HOUSTON COUNTY HIGH SCHOOL

COVID-Net: A Deep Convolutional Neural Network model for improving COVID-19 detection

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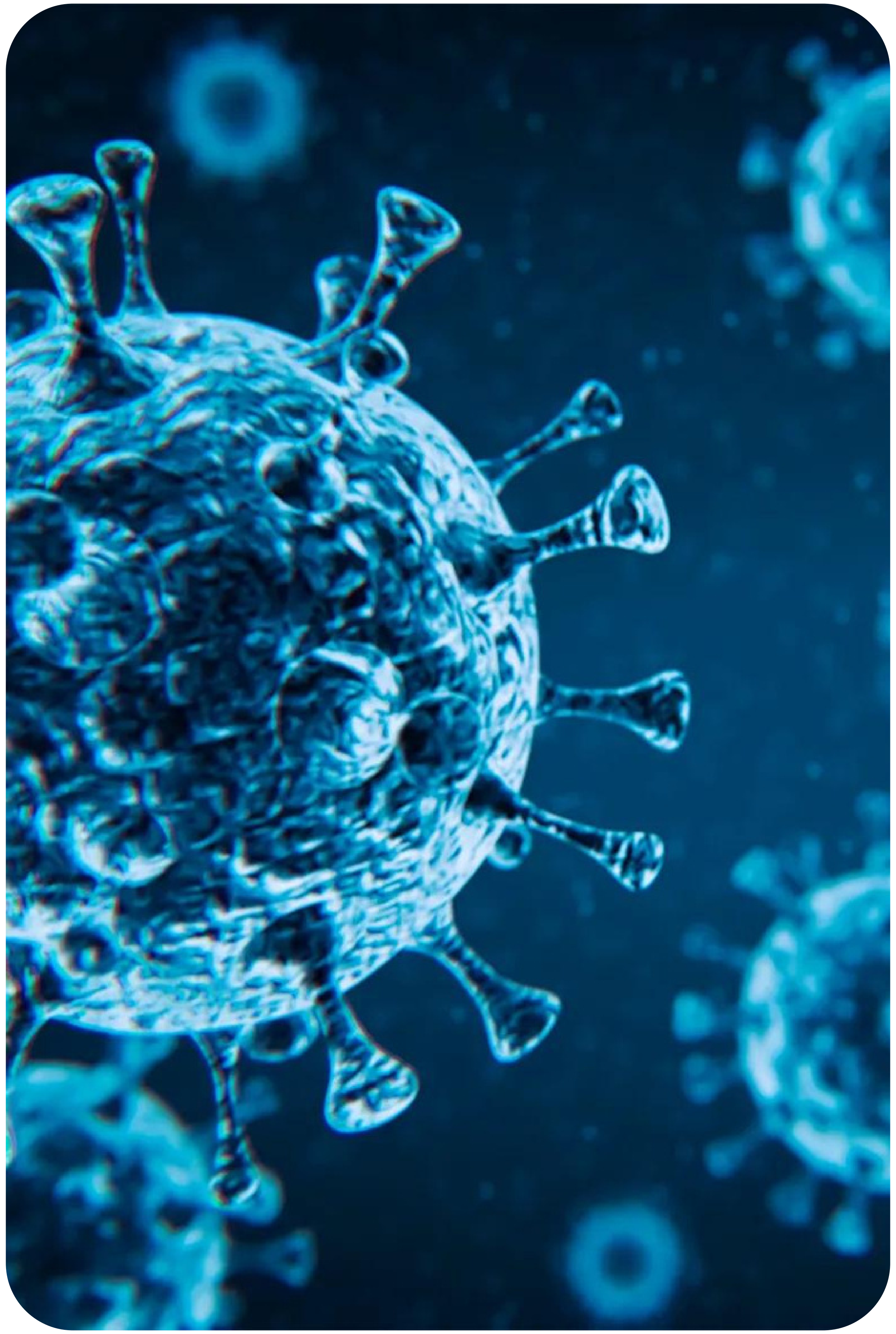
(Alamy Images)

Background

- COVID-19 is a viral **respiratory illness** caused by SARS-CoV-2

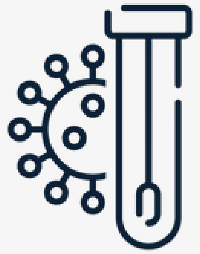
- As of February 2023 (WHO):
  - **756,581,850** reported positive cases
  - **6,844,267** COVID-19 related deaths

- Many efforts in place to control the spread:
  - **Vaccines**
  - **Lockdown**
  - **Masks**



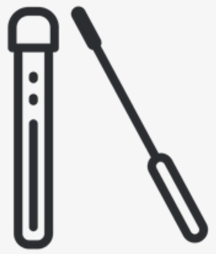
COVID-19 Virus (The Hill)

Current COVID-19 detection methods



RT-PCR Test

- **89.9%** sensitivity
- **2-3 days** turnaround time (typical)



