

DEEP COVID

Predicting COVID-19 From Chest X-Ray Images Using Deep Transfer Learning
<https://arxiv.org/abs/2004.09363>



Parsa Mohammadian

Sharif University of Technology

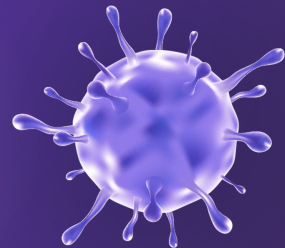


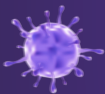


TABLE OF CONTENTS

01

INTRODUCTION

COVID-19 pandemic, how to detect it

**02**

DATASET

COVID-Xray-5k Dataset, and splitting it

03

FRAMEWORK

Training four popular CNNs using transfer learning

04

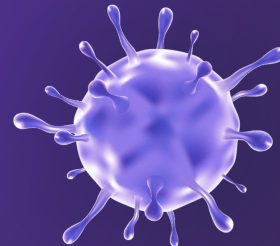
RESULTS

Evaluate model performance using two metrics

05

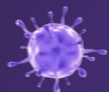
CONCLUSION

Achievements of this paper

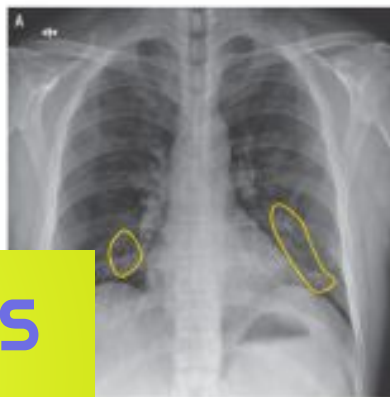


INTRODUCTION

- The COVID-19 pandemic is causing a major outbreak in more than 150 countries
- Early diagnosis is of real importance
- There are specific abnormalities in the chest radiographs of patients infected with COVID-19
 - Ground glass
 - Mixed attenuation
- Abnormalities can only be interpreted by expert radiologists
- Considering huge rate of suspected people and limited number of trained radiologists
 - Diagnosing takes several hours or even days
 - AI/machine learning solutions are potentially powerful tools to assist radiologists



3



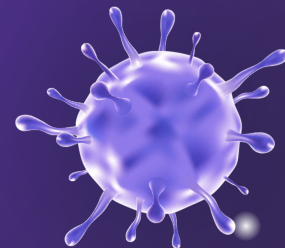
HOW RADIOLOGISTS DETECT DISEASE

Fig. 1. Three sample COVID-19 images, and the corresponding marked areas by our radiologist.



DATASET

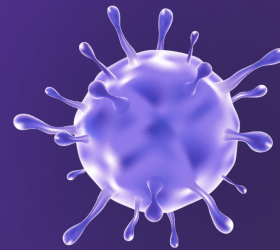
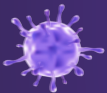
- COVID-Xray-5k Dataset
 - Covid-Chestxray Dataset
 - Chexpert Dataset
- Covid-Chestxray is an small dataset
 - Augmentation

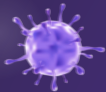




COVID-Xray-5k Dataset

| SPLIT | COVID-19 | NON-COVID |
|--------------|----------|-----------|
| Training Set | 84 → 420 | 2000 |
| Test Set | 100 | 3000 |

