DL for Covid-19 and Pneumonia Classification from Chest X-Rays

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1. Introduction & Motivation
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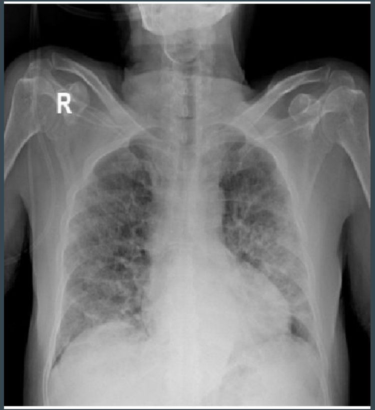
Motivation

- Covid-19 continues to pose **diagnostic challenges**
- **Chest X-Rays** are fast and widely available
- Distinguishing **Covid vs. Viral Pneumonia vs. Normal** is difficult
- **RT-PCR** remains the gold standard, but it is slow and resource intensive
- DL can support faster screening and triage

Medical Background

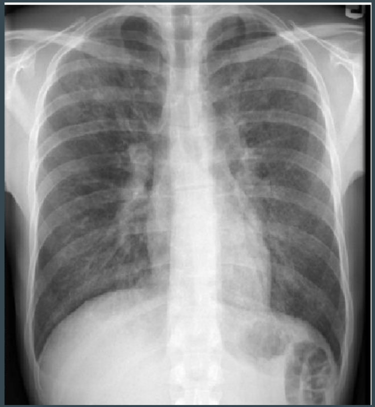
Covid-19

Bilateral peripheral ground-glass opacities



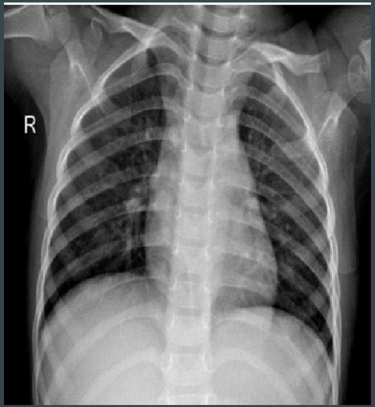
Viral Pneumonia

Patchy, asymmetric infiltrates



Normal

Clear lung fields



Chest imaging alone cannot reliably differentiate these conditions
Fleischer Society (2020) - imaging must be combined with clinical and RT-PCR testing

Research Context

- Prior models often used 2-class datasets:
    - Covid vs Normal
- Achieved very high accuracy (~97-99%)
- Differentiating Pneumonia has major implications in treating illnesses that can progress to severe complications
- multiclass classification remains understudied

Our project addresses this gap!

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Example Images from Dataset

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Dataset and Preprocessing

- Kaggle *Covid-19 Chest X-ray Dataset*
- 3 classes:
  1. Covid
  2. Viral Pneumonia
  3. Normal
- Cleaning & Preprocessing:
  - removed corrupt images
  - standardized RGB format
  - Resized to 224x224
  - normalized
  - augmented images
- Split Train/Val/Test using *TensorFlow*

	Class	Train Count	Val Count	Test Count	Total	Percent (%)
0	Covid	87	24	26	137	43.22
1	Normal	58	12	20	90	28.39
2	Viral Pneumonia	56	14	20	90	28.39