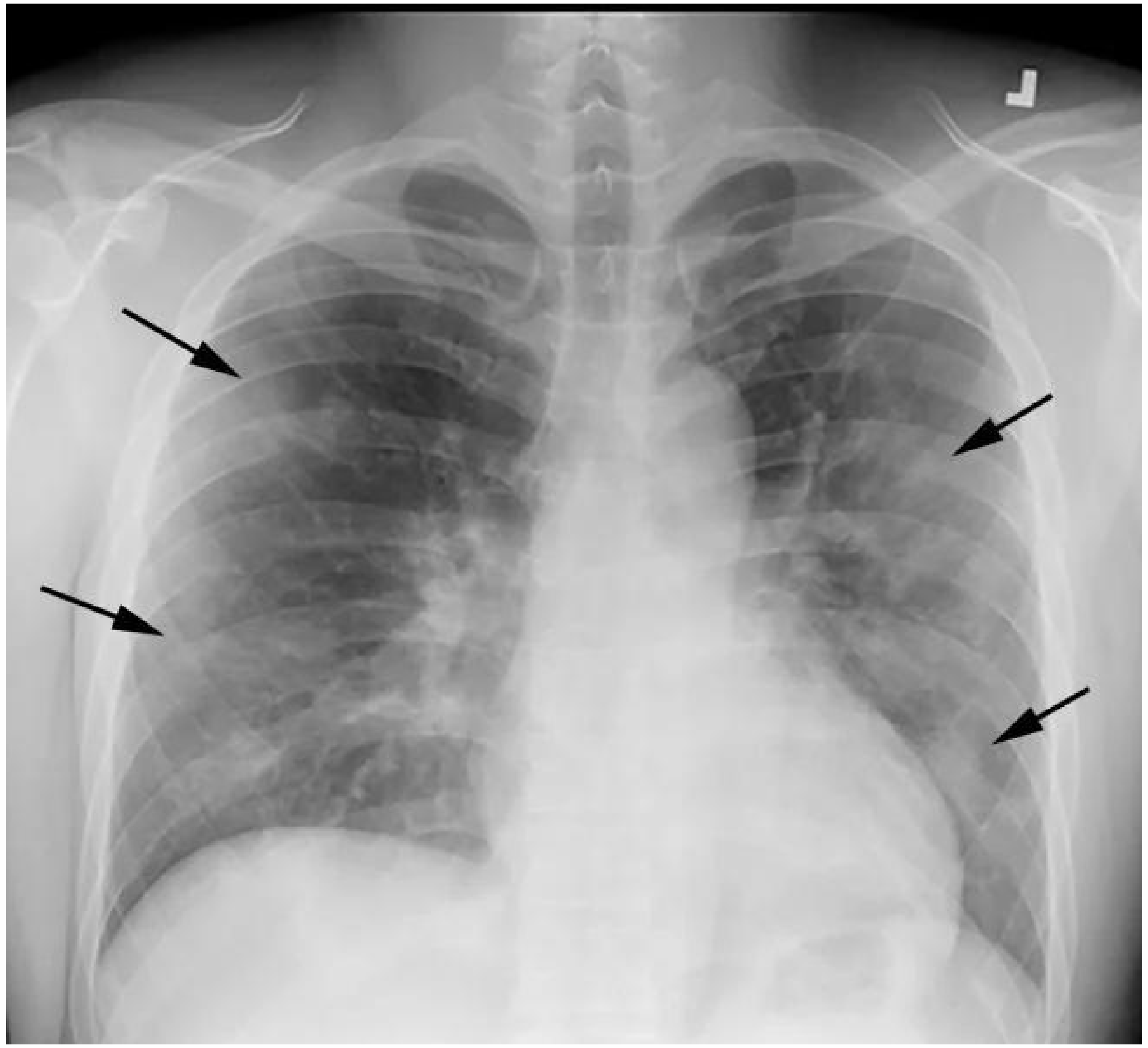
Rapid Antigen Test

- **60-85%** sensitivity
- **15-30 minutes** turnaround time (typical)

Due to the **limited sensitivities** and **long turnaround times** of these methods, an alternative method of COVID-19 detection is needed.

Radiology methods of COVID-19 detection

- CT scans and **Chest X-Ray (CXR)** imaging have been used to visually diagnose COVID-19
- Conditions in COVID-19, such as Ground Glass Opacities, are very **similar** to those in other respiratory diseases
- It can be **difficult** and **time-consuming** for radiologists to differentiate COVID-19 from other common respiratory diseases
- Radiologists had a **47%** sensitivity and **79%** specificity in detecting COVID-19 (Dorr et. al)



COVID-19 Chest X-Ray (Imaging Technology News)

The application of AI and Deep Learning

The Convolutional Neural Network (CNN) has shown the potential to identify patterns in CXR imaging

- Several CNN models have already been developed to detect respiratory diseases from CXR imaging, including:
  - Pneumonia
  - Tuberculosis
  - Lung Cancer

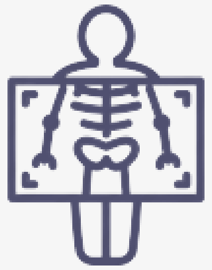
CNN models have shown to outperform radiologists

- Radiologists are prone to external factors, such as fatigue, that can **hinder** their performance
- A trained CNN model has been shown to **outperform** radiologists in detection of 11/14 pathologies (Jones et. al)

CNN models have been successful at COVID-19 detection

- Various CNN models have already been created for COVID-19 detection, ranging from **86%** to **98.7%** accuracy

Shortcomings of existing models



Trained on limited/unbalanced datasets

Cannot differentiate between COVID and other respiratory diseases

Not tested in a clinical setting

Engineering Goal

Problem: Current COVID-19 detection methods are limited due to long turnaround times and limited sensitivites. Current CNN models built for COVID-19 detection have severe limitations that need to be addressed.