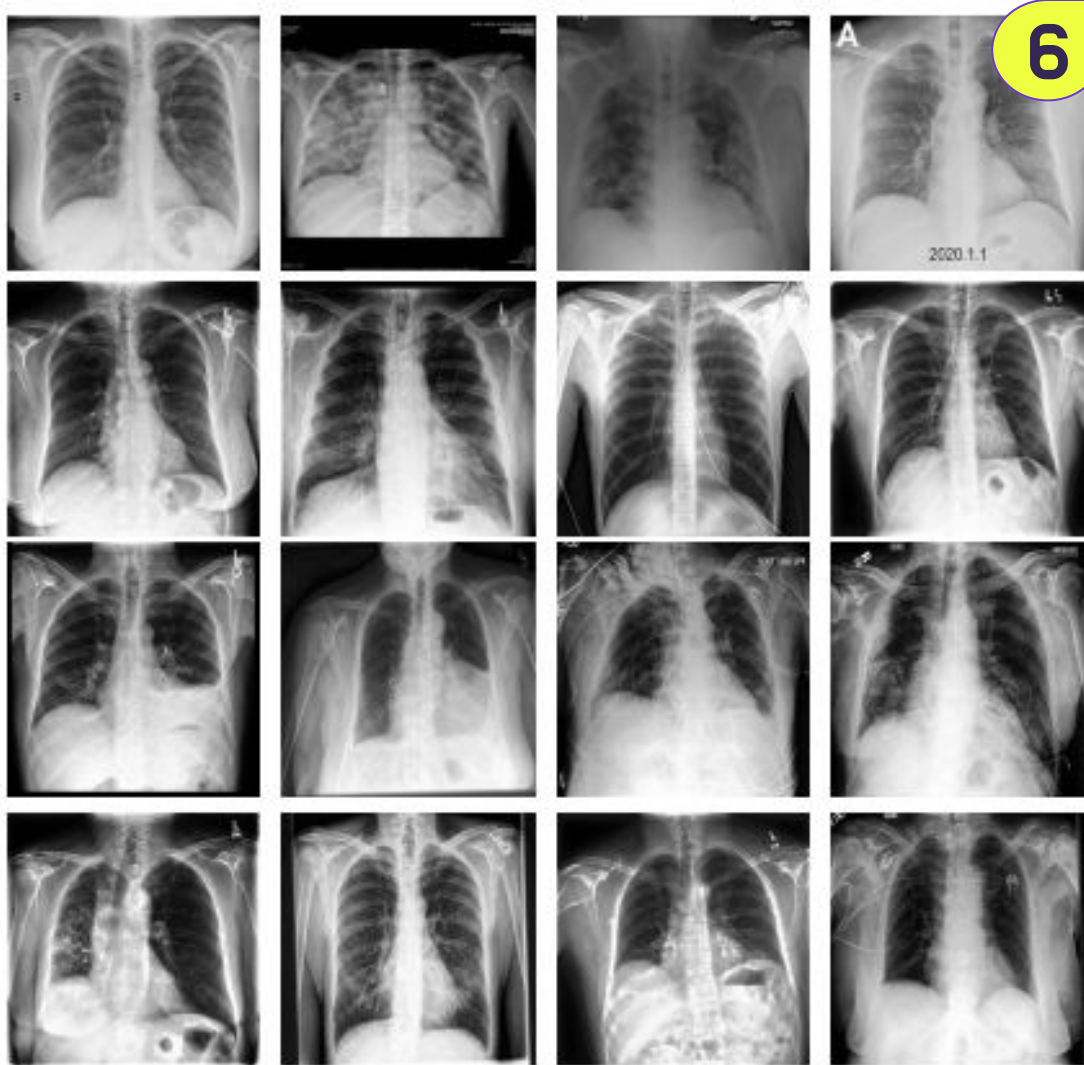




COVID-19

NO DISEASE

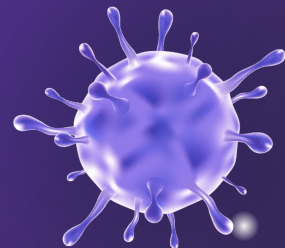
OTHER DISEASE





FRAMEWORK

- Transfer learning approach
 - Model repurposed
 - Suitable for small datasets
 - Two ways
 - As feature extractor
 - Whole network get tuned
- We use both on ImageNet dataset
 - Fine-tuning last layer
 - Extracting feature



Used Convolutional Models



ResNet

The core idea of ResNet is introducing a so-called identity shortcut connection that skips one or more layers.



SqueezeNet

They alternate a 1x1 layer that "squeezes" the incoming data in the vertical dimension followed by two parallel 1x1 and 3x3 convolutional layers that "expand" the depth of the data again.



DenseNet

Each layer obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers.