Class Distribution

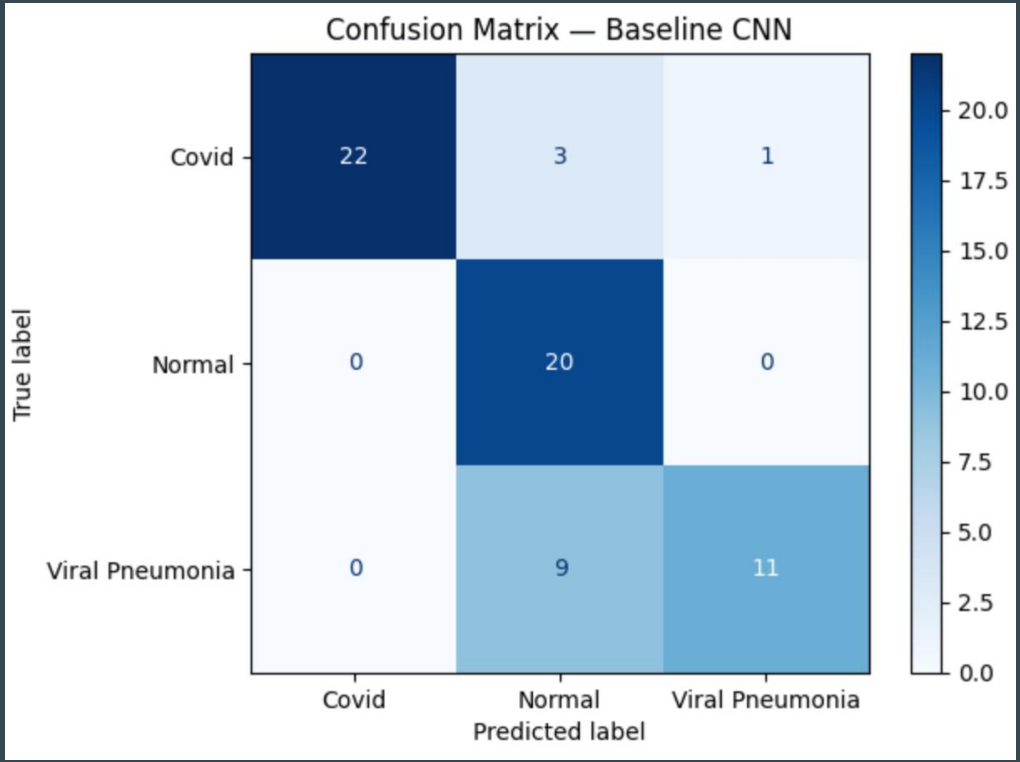
Baseline CNN

Architecture:

- 3 Convolutional Blocks
  - 32 —> 64 —> 128 Filters
- Dense Layer with 256 units + dropout
- Softmax for 3-class output

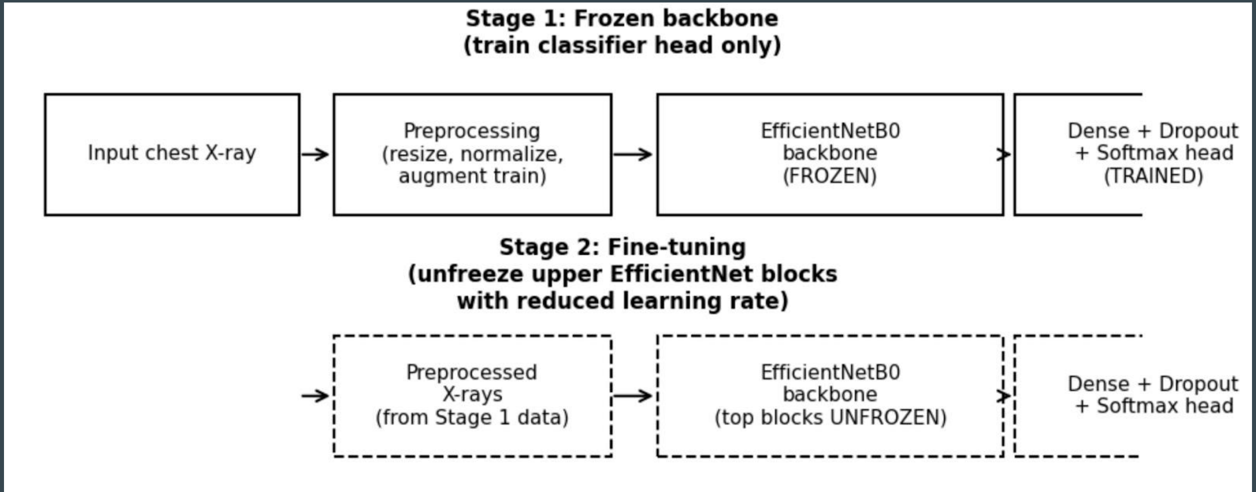
Performance:

- Accuracy: **80.3%**
- Covid F1: **0.917**
- Normal & Viral cases were harder to distinguish



Transfer Learning: EfficientNetB0

1. Loaded pre trained EfficientNetB0 as feature extractor
2. Frozen Backbone —> trained classifier head
3. Fine tuned upper convolutional blocks
4. Lower LR to ensure stability



Explainability Overview

We applied 3 complementary methods to explore interpretability of our model.