Goal: To create a **novel**, **CNN-based** Computer-Aided Diagnosis system to assist radiologists in performing **rapid**, **high accuracy** COVID-19 diagnosis from Chest X-Rays.

Methodology

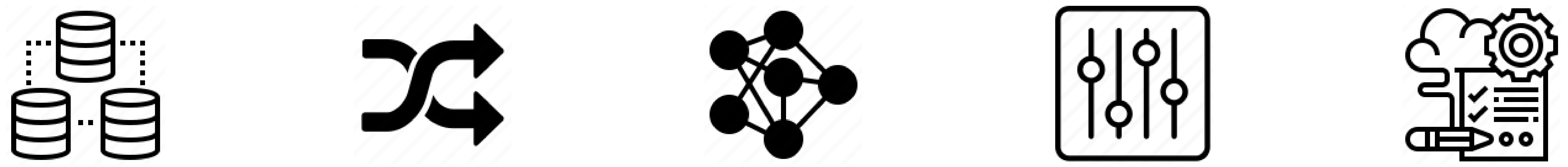
Data Acquisition

Data Preprocessing/ Augmentation

Model Building

Hyperparameter Tuning

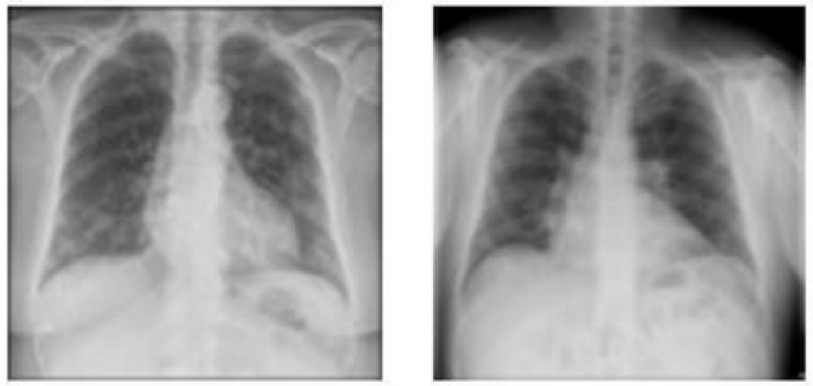
Evaluation



Data Acquisition

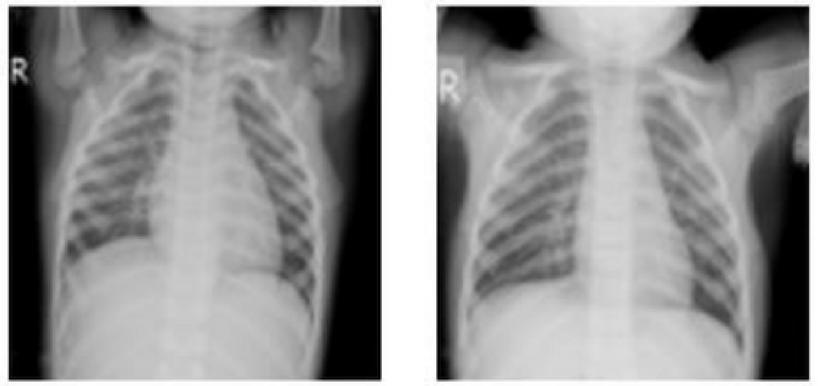
- The dataset used for this study was the **COVID-QU-Ex dataset** from Kaggle
- Contains **33,920** CXR images
- **3 classes**
  - 11,956 **COVID-19**
  - 11,263 **Non-COVID infections** (Viral and Bacterial Pneumonia)
  - 10,701 **Normal**
- All CXR images were pre-classified

COVID-19



Non-COVID

Normal



Data Preprocessing/Augmentation

Data Preprocessing

- All images were **resized** to 256 x 256 pixels
- Pixel values were **normalized** between 0-1
- **8:2** train-test split

Data Augmentation

- Data augmentation is a popular technique used to increase the **diversity** of **training samples**
- Generates **modified** versions of existing data
- **Three** unique image augmentation techniques were used:
  - **Random Rotation**
  - **Random Horizontal Flip**
  - **Random Zoom**

