X-Ray Predictive Analytics for Pneumonia Diagnosis Utilizing AI and Big Data

Importing required libraries

```
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Conv2D,
MaxPooling2D, Flatten, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import precision_recall_curve, roc_curve,
accuracy_score, confusion_matrix, precision_score, recall_score
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import os
import numpy as np
import cv2
%matplotlib inline
```

Initiating spark session for image pre-processing

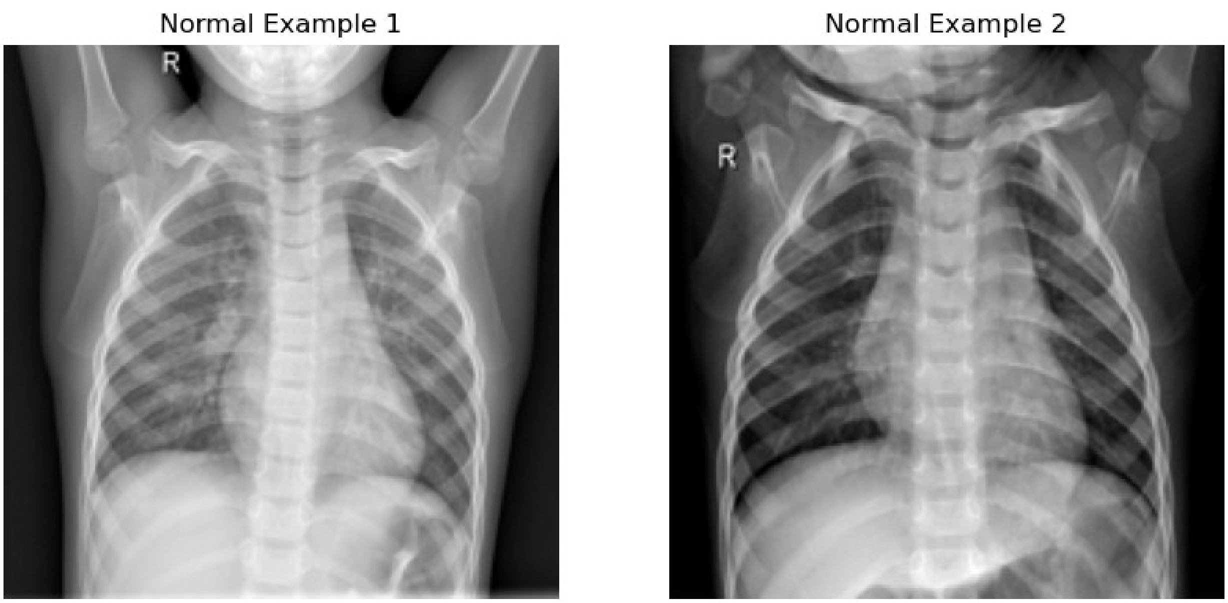
```
from pyspark.sql import SparkSession
from PIL import Image
import io

# Initialize Spark session
spark = SparkSession.builder \
    .appName("Image pre-Processing") \
    .config("spark.master", "local[*]") \
    .config("spark.hadoop.fs.defaultFS", "hdfs://localhost:9000") \
    .config("spark.executor.memory", "4g") \
    .config("spark.driver.memory", "4g") \
    .config("spark.network.timeout", "600s") \
    .config("spark.sql.broadcastTimeout", "1200") \
    .config("spark.task.maxFailures", "10") \
    .getOrCreate()


# Define labels and image size
labels = ['Normal', 'Pneumonia']
img_size = 200
```

```
def preprocess_image(content):
    # Opens an image and converts it to greyscale and resizes it
    image = Image.open(io.BytesIO(content))
    image = image.resize((img_size, img_size)).convert('L')
    return np.array(image).reshape(img_size, img_size, 1)

def process_images(image_rdd, label):
    # Filters files based on label and preprocesses them
    filtered_images = image_rdd.filter(lambda file: label in file[0])
    return filtered_images.map(lambda img: (label,
preprocess_image(img[1])))

def save_as_object_files(processed_images, output_dir):
    # Saves processed images as object files in HDFS
    for label, images in processed_images.items():
        images.saveAsPickleFile(f"{output_dir}/{label}_new")

# Defining paths for training, testing, and validation datasets
paths = {
    "train": "hdfs://localhost:9000/xrays/train/*/*.jpeg",
    "test": "hdfs://localhost:9000/xrays/test/*/*.jpeg",
    "val": "hdfs://localhost:9000/xrays/val/*/*.jpeg"
}

processed_data = {}
for dtype, path in paths.items():
    image_rdd = spark.sparkContext.binaryFiles(path)
    processed_images = {label: process_images(image_rdd, label) for
label in labels}
    save_as_object_files(processed_images, f"pro_{dtype}")

spark.stop()
```