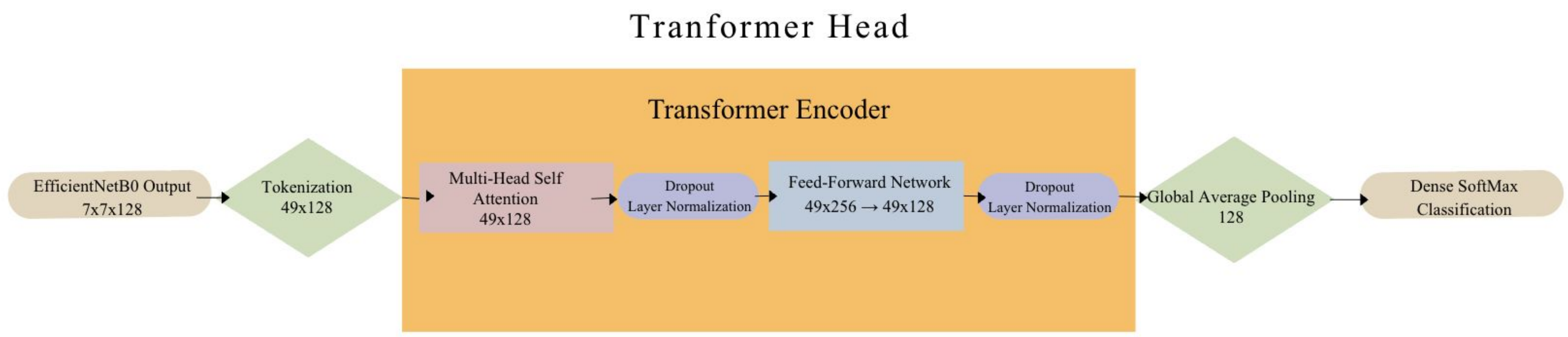
1. **Grad-CAM:** Course heatmaps of important regions
2. **Saliency Maps** : pixel-level sensitivity
3. **Occlusion Maps:** confidence drop from masking patches

Crucial in medical AI because allows clinicians to understand how an AI reached a decision, enabling them to verify its reasoning and identify potential errors or biases.

Transformer Head

1. Added on top of EfficientNet pretrained model
2. Trained with learning rate warmup (stability)
3. Unfroze top 100 layers of EfficientNet
4. Retrained with low learning rate ($1e^{-6}$)

49 tokens are able to interact with each other capturing global interaction importance across lung regions



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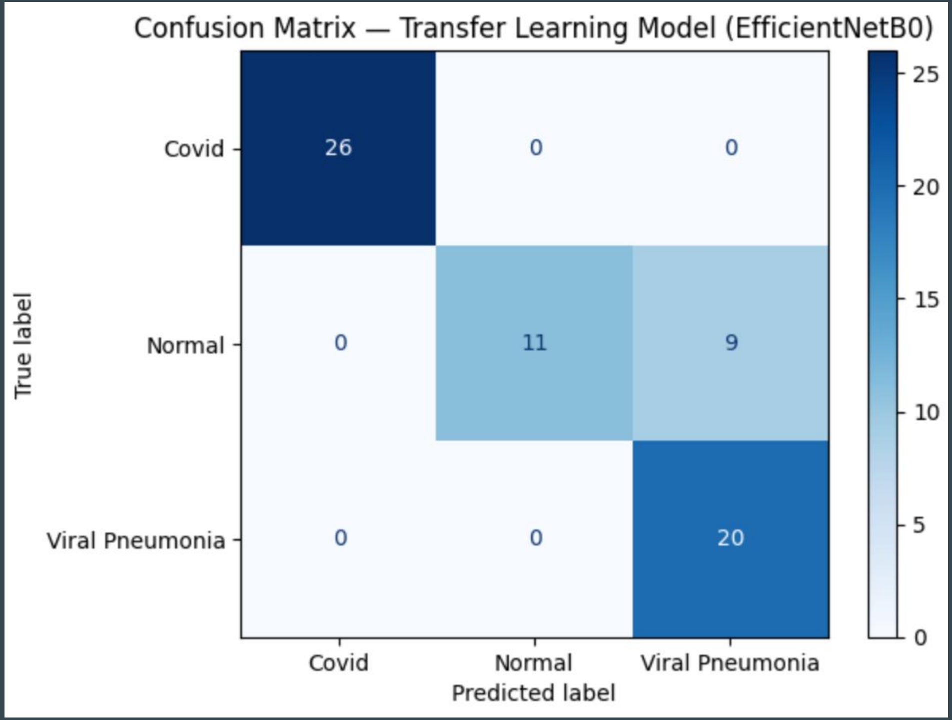
Transfer Learning Model