Raw Image

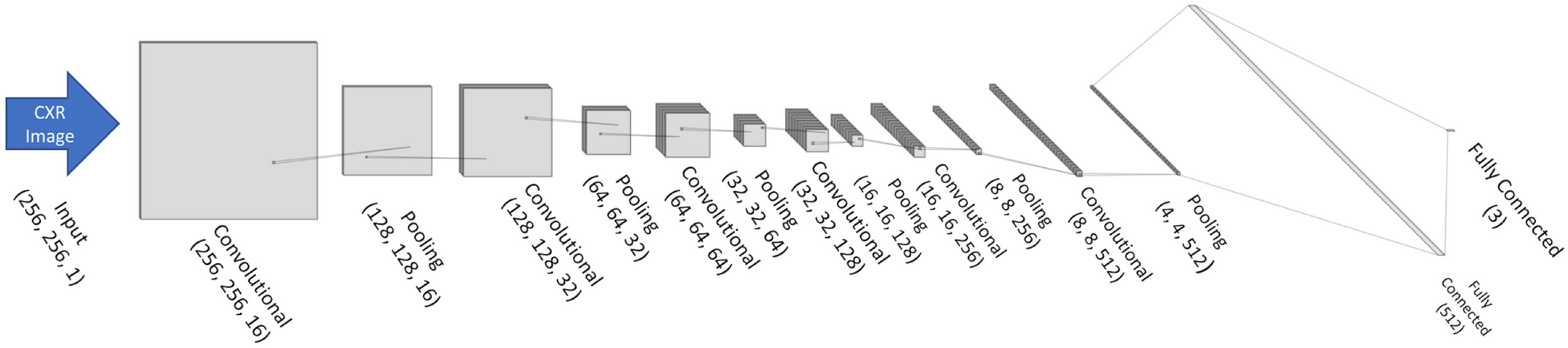
Random Zoom

Random Rotation

Random Horizontal Flip

Model Building

My novel **COVID-Net** architecture consisted of 6 **convolutional** layers, 6 **pooling** layers, and 2 **fully connected** layers. The **dropout** technique was also used before the fully connected layers to reduce overfitting.



Hyperparameter Tuning

Overfitting: Model learns the training data too well. **Cannot** predict additional data reliably.

Underfitting: Model does not learn the training data well enough. **Cannot** predict additional data reliably.

Epochs - 100

Batch Size - 256

Learning Rate - 0.001

Optimizer - Adam

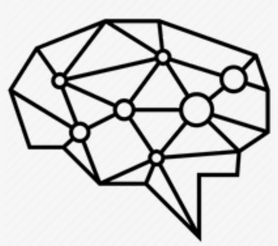
Dropout Rate - 0.2

Activation Function - ReLU

COVID-Net was built and trained on Google Colab using the TensorFlow and Keras libraries. The NVIDIA P100 GPU was used for hardware acceleration.

Evaluation

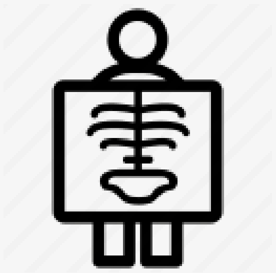
3 different methods of testing



Performance against transfer-learned architectures

COVID-QU-Ex dataset

- VGG-16
- ResNet50
- MobileNetV2



Performance against radiologists

Dorr et al. dataset

- 20 COVID CXR
- 20 Non-COVID CXR
- 20 Normal CXR

Performance in a clinical setting

Clinical dataset

- 23 COVID CXR
- 34 Non-COVID CXR
- 28 Normal CXR

Evaluation Metrics

Accuracy: $\frac{TP + TN}{TP + TN + FP + FN}$

Recall/Sensitivity: $\frac{TP}{TP + FN}$

Specificity: $\frac{TN}{TN + FP}$

Precision: $\frac{TP}{TP + FP}$

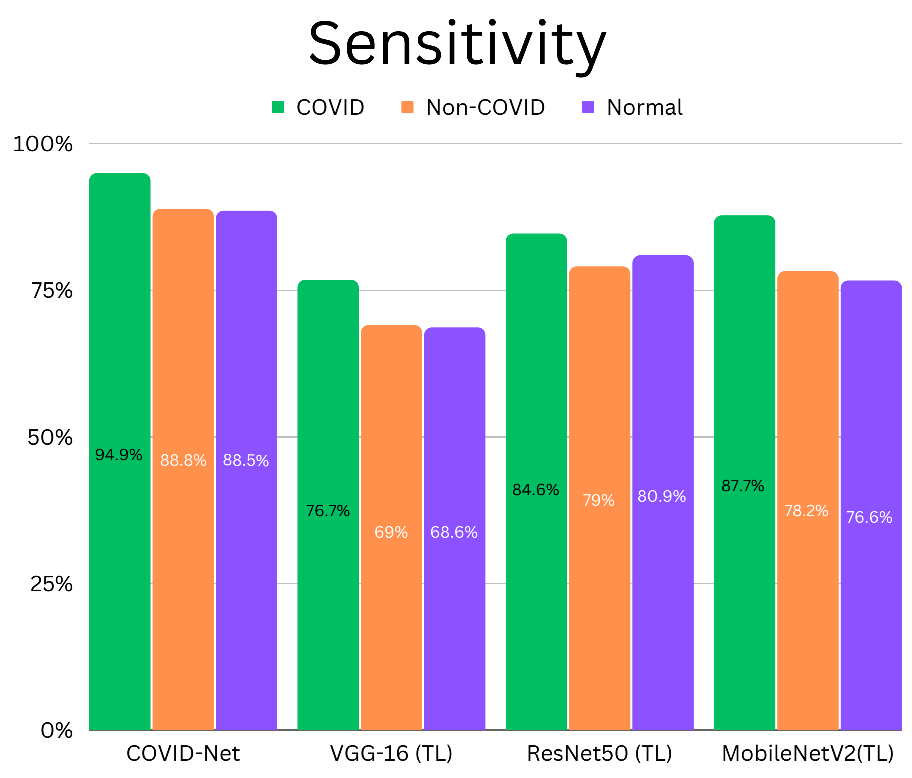
F1 Score: $\frac{2 * precision \ * recall}{precision + recall}$