RESULTS

- Model Hyper-parameters
 - 100 epochs
 - 20 batch size
 - ADAM optimizer
 - 0.0001 learning rate
 - Images are down-sampled to 224x224
- Evaluation metrics are as shown below

$$\text{Sensitivity} = \frac{\text{\#Images correctly predicted as COVID-19}}{\text{\#Total COVID-19 Images}},$$
$$\text{Specificity} = \frac{\text{\#Images correctly predicted as Non-COVID}}{\text{\#Total Non-COVID Images}}.$$

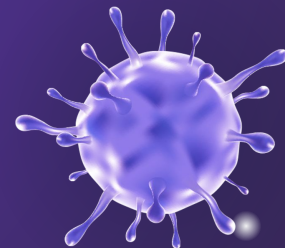


Table 2. Sensitivity and specificity rates of ResNet18 model, for different threshold values.

| Threshold | Sensitivity | Specificity |
|-----------|-------------|-------------|
| 0.1 | 100% | 72.4% |
| 0.17 | 98% | 90.7% |
| 0.2 | 95% | 92.4% |
| 0.25 | 91% | 95.8% |
| 0.35 | 85% | 98.3% |

Table 5. Sensitivity and specificity rates of DenseNet-121 model, for different threshold values.

| Threshold | Sensitivity | Specificity |
|-----------|-------------|-------------|
| 0.19 | 98% | 75.1% |
| 0.25 | 95% | 88.9% |
| 0.3 | 90% | 94.6% |
| 0.4 | 79% | 98.9% |

Table 3. Sensitivity and specificity rates of ResNet50 model, for different threshold values.

| Threshold | Sensitivity | Specificity |
|-----------|-------------|-------------|
| 0.15 | 100% | 78.2% |
| 0.205 | 98% | 89.6% |
| 0.25 | 93% | 94.2% |
| 0.3 | 90% | 97.3% |
| 0.35 | 85% | 98.4% |

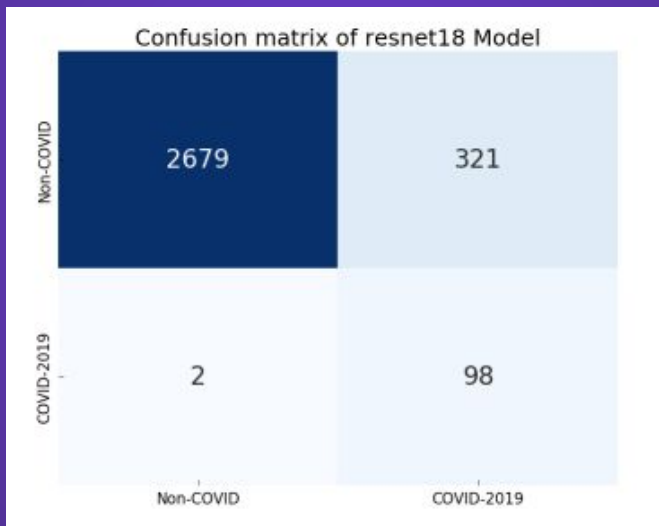
Table 4. Sensitivity and specificity rates of SqueezeNet model, for different threshold values.

| Threshold | Sensitivity | Specificity |
|-----------|-------------|-------------|
| 0.1 | 100% | 89.9% |
| 0.15 | 98% | 92.9% |
| 0.2 | 96.0% | 94.6% |
| 0.4 | 92% | 97.6% |
| 0.5 | 87% | 98.3% |

Table 6. Comparison of sensitivity and specificity of four state-of-the-art deep neural networks.

| Model | Sensitivity | Specificity |
|--------------|------------------|--------------------|
| ResNet18 | $98\% \pm 2.7\%$ | $90.7\% \pm 1.1\%$ |
| ResNet50 | $98\% \pm 2.7\%$ | $89.6\% \pm 1.1\%$ |
| SqueezeNet | $98\% \pm 2.7\%$ | $92.9\% \pm 0.9\%$ |
| Densenet-121 | $98\% \pm 2.7\%$ | $75.1\% \pm 1.5\%$ |