Accuracy: **86.36%**

Covid F1: **1.00**

Strong improvements for Viral Pneumonia



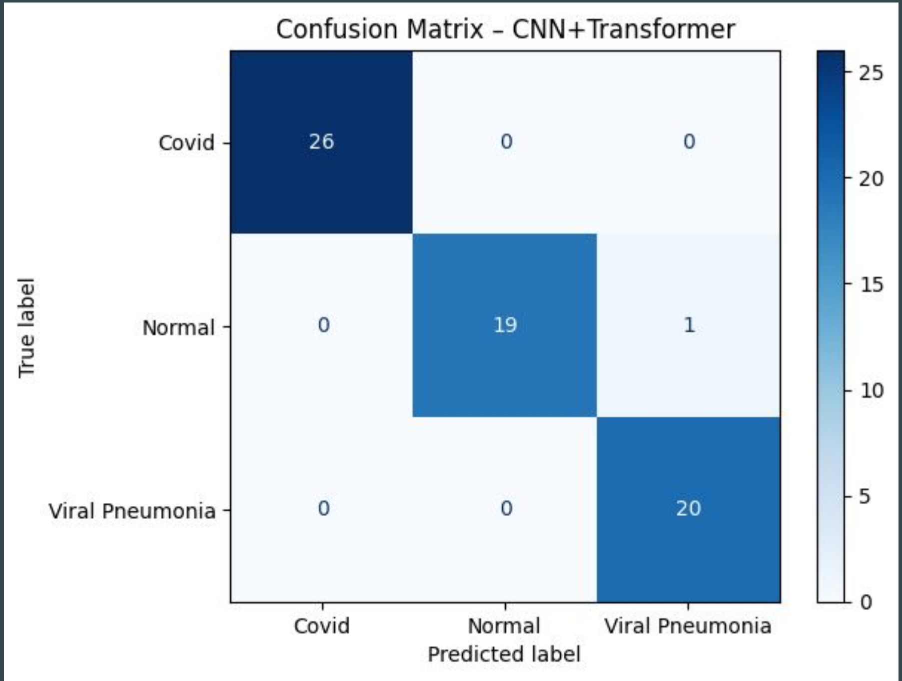
CNN + Transformer Model

Accuracy: **94.48%**

Covid F1: **1.00**

Only one misclassified test case (True Normal)

