

Disease Detection from

Chest X-ray Images

Using Deep Learning

Adithya Asokan and Subhan Ahmad

Faculty Mentor: Professor Ole Forsberg

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Can Al detect disease from a simple X-ray?"



Scalable diagnosis in low-resource settings

Literature Review

CheXNet (Rajpurkar et al., 2017)

- A 121-layer DenseNet trained on the ChestX-ray14 dataset (over 100,000 images, 14 diseases).
- Surpassed average radiologist performance in detecting pneumonia, achieving an F1-score of 0.435 compared to the average radiologist F1 of 0.387.
- Used Class Activation Maps (CAMs) to provide visual explanations for predictions.

What We Add

- Used two datasets (NIH ChestX-ray14 + Kaggle's pneumonia dataset) for cross-domain evaluation.
- Integrated Grad-CAM extensively not just to explain predictions, but also to analyze misclassified cases.



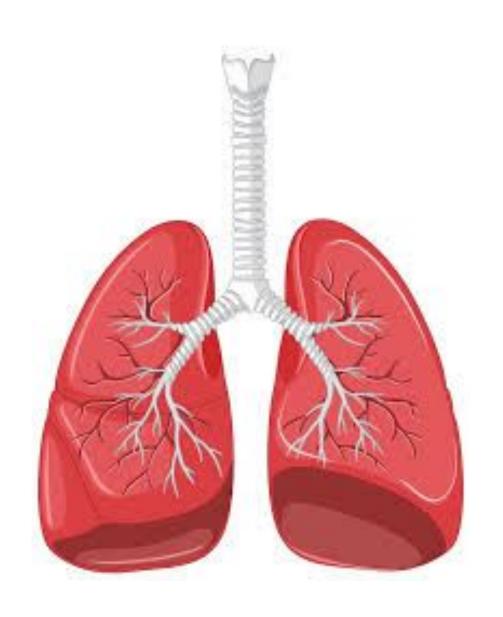
Input Chest X-Ray Image

CheXNet 121-layer CNN

Output Pneumonia Positive (85%)



Research Question



How accurately can deep learning classify X-rays into NORMAL or PNEUMONIA?

Datasets

Kaggle Dataset (Guangzhou Medical Center): Balanced pneumonia/normal images

```
# === 1. Load Full Dataset ===
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
 './data/chest_xray/chest_xray/train',
 validation_split=0.3,
 subset='training',
 seed=123,
 image_size=(224, 224),
 batch_size=32
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
 '/data/chest_xray/chest_xray/train',
 validation_split=0.3,
 subset='validation',
 seed=123,
 image_size=(224, 224),
 batch_size=32
```

Datasets

• NIH ChestX-ray14: 2881 images, US-based

import pandas as pd import os

```
# Set path to the downloaded dataset
dataset_path = '/home/jovyan/.cache/kagglehub/datasets/nih-chest-xrays/data/versions/3'
```

```
# Load metadata
csv_path = os.path.join(dataset_path, 'Data_Entry_2017.csv')
df = pd.read_csv(csv_path)
```

View basic info
print("Number of images:", len(df))
print("Unique diseases:", df['Finding Labels'].str.split('|').explode().nunique())
print("Sample labels:", df['Finding Labels'].unique()[:5])
df.head()

Follow- Patient Pi

ead()	Image Index	Finding Labels	Follow- up #	Patient ID		Patient Gender	View Position	Original Image [Width	Height]
0	00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749
1	00000001_001.png	Cardiomegaly Emphysema	1	1	58	М	PA	2894	2729
2	00000001_002.png	Cardiomegaly Effusion	2	1	58	М	PA	2500	2048
3	00000002_000.png	No Finding	0	2	81	М	PA	2500	2048
4	00000003_000.png	Hernia	0	3	81	F	PA	2582	2991

Unique labels in the NIH Chest X-ray dataset:

- Atelectasis
- Cardiomegaly
- Consolidation
- Edema
- Effusion
- Emphysema
- Fibrosis
- Hernia
- Infiltration
- Mass
- No Finding
- Nodule
- Pleural_Thickening
- Pneumonia
- Pneumothorax