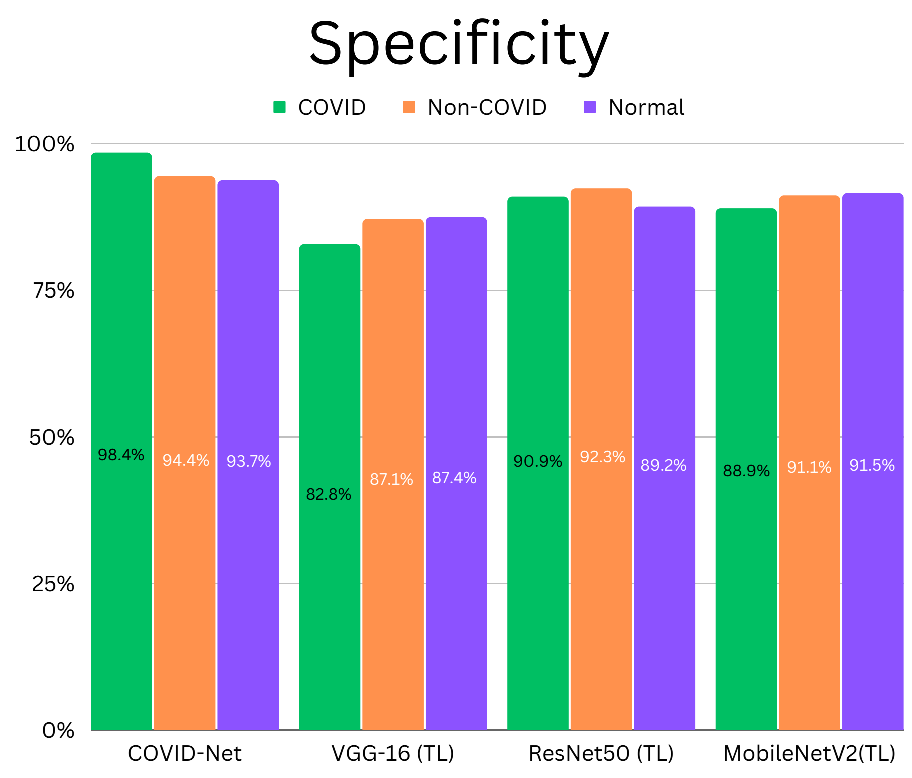
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

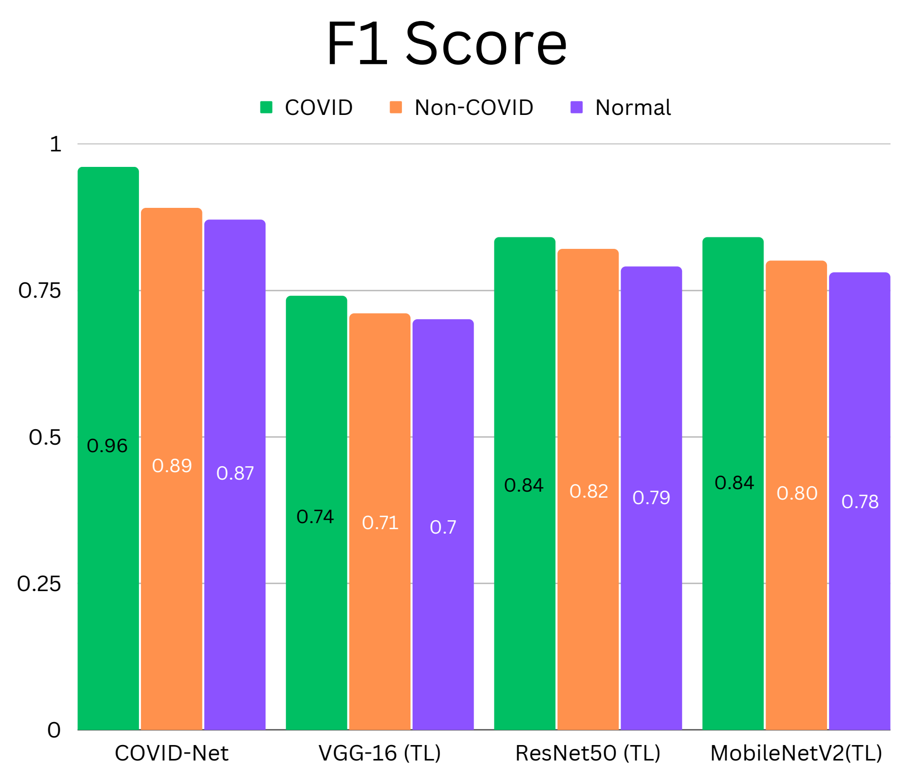
Weighted layers: # of trainable layers

The **two proportion z-test** was used in statistical analysis.