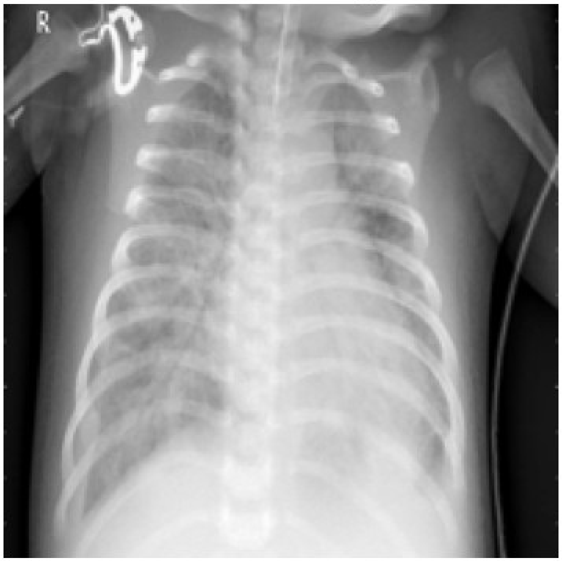
Displaying Sample image from each label

```
# Initializing Spark session for displaying image
spark = SparkSession.builder \
    .appName("Image Display") \
    .config("spark.master", "local[*]") \
    .config("spark.hadoop.fs.defaultFS", "hdfs://localhost:9000") \
    .getOrCreate()

def load_and_display_images(directory, label, num_images=2):
    path = f"{directory}/{label}_new"

    # Loading the images
    rdd = spark.sparkContext.pickleFile(path)

    # Taking a few images for display
```

```
    images = rdd.take(num_images)

    # Displays the images
    fig, axs = plt.subplots(1, num_images, figsize=(10, 5))
    for i, img in enumerate(images):
        axs[i].imshow(img[1].squeeze(), cmap='gray')  # img[1] because
it's a tuple (label, image_array)
        axs[i].set_title(f"{label} Example {i+1}")
        axs[i].axis('off')
    plt.show()

# Specifying the base directory where images are stored
base_directory = "hdfs://localhost:9000/user/affuk/pro_train"

# Displaying images for both labels
load_and_display_images(base_directory, "Normal")
load_and_display_images(base_directory, "Pneumonia")

spark.stop()
```