The Heatmap of Potentially Infected Regions



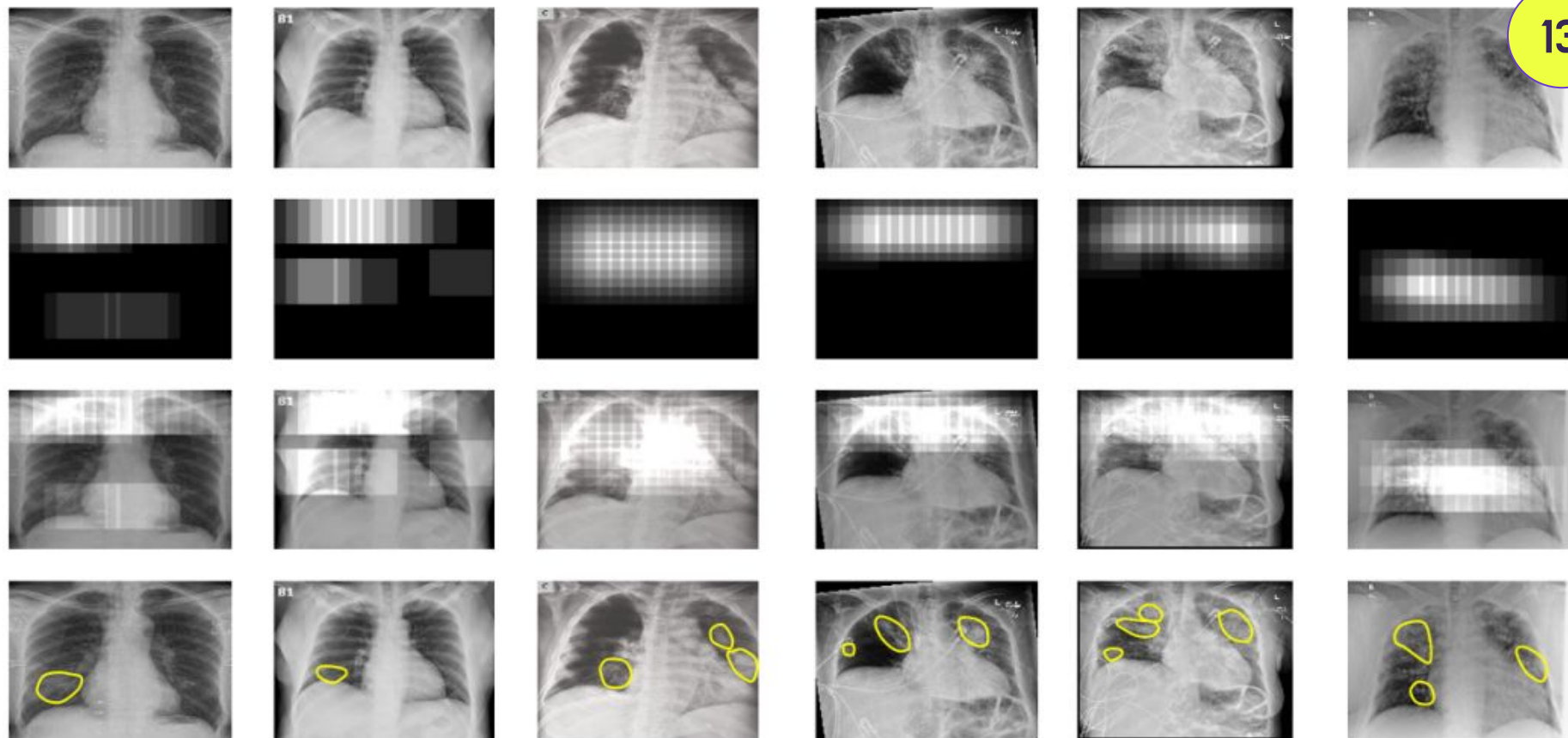


Fig. 14. COVID-19 infected regions detected by our ResNet18 model, in six chest X-ray images from the test set. Vertical sets give the Original images (top row), COVID-19 region heatmap (2nd row), heatmap overlaid on the image (3rd row), and the independent standard of radiologist-marked COVID-19 disease regions (bottom row).

CONCLUSIONS

We performed a detail experimental analysis evaluating the performance of each of these 4 models on the test set of of COVID-Xray-5k Dataset, in terms of sensitivity, specificity. For a sensitivity rate of 98%, these models achieved a specificity rate of around 90% on average. This is really encouraging, as it shows the promise of using X-ray images for COVID-19 diagnostics. This study is



THANKS!

Does anyone have any questions?



CREDITS: This presentation template was created by **Slidesgo**,
including icons by **Flaticon** and infographics & images by **Freepik**