Datasets

 NIH ChestX-ray14: 2881 images, US-based

```
# Load NIH labels and map to binary

def binary_label(finding):

if 'Pneumonia' in finding:

return 'PNEUMONIA'

elif finding.strip() == 'No Finding':

return 'NORMAL'

return None

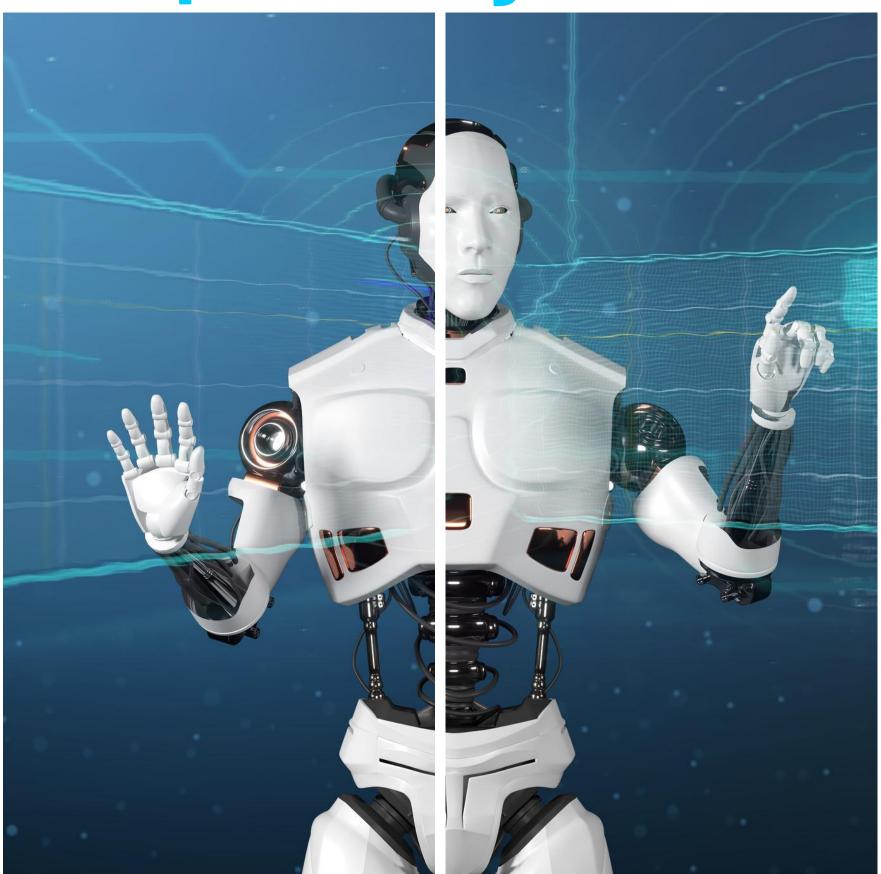
label['binary_label'] = label['label'].apply(binary_label)

balanced_df = label.dropna(subset=['binary_label'])

image_path
```

bal	anced_df = label.dropna(subset=['binary_label']) image_path	image_name	binary_label
0	/home/jovyan/.cache/kagglehub/datasets/nih-che	00011062_001.png	NORMAL
1	/home/jovyan/.cache/kagglehub/datasets/nih-che	00000 <mark>4</mark> 68_029.png	PNEUMONIA
2	/home/jovyan/.cache/kagglehub/datasets/nih-che	00017710_009.png	PNEUMONIA
3	/home/jovyan/.cache/kagglehub/datasets/nih-che	00003028_050.png	PNEUMONIA
4	/home/jovyan/.cache/kagglehub/datasets/nih-che	00011721_000.png	NORMAL

Preprocessing

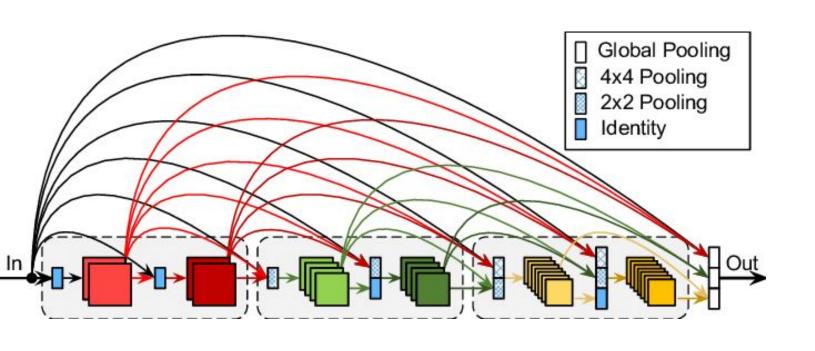


```
def load_image(path, label):
    image = tf.io.read_file(path)
    image = tf.image.decode_png(image, channels=3)
    image = tf.image.resize(image, [224, 224])
    image = image/255.0
    return image, label

train_ds = tf.data.Dataset.from_tensor_slices((paths, labels))
train_ds = train_ds.map(load_image).batch(32).prefetch(tf.data.AUTOTUNE)
```