Pneumonia Example 1



Pneumonia Example 2

Image processing

```
# Initialize Spark session
spark = SparkSession.builder \
    .appName("Image Processing") \
    .config("spark.master", "local[*]") \
    .config("spark.hadoop.fs.defaultFS", "hdfs://localhost:9000") \
    .getOrCreate()

def preprocess_image(content):
    image = Image.open(io.BytesIO(content))
    image = image.resize((200, 200)).convert('L')  # Resizng and
convert to grayscale
    return np.array(image).reshape(200, 200, 1)  # Reshaping for
consistency

def load_and_process_data(path, label):
    image_rdd = spark.sparkContext.binaryFiles(path)
    processed_images = image_rdd.map(lambda file_content:
preprocess_image(file_content[1])).collect()
    labels = [0 if label == 'Normal' else 1] * len(processed_images)
    return np.array(processed_images), np.array(labels)

# Defining paths for datasets
dataset_paths = {
    'Normal': {
        'train': "hdfs://localhost:9000/xrays/train/Normal/*.jpeg",
        'val': "hdfs://localhost:9000/xrays/val/Normal/*.jpeg",
        'test': "hdfs://localhost:9000/xrays/test/Normal/*.jpeg"
    },
    'Pneumonia': {
```

```
        'train': "hdfs://localhost:9000/xrays/train/Pneumonia/*.jpeg",
        'val': "hdfs://localhost:9000/xrays/val/Pneumonia/*.jpeg",
        'test': "hdfs://localhost:9000/xrays/test/Pneumonia/*.jpeg"
    }
}

# Load and process all datasets
X_train_normal, y_train_normal =
load_and_process_data(dataset_paths['Normal']['train'], 'Normal')
X_train_pneumonia, y_train_pneumonia =
load_and_process_data(dataset_paths['Pneumonia']['train'],
'Pneumonia')

# Upsampling the Normal class
upsample_size = len(y_train_pneumonia) - len(y_train_normal)
upsampled_normal_indices =
np.random.choice(np.arange(len(y_train_normal)), size=upsample_size,
replace=True)
X_train_normal_upsampled = X_train_normal[upsampled_normal_indices]
y_train_normal_upsampled = y_train_normal[upsampled_normal_indices]

# Combining and shuffling the training data
X_train = np.vstack([X_train_normal, X_train_pneumonia,
X_train_normal_upsampled])
y_train = np.hstack([y_train_normal, y_train_pneumonia,
y_train_normal_upsampled])

# Shuffling the dataset
shuffle_indices = np.random.permutation(len(X_train))
X_train = X_train[shuffle_indices]
y_train = y_train[shuffle_indices]

# Loading validation and test data
X_val, y_val = np.vstack([
    load_and_process_data(dataset_paths['Normal']['val'], 'Normal')
[0],
    load_and_process_data(dataset_paths['Pneumonia']['val'],
'Pneumonia')[0]
]), np.hstack([
    load_and_process_data(dataset_paths['Normal']['val'], 'Normal')
[1],
    load_and_process_data(dataset_paths['Pneumonia']['val'],
'Pneumonia')[1]
])

X_test, y_test = np.vstack([
    load_and_process_data(dataset_paths['Normal']['test'], 'Normal')
[0],
    load_and_process_data(dataset_paths['Pneumonia']['test'],
'Pneumonia')[0]
```

```
]), np.hstack([
    load_and_process_data(dataset_paths['Normal']['test'], 'Normal')
[1],
    load_and_process_data(dataset_paths['Pneumonia']['test'],
'Pneumonia')[1]
])

# Normalizing the data
X_train, X_val, X_test = X_train / 255.0, X_val / 255.0, X_test /
255.0

# Merging training and validation data as validation data is too small
X_train, y_train = np.vstack([X_train, X_val]), np.hstack([y_train,
y_val])
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
test_size=0.10, random_state=32)

spark.stop()

# Output the shape of datasets to confirm
print("Training data shape:", X_train.shape, y_train.shape)
print("Validation data shape:", X_val.shape, y_val.shape)
print("Test data shape:", X_test.shape, y_test.shape)
```

```
Training data shape: (6989, 200, 200, 1) (6989,)
Validation data shape: (777, 200, 200, 1) (777,)
Test data shape: (624, 200, 200, 1) (624,)
```

Data Augmentation

```
# Setting up data augmentation configuration
datagen = ImageDataGenerator(
    rotation_range=30,  # Allows random rotations up to 30 degrees
    zoom_range=0.05,  # Allows random zoom up to 5%
    width_shift_range=0.05,  # Allows random horizontal shifts up to
5%
    height_shift_range=0.05,  # Allows random vertical shifts up to 5%
    horizontal_flip=True,  # Allows horizontal flipping
    fill_mode='nearest'  # Fills in new pixels after a rotation or
width/height shift
)


# Apply the augmentation to the training data
datagen.fit(X_train)
```

CNN

```
from tensorflow.keras.regularizers import l2
```

```python
# Defining the CNN model architecture with some modifications
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(200, 200, 1),
padding='same'),
    BatchNormalization(),
    MaxPooling2D(2, 2),

    Conv2D(64, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D(2, 2),

    Conv2D(128, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D(2, 2),

    Conv2D(256, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D(2, 2),

    Flatten(),

    Dense(256, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.5),

    Dense(128, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.5),

    Dense(1, activation='sigmoid')
])

# Compiling the model with a potentially lower learning rate
from tensorflow.keras.optimizers import Adam

model.compile(optimizer=Adam(learning_rate=0.0001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```
C:\Users\affuk\anaconda3\Lib\site-packages\keras\src\layers\
convolutional\base_conv.py:99: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in
the model instead.
  super().__init__(
```

```python
model.summary()
```

```
Model: "sequential"

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━━━━━━━━━━━━━━━━━┓
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 200, 200, 32)	320
batch_normalization (BatchNormalization)	(None, 200, 200, 32)	128
max_pooling2d (MaxPooling2D)	(None, 100, 100, 32)	0
conv2d_1 (Conv2D)	(None, 100, 100, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 100, 100, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 50, 50, 64)	0
conv2d_2 (Conv2D)	(None, 50, 50, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 50, 50, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 25, 25, 128)	0
conv2d_3 (Conv2D)	(None, 25, 25, 256)	295,168

