Vision transformer medical imaging explanations using Relevance Propagation

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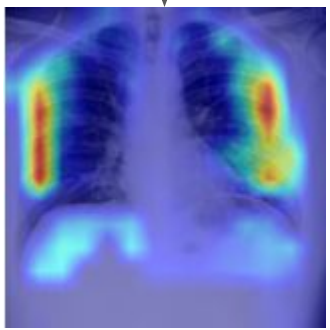
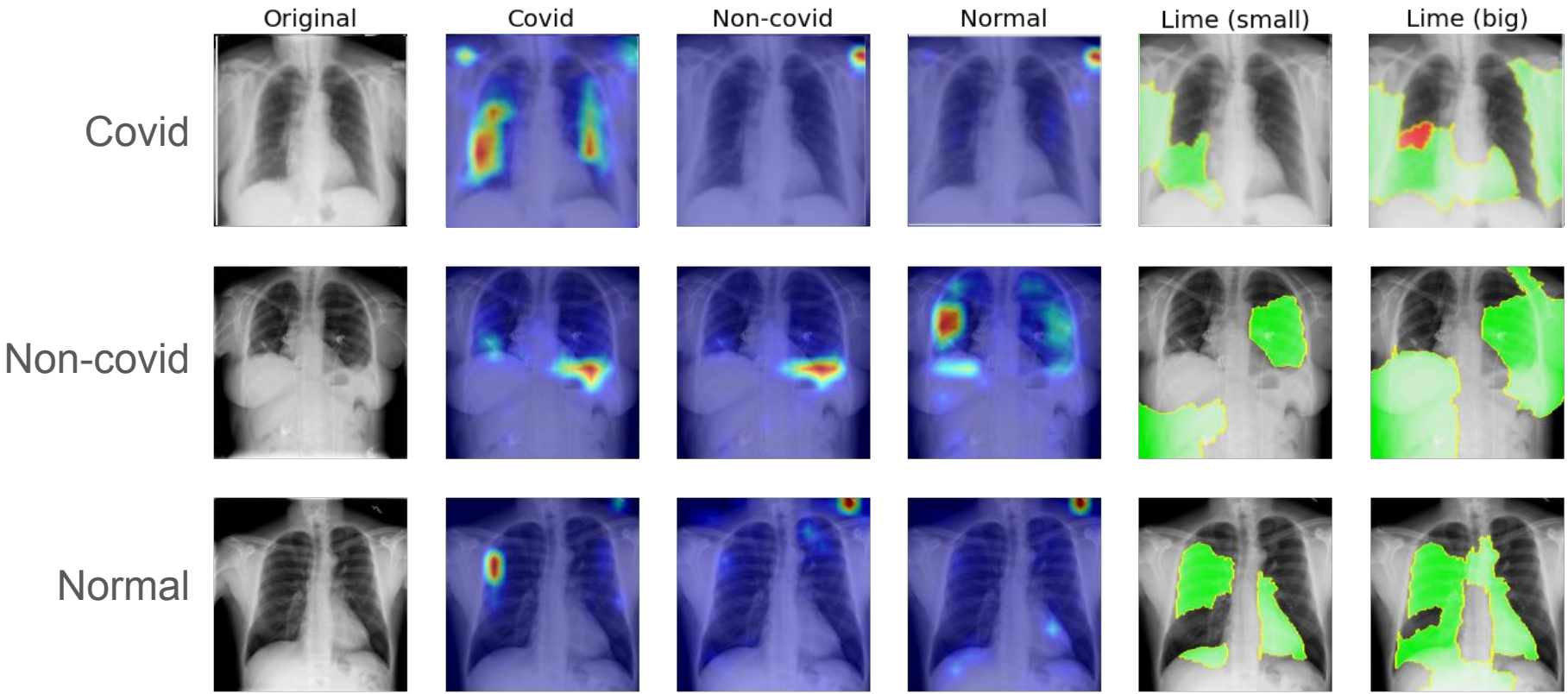
2. LRP for saliency maps

1. Train model



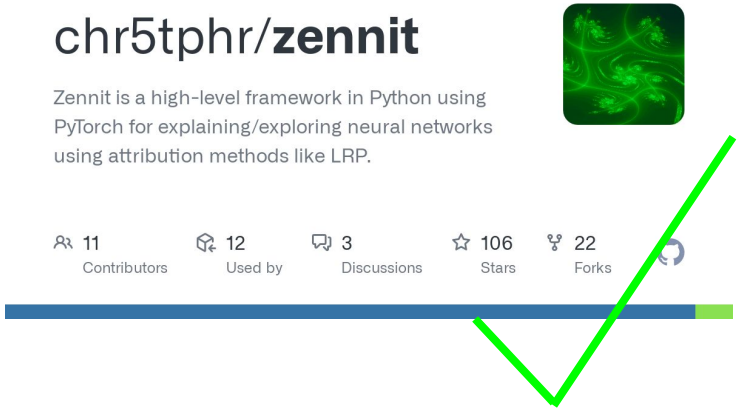
Visual Results



Quantitative results

Explanation type	Faithfulness Correlation (avg)	Average Sensitivity (avg)
baseline (LIME)	0.35	0.45
TransformerLRP	0.47	0.34

Quantus - bugfix




```
x.register_hook(self.save_inp_grad)
```

```
def predict(self, x: np.ndarray, grad: bool = True, **kwargs) -> np.array:
    """
    Predict on the given input.

    Parameters
    ----------
    x: np.ndarray
        A given input that the wrapped model predicts on.
    grad: boolean
        Indicates if gradient-calculation is disabled or not.
    kwargs: optional
        Keyword arguments.
```

Key takeaways

- We trained a Vision Transformer for Medical Imaging (Covid vs other lung infection vs healthy)
- A novel relevance propagation explanation (Chefer et al., 2020) designed specifically for Transformers was used to visualise features learned by the model
- The explanations were validated using the Quantus package (required significant engineering effort due to the explanation not being native to Quantus)
- The explanation method produces explanations that are higher quality compared to baselines, both visually and metric-wise