- 224x224 resizing, normalization
- Augmentation: flip, rotate, zoom
- Balanced classes (e.g., 1450 normal samples)

Model Architecture

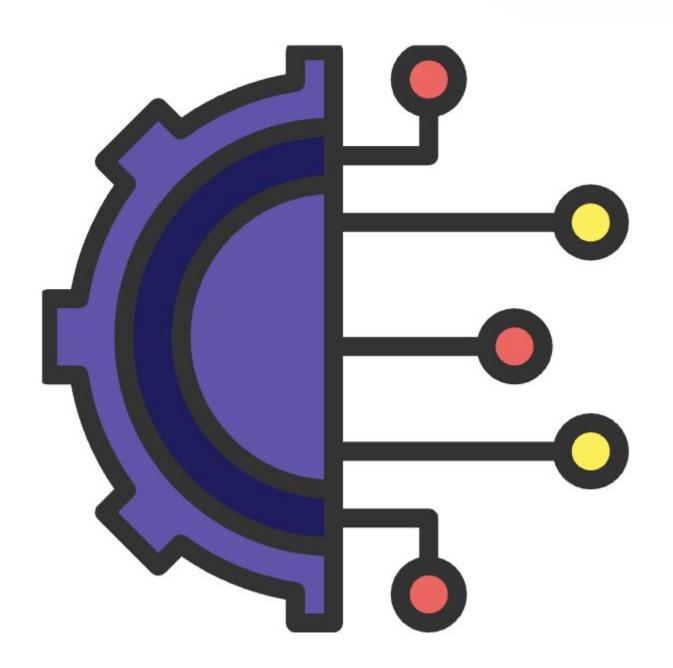


```
base_model = DenseNet121(include_top=False, weights='imagenet', input_shape=(224, 224, 3))
base_model.trainable = False

model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1, activation='sigmoid')
])
```

- Block diagram: DenseNet121 → GAP → Dense → Dropout →
 Sigmoid
- Transfer learning (ImageNet weights)

Training Details



- Binary cross-entropy loss
- Adam optimizer (lr=1e-5)
- Early stopping, ReduceLROnPlateau
- Class weights

```
model.compile(
    optimizer=tf.keras.optimizers.Adam(1e-5),
    loss='binary_crossentropy;
    metrics=['accuracy']
)

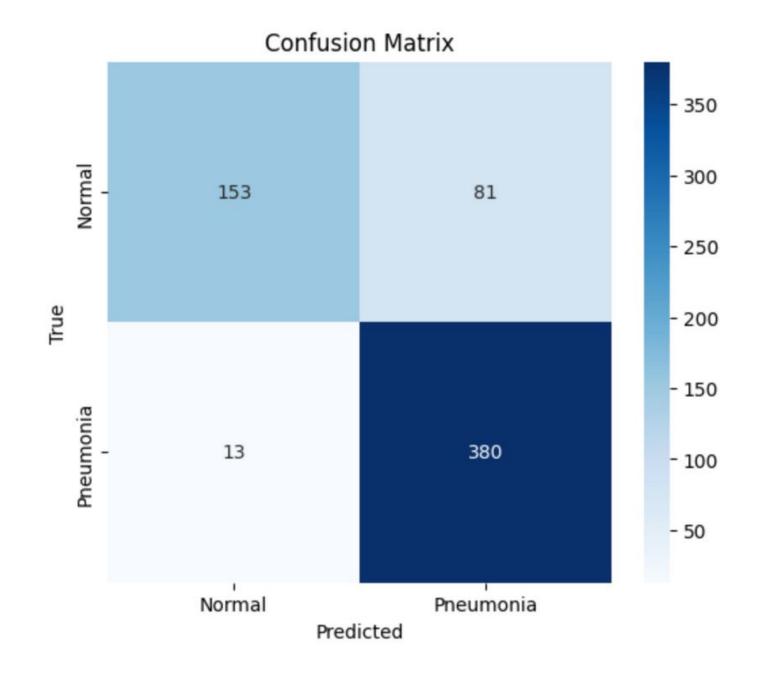
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30,
    class_weight=class_weights,
    callbacks=[early_stop, reduce_lr]
)
```