```
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│ batch_normalization_3                      │ (None, 25, 25, 256)          │
1,024 │
│ (BatchNormalization)                       │                              │
│
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ max_pooling2d_3 (MaxPooling2D)             │ (None, 12, 12, 256)          │
0 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ flatten (Flatten)                          │ (None, 36864)                │
0 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ dense (Dense)                              │ (None, 256)                  │
9,437,440 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ dropout (Dropout)                          │ (None, 256)                  │
0 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ dense_1 (Dense)                            │ (None, 128)                  │
32,896 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ dropout_1 (Dropout)                        │ (None, 128)                  │
0 │
├────────────────────────────────────────────┼──────────────────────────────┼
──────────────────┤
│ dense_2 (Dense)                            │ (None, 1)                    │
129 │
└────────────────────────────────────────────┴──────────────────────────────┴
──────────────────┘

 Total params: 9,860,225 (37.61 MB)

 Trainable params: 9,859,265 (37.61 MB)

 Non-trainable params: 960 (3.75 KB)
```

Training the model

```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,
ReduceLROnPlateau

# Callback for early stopping
early_stopping = EarlyStopping(
    monitor='val_loss',
```

```python
    patience=10,
    verbose=1,
    restore_best_weights=True
)

# Callback for saving the best model during training
model_checkpoint = ModelCheckpoint(
    'best_model.keras',  # Updated file extension to .keras
    monitor='val_loss',
    save_best_only=True,
    verbose=1
)


# Callback for reducing the learning rate when a metric has stopped
improving
reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.2,
    patience=5,
    verbose=1,
    min_lr=1e-6
)

# Calculate class weights
from sklearn.utils.class_weight import compute_class_weight
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.unique(y_train),
    y=y_train
)
class_weights_dict = dict(enumerate(class_weights))

# Train the model using the data generator
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_val, y_val),
    epochs=20,
    callbacks=[early_stopping, model_checkpoint, reduce_lr],
    class_weight=class_weights_dict,
    verbose=2
)
```

```
Epoch 1/20
```

```
C:\Users\affuk\anaconda3\Lib\site-packages\keras\src\trainers\
data_adapters\py_dataset_adapter.py:120: UserWarning: Your `PyDataset`
class should call `super().__init__(**kwargs)` in its constructor.
`**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will
```

```
be ignored.
  self._warn_if_super_not_called()


Epoch 1: val_loss improved from inf to 10.98748, saving model to
best_model.keras
219/219 - 259s - 1s/step - accuracy: 0.8466 - loss: 1.0994 -
val_accuracy: 0.5122 - val_loss: 10.9875 - learning_rate: 1.0000e-04
Epoch 2/20

Epoch 2: val_loss improved from 10.98748 to 4.29818, saving model to
best_model.keras
219/219 - 256s - 1s/step - accuracy: 0.9073 - loss: 0.8630 -
val_accuracy: 0.5122 - val_loss: 4.2982 - learning_rate: 1.0000e-04
Epoch 3/20

Epoch 3: val_loss improved from 4.29818 to 0.70560, saving model to
best_model.keras
219/219 - 256s - 1s/step - accuracy: 0.9250 - loss: 0.7662 -
val_accuracy: 0.9434 - val_loss: 0.7056 - learning_rate: 1.0000e-04
Epoch 4/20

Epoch 4: val_loss improved from 0.70560 to 0.59899, saving model to
best_model.keras
219/219 - 266s - 1s/step - accuracy: 0.9326 - loss: 0.6986 -
val_accuracy: 0.9511 - val_loss: 0.5990 - learning_rate: 1.0000e-04
Epoch 5/20

Epoch 5: val_loss improved from 0.59899 to 0.55653, saving model to
best_model.keras
219/219 - 264s - 1s/step - accuracy: 0.9415 - loss: 0.6364 -
val_accuracy: 0.9601 - val_loss: 0.5565 - learning_rate: 1.0000e-04
Epoch 6/20

Epoch 6: val_loss improved from 0.55653 to 0.51497, saving model to
best_model.keras
219/219 - 261s - 1s/step - accuracy: 0.9379 - loss: 0.5975 -
val_accuracy: 0.9537 - val_loss: 0.5150 - learning_rate: 1.0000e-04
Epoch 7/20

Epoch 7: val_loss did not improve from 0.51497
219/219 - 258s - 1s/step - accuracy: 0.9456 - loss: 0.5370 -
val_accuracy: 0.9331 - val_loss: 0.5798 - learning_rate: 1.0000e-04
Epoch 8/20