Results vs TL Architectures







Architecture	Accuracy	Average Sensitivity	Average Specificity	Average F1 Score	Weighted Layers
COVID-Net	91.1%	90.7%	95.5%	0.91	12
VGG16	71.6%	71.4%	85.8%	0.72	16
ResNet50	81.6%	81.5%	90.8%	0.82	50
MobileNetV2	81.1%	80.8%	90.5%	0.81	53

Statistical Tests

Null Hypothesis: There is no statistically difference in the performance of COVID-Net and the Transfer Learned architectures(VGG-16/ResNet50/MobileNetV2)

Alternative Hypothesis: COVID-Net has a higher performance than the Transfer Learned architectures (VGG-16/ResNet50/MobileNetV2)

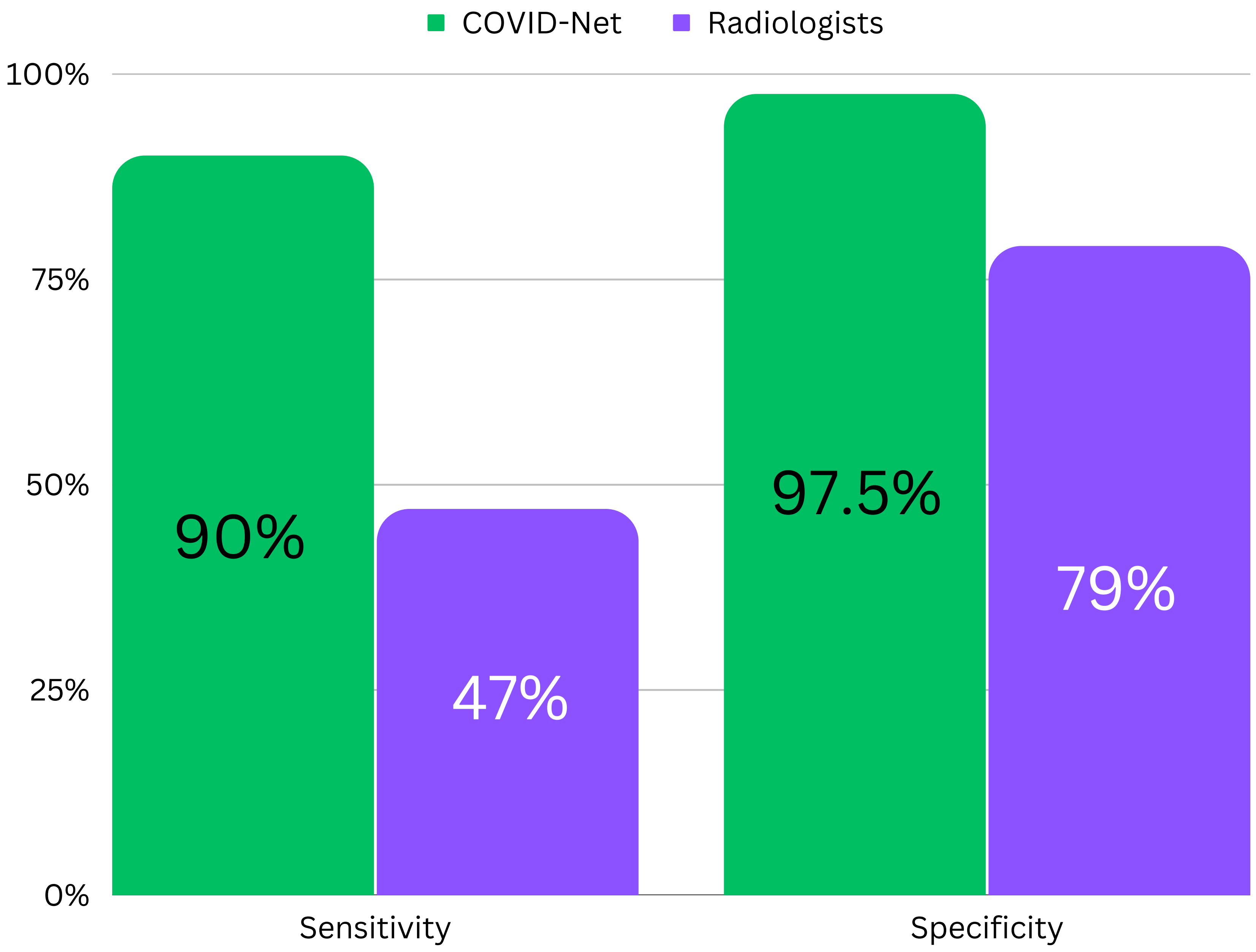
Metric	MobileNetV2	ResNet50	VGG-16	F1 Score
Accuracy	$p < .01$	$p < .01$	$p < .01$	$p < .01$
Avg. Sensitivity	$p < .01$	$p < .01$	$p < .01$	$p < .01$
Avg. Specifity	$p < .01$	$p < .01$	$p < .01$	$p < .01$
Avg. F1 Score	$p < .01$	$p < .01$	$p < .01$	$p < .01$

All results statistically significant at a = 0.05.

COVID-Net outperformed each TL architecture by a statistically significant amount margin in every metric.