Results (Kaggle Model)

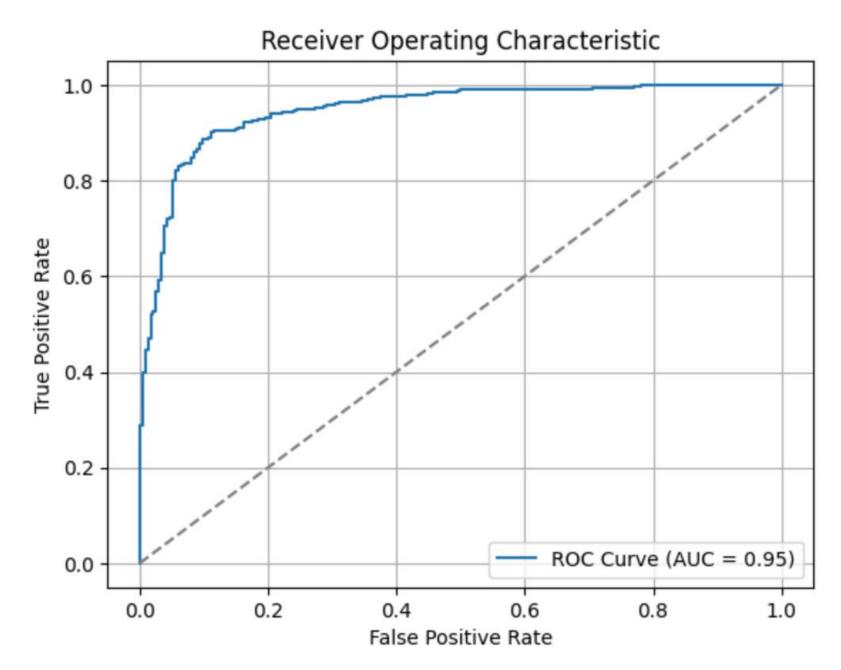
Confusion matrix

cm = confusion_matrix(y_true, y_pred)

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues'



#ROC Curve fpr, tpr, _ = roc_curve(y_true, y_probs) plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')

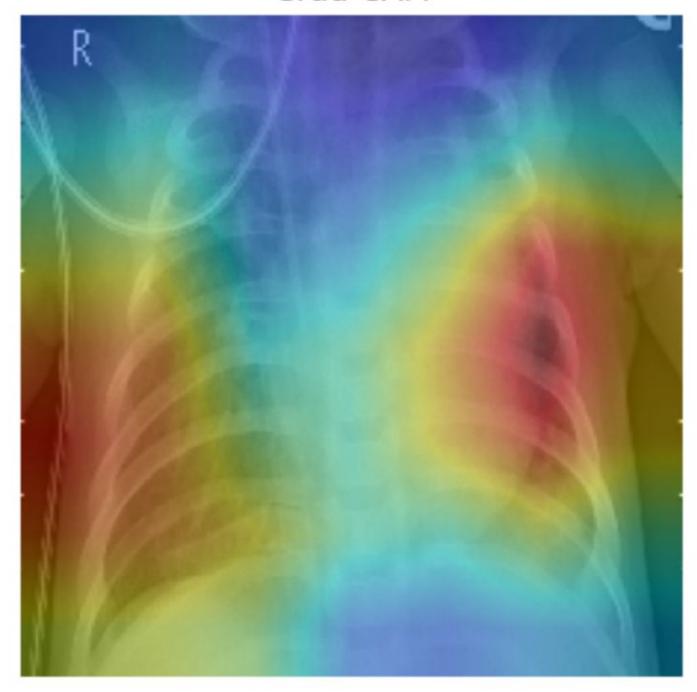


Results (Kaggle Model)