Perfect recall for both illness classes

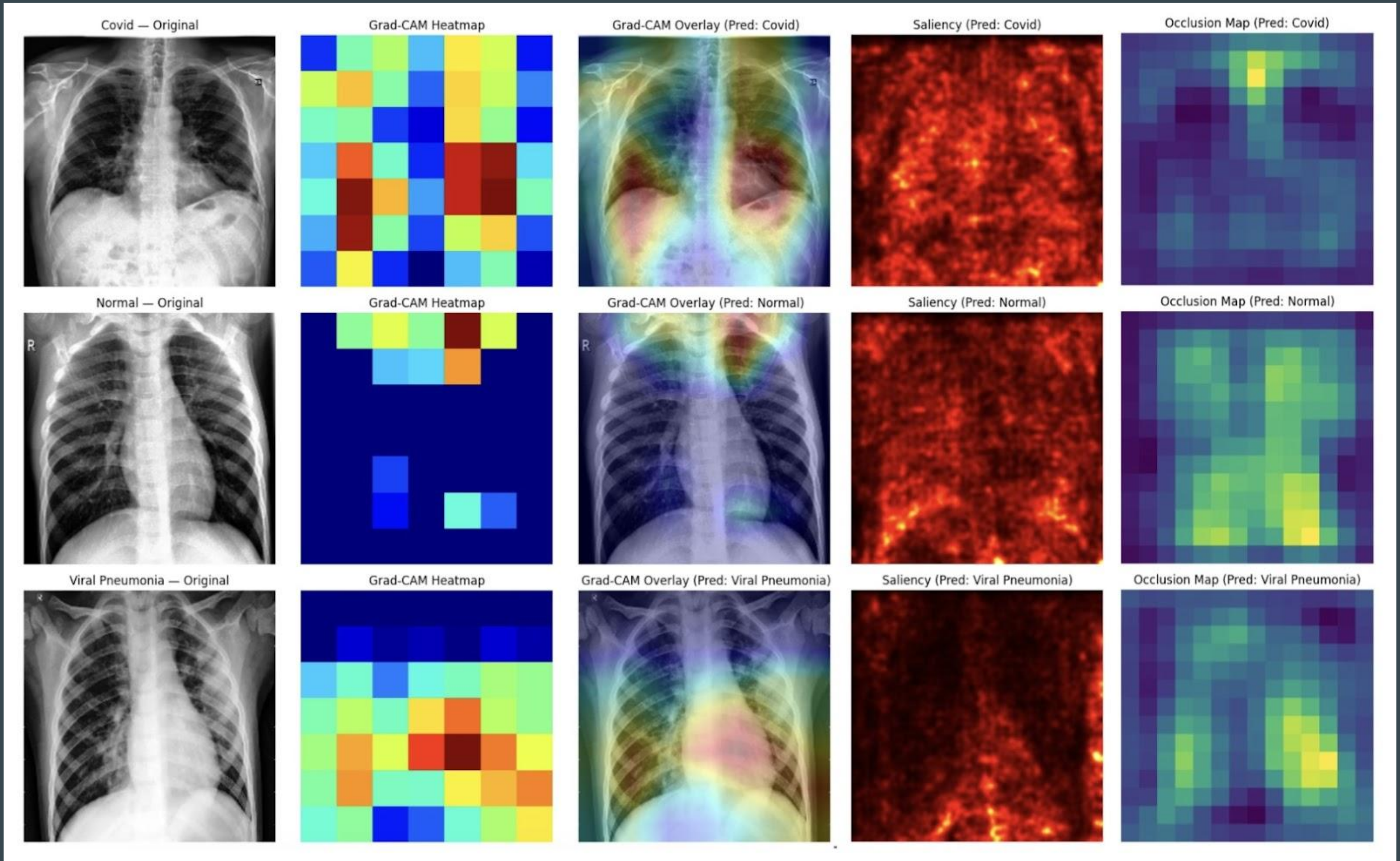


Model Comparison Table

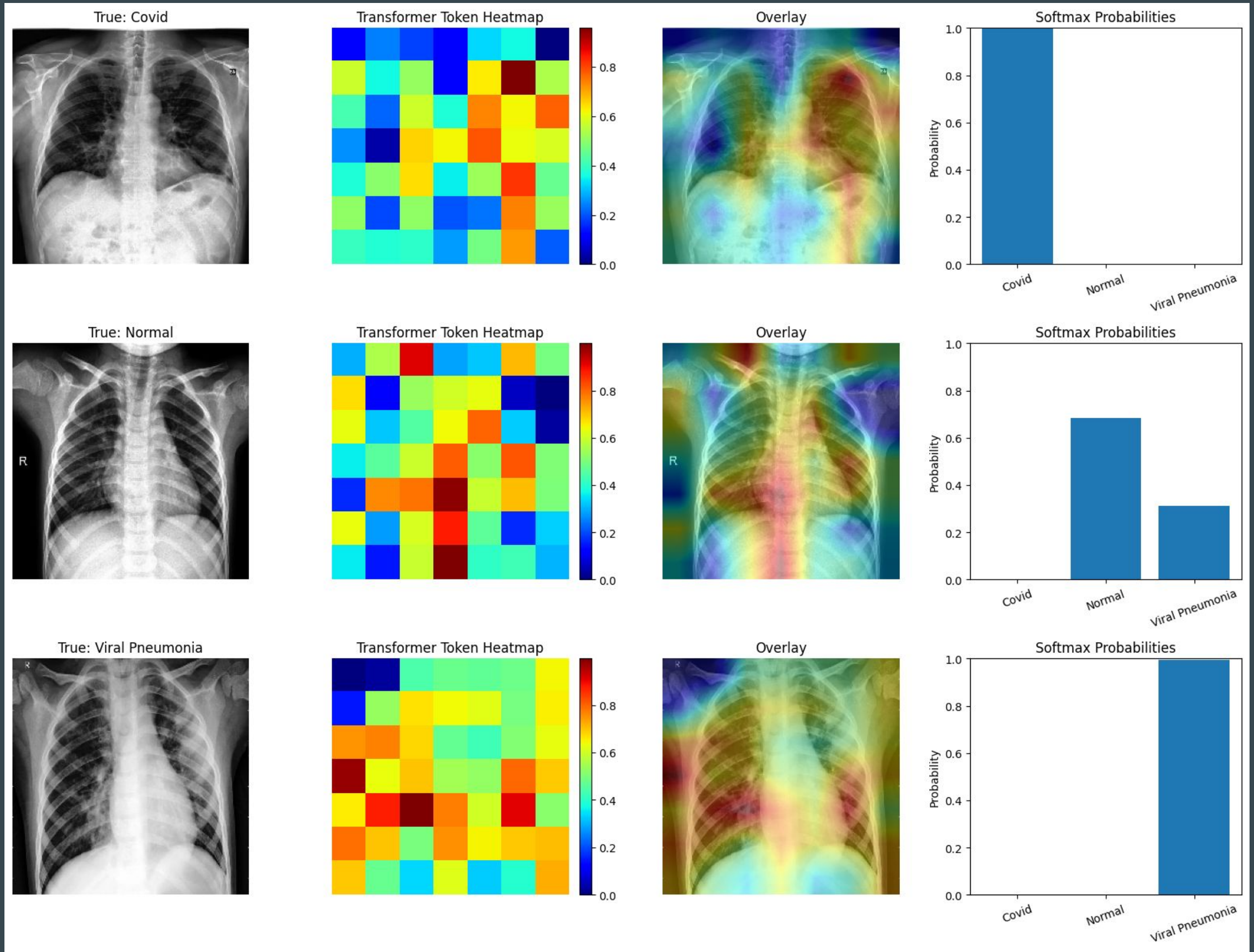
	Metric	Baseline CNN	Transfer Learning (EffNetB0)	CNN + Transformer
0	Accuracy	0.80303	0.86364	0.98484
1	Covid F1	0.91700	1.00000	1.00000
2	Viral Pneumonia F1	0.76900	0.70600	0.97560
3	Normal F1	0.68800	0.81600	0.97435

- EffNet and Transformer models perfect F1 Scores
- Transfer Learning improved across the board from baseline CNN
- Transformer model greatly improve Viral Pneumonia and Normal F1 Scores

Explainability Results (Transfer Learning)



Explainability Results (CNN + Transformer)



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Limitations

- Small dataset —> limits robustness
- Chest X-ray variability across institutions
- Normal vs viral pneumonia shows more challenging
- Not validated clinically

Future Work

- Train on larger, multi-institution datasets
- Explore deeper EfficientNet or ViT architectures
- Add lung segmentation before classification
- Incorporate clinical data with imaging
- Build ensemble models for robustness
- Build implemented system for efficiency in medical setting