Results vs Radiologists

COVID-19 Sensitivity and Specificity



Actual \ Predicted	COVID	Non-COVID	Normal
COVID	18	1	1
Non-COVID	1	19	0
Normal	0	0	20

Statistical Tests

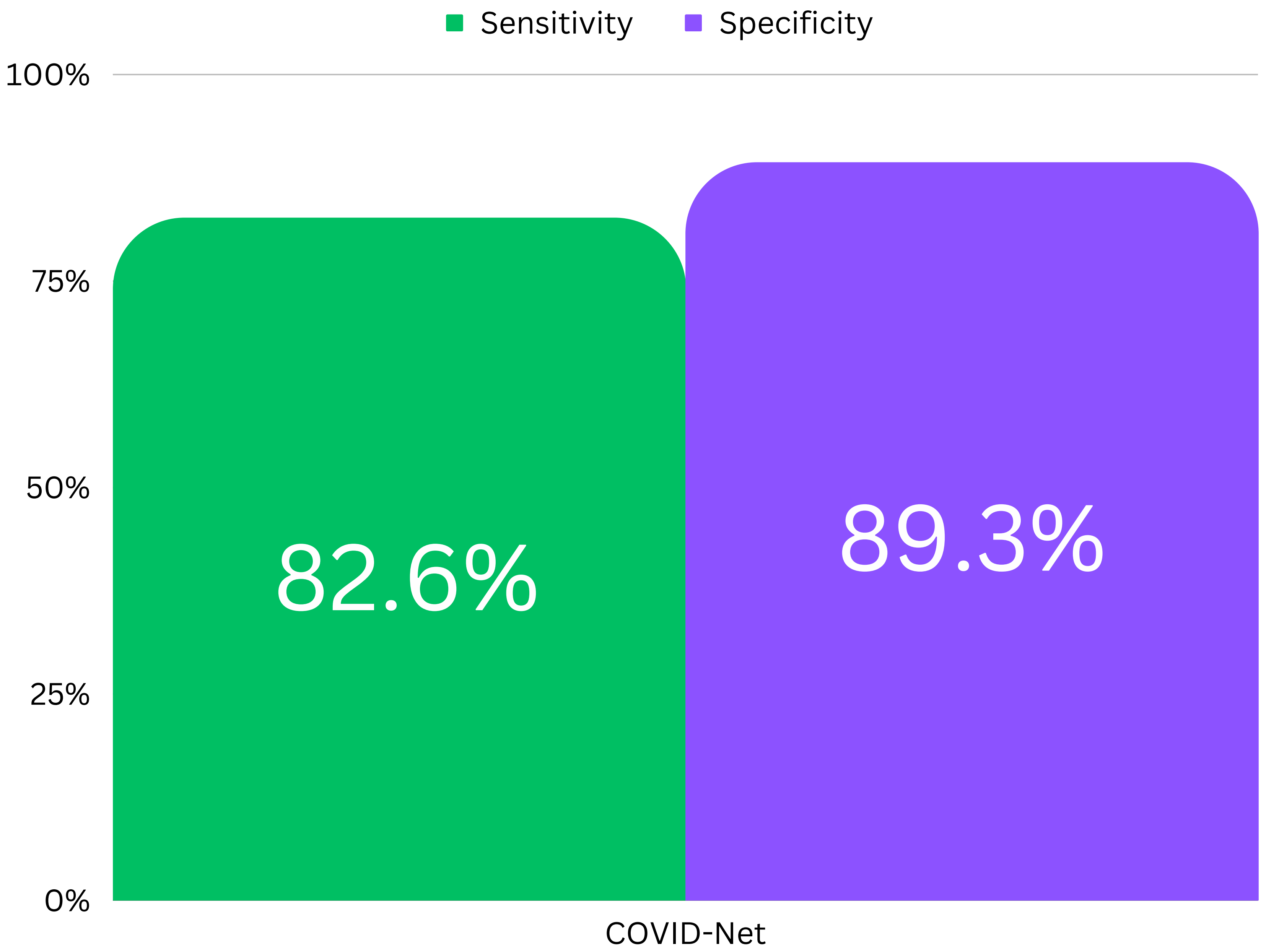
Null Hypothesis: There is no statistically difference in the performance of COVID-Net and radiologists in correctly classifying COVID-19 CXR images from the test dataset.
Alternative Hypothesis: COVID-Net has a higher performance than the radiologists in correctly classifying COVID-19 CXR images from the test dataset.

Metric	COVID-Net	Radiologists	p-value
Sensitivity	90%	47%	$p < .01$
Specificity	97.5%	79%	$p < .01$

All results statistically significant at a = 0.05.
COVID-Net outperformed the radiologists by a statistically significant margin in specificity and sensitivity.

Results in Clinical Trial

COVID-19 Sensitivity and Specificity



Actual \ Predicted	COVID	Non-COVID	Normal
COVID	19	2	2
Non-COVID	4	27	3
Normal	2	3	23