Prediction: PNEUMONIA



Grad-CAM

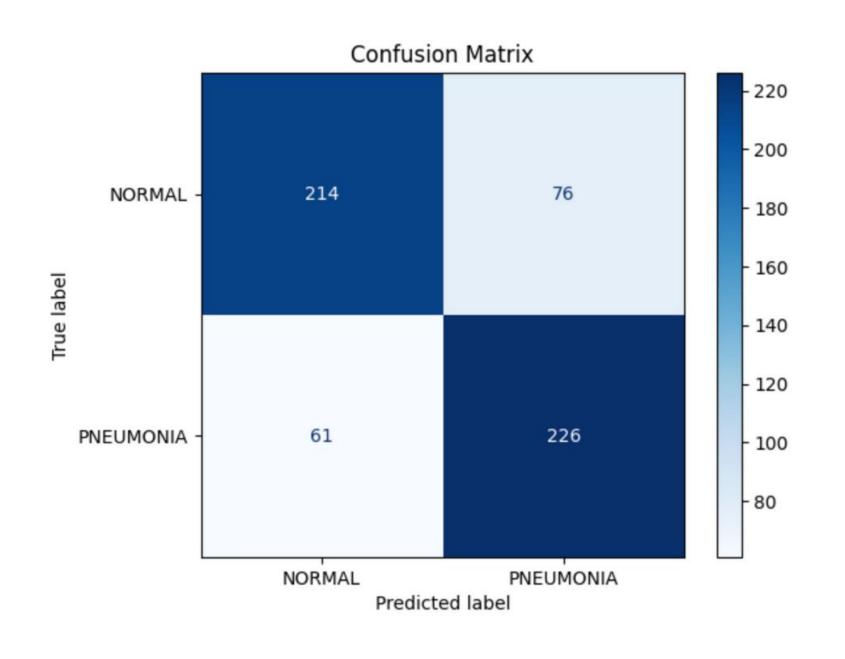


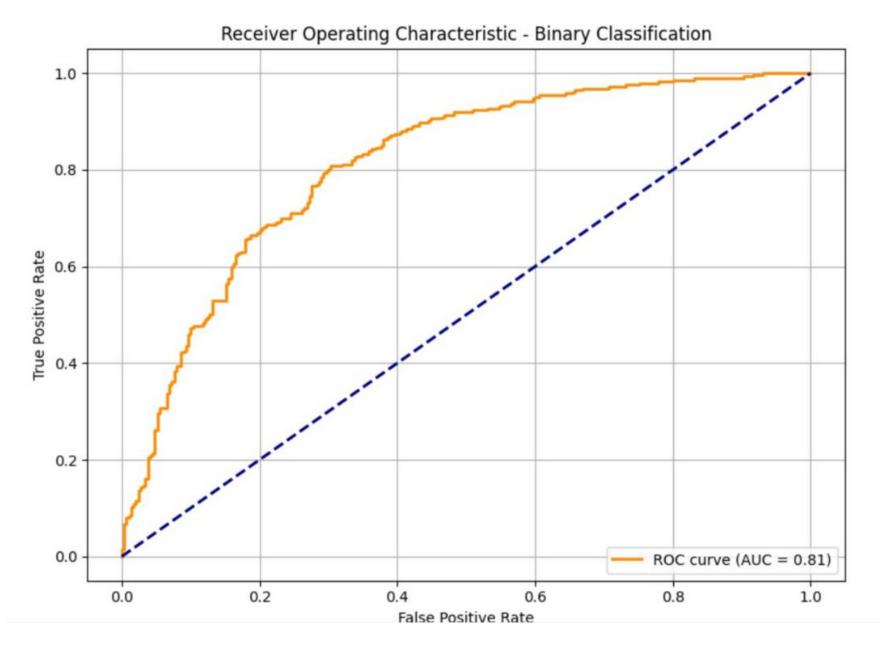
Results (Kaggle Model)

Classification Report

Class	Precision	Recall	F1-Score	Support
Normal	0.92	0.65	0.77	234
Pneumonia	0.82	0.97	0.89	393
Accuracy			0.85	627
Macro Avg	0.87	0.81	0.83	627
Weighted Avg	0.86	0.85	0.84	627

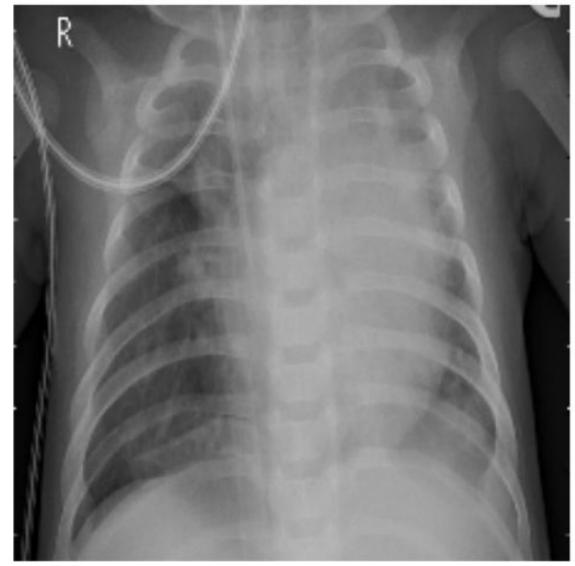
Results (NIH Model)

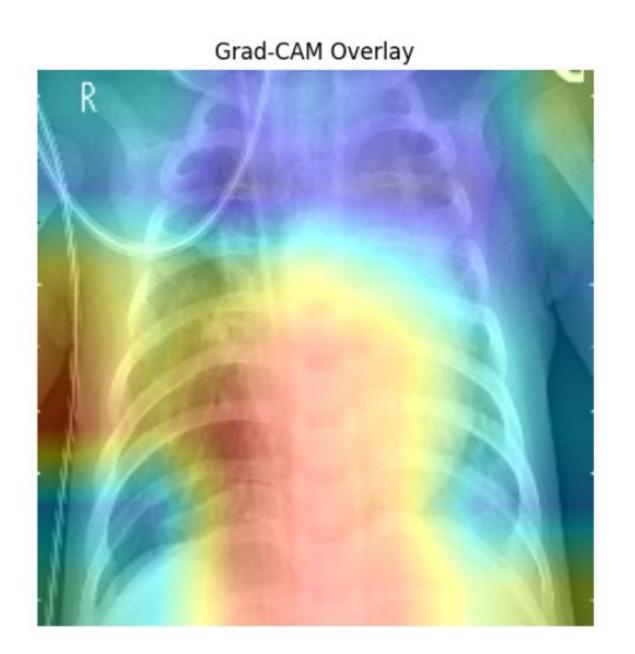




Results (NIH Model)

Original Image Prediction: PNEUMONIA (score: 0.61)

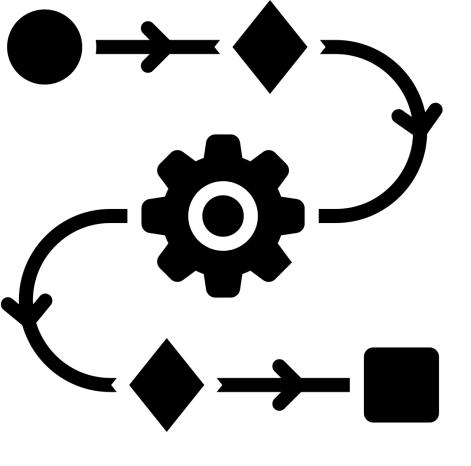




Results (NIH Model)

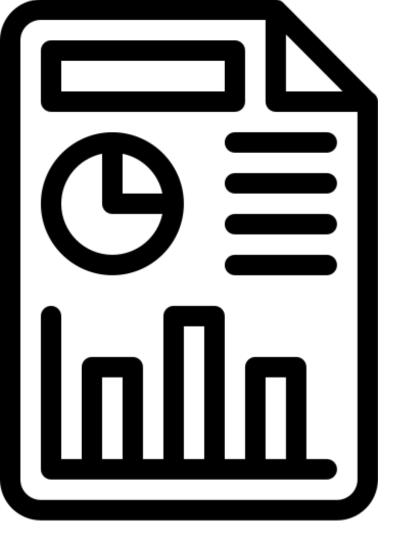
Classification report

Class	Precision	Recall	F1-Score	Support
NORMAL	0.78	0.74	0.76	290
PNEUMONIA	0.75	0.79	0.77	287
Accuracy			0.76	577
Macro Avg	0.76	0.76	0.76	577
Weighted Avg	0.76	0.76	0.76	577



Analysis & Future Work

- Class imbalance in NIH dataset (more pneumonia cases)
- Noisy labels from automated report extraction
- Lower recall for "Normal" class due to skewed training
- Tune prediction threshold using ROC/F1 to optimize clinical performance
- Implement multi-label classification (detect multiple conditions per image)
- Integrate Med-GEMMA for vision-language reasoning and report generation
- Expand dataset with CheXpert, MIMIC-CXR, RSNA for better generalization
- Fine-tune model on balanced datasets for improved reliability



Conclusion

- Used NIH and Kaggle (Guangzhou) chest X-ray datasets
- Kaggle dataset (balanced) gave better performance than NIH (imbalanced, noisy)
- Achieved up to 85% accuracy on validation set
- Integrated Grad-CAM for model explainability
- Model focused on clinically relevant lung regions
- Shows potential for Al-assisted diagnosis in real-world use cases

Thank You For Watching and ask any questions