Discussion

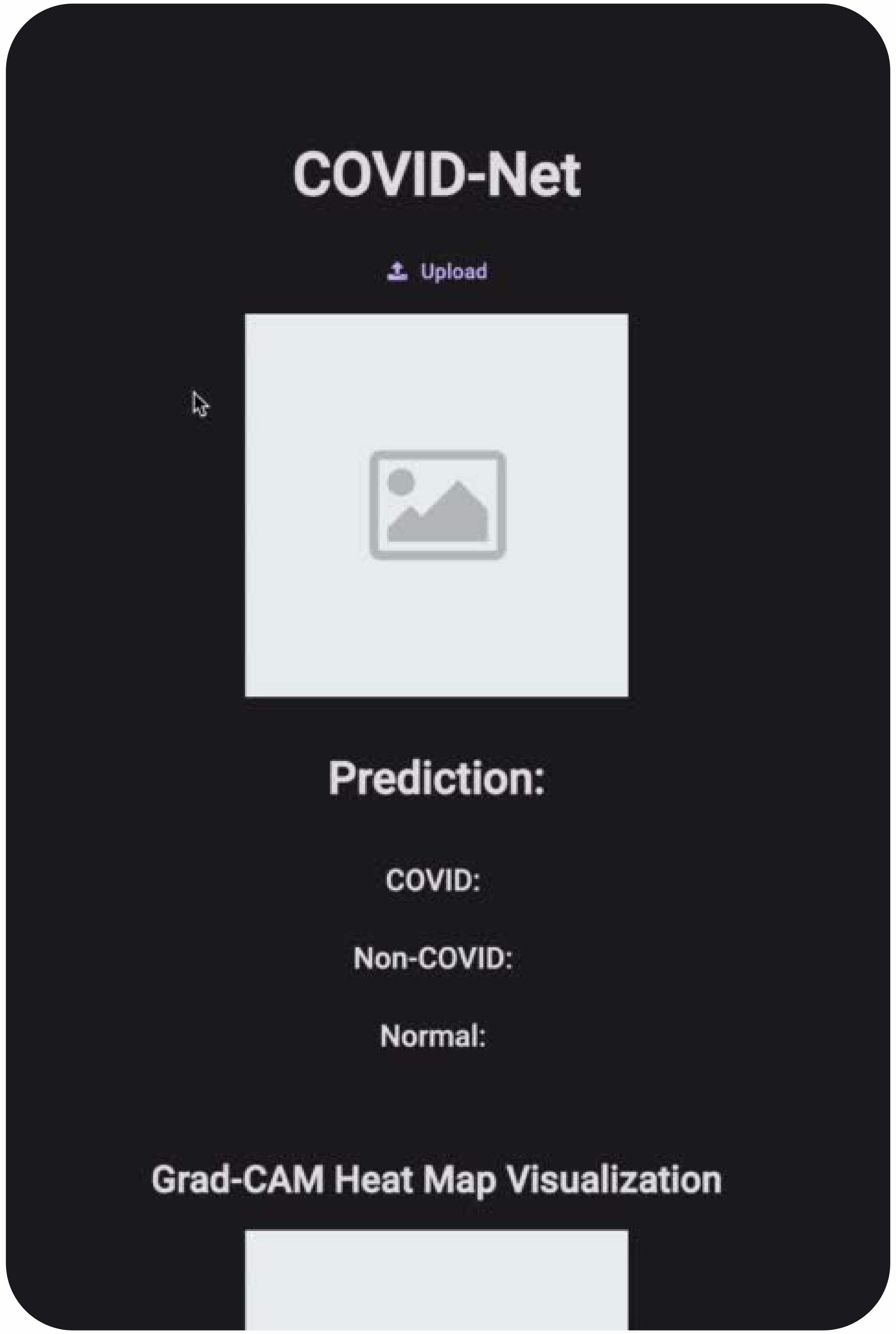
- COVID-Net **outperformed** the VGG-16, ResNet50, and MobileNetV2 models in many metrics by a statistically significant margin, including:
    - Accuracy (**91.2%** vs 71.6%, 81.6%, and 81.1%)
    - Average Sensitivity (**90.7%** vs 71.4%, 81.5%, and 80.8%)
    - Average Specificity (**95.5%** vs 85.8%, 90.8%, and 90.5%)
    - Average F1 Score (**0.91** vs 0.72, 0.82, and 0.81)
    - Number of weighted layers (**12** vs 16, 50, and 53)

- COVID-Net also **outperformed** professionally trained radiologists in COVID-19 detection in two major metrics by a statistically significant margin:
    - Specificity (**97.5%** vs 79%)
    - Sensitivity (**90%** vs 47%)

- COVID-Net also **outperforms** the RT-PCR and COVID-19 Antigen tests in in two major metrics:
    - Sensitivity (**94.9%** vs 89.9% vs 60-85%)
    - Turnaround Time (**2-3 seconds**, 2-3 days, 15-30 minutes)

Website Deployment

- Configured with Anvil library
- Only requires an internet-connected device
- Easy-to-use interface
- 100% free-to-use



Future Research

- Further training of COVID-Net on **other respiratory diseases**, such as tuberculosis and lung cancer, to help differentiate COVID-19 from a wider variety of diseases
- Using a wider variety of **data/data augmentation techniques** to further train the model and reduce the discrepancy between theoretical and clinical results
- Implement **GRAD-Cam visualizations** into the COVID-Net API to help radiologists localize areas of interest in CXRs.

Conclusion

- COVID-Net is a much **quicker** and **more accurate** diagnosis tool than existing methods such as:
  - RT-PCR / Rapid Antigen tests
  - State-of-the-art CNN architectures
  - Radiologists alone
- With our clinical testing results, we can confirm that COVID-Net can be used to **assist radiologists** in the interpretations of CXRs
- Our **free**, **easy-to-use** COVID-Net **web application** can be used to detect COVID-19 universally
- COVID-Net can be used as a **primary detection method** in areas where RT-PCR / Rapid Antigen tests / Radiologists are not readily available

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All figures were created by the researcher, Shiva Soundappan, unless otherwise stated.

Special thanks to my research advisor, Dr. Chunhua Dong, for all of her assistance in this project.

Thank you!

I appreciate your time! Please let me know if you have any questions.