Epoch 8: val_loss improved from 0.51497 to 0.42568, saving model to
best_model.keras
219/219 - 256s - 1s/step - accuracy: 0.9498 - loss: 0.4973 -
val_accuracy: 0.9640 - val_loss: 0.4257 - learning_rate: 1.0000e-04
Epoch 9/20
```

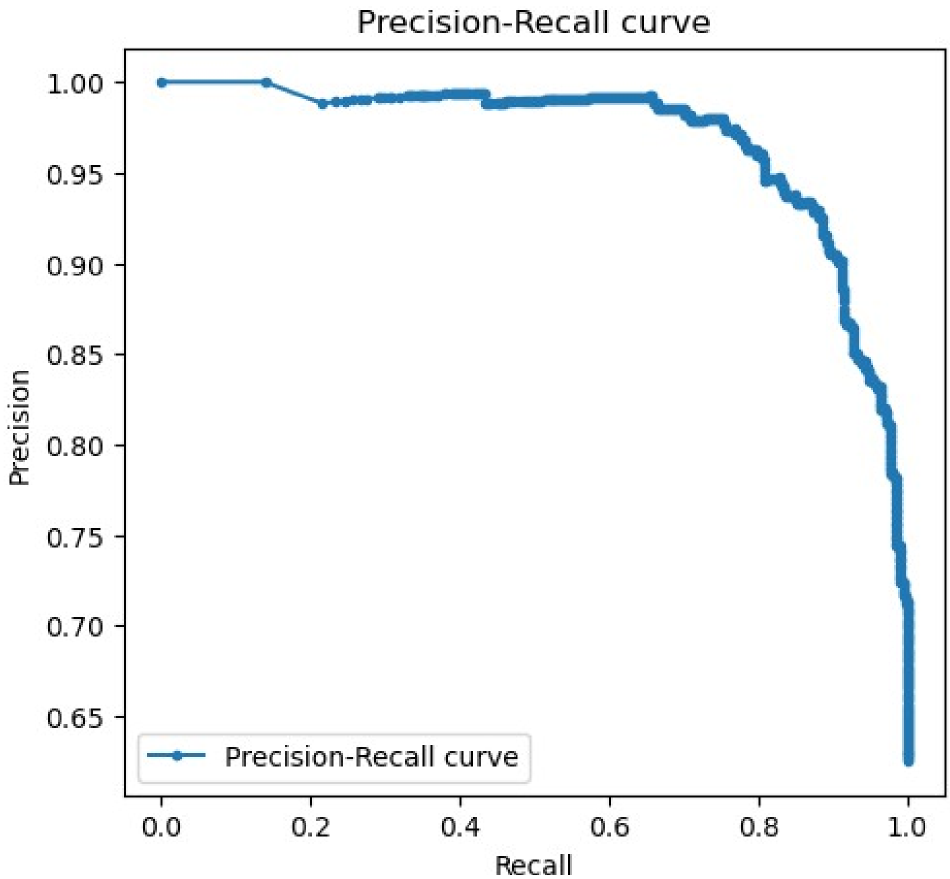
```
Epoch 9: val_loss did not improve from 0.42568
219/219 - 253s - 1s/step - accuracy: 0.9561 - loss: 0.4496 -
val_accuracy: 0.9447 - val_loss: 0.4900 - learning_rate: 1.0000e-04
Epoch 10/20

Epoch 10: val_loss improved from 0.42568 to 0.36212, saving model to
best_model.keras
219/219 - 255s - 1s/step - accuracy: 0.9493 - loss: 0.4350 -
val_accuracy: 0.9717 - val_loss: 0.3621 - learning_rate: 1.0000e-04
Epoch 11/20

Epoch 11: val_loss improved from 0.36212 to 0.34162, saving model to
best_model.keras
219/219 - 258s - 1s/step - accuracy: 0.9569 - loss: 0.3971 -
val_accuracy: 0.9678 - val_loss: 0.3416 - learning_rate: 1.0000e-04
Epoch 12/20

Epoch 12: val_loss did not improve from 0.34162
219/219 - 259s - 1s/step - accuracy: 0.9584 - loss: 0.3596 -
val_accuracy: 0.9434 - val_loss: 0.4144 - learning_rate: 1.0000e-04
Epoch 13/20

Epoch 13: val_loss improved from 0.34162 to 0.29681, saving model to
best_model.keras
219/219 - 258s - 1s/step - accuracy: 0.9581 - loss: 0.3394 -
val_accuracy: 0.9704 - val_loss: 0.2968 - learning_rate: 1.0000e-04
Epoch 14/20

Epoch 14: val_loss improved from 0.29681 to 0.28163, saving model to
best_model.keras
219/219 - 256s - 1s/step - accuracy: 0.9579 - loss: 0.3245 -
val_accuracy: 0.9704 - val_loss: 0.2816 - learning_rate: 1.0000e-04
Epoch 15/20

Epoch 15: val_loss improved from 0.28163 to 0.25823, saving model to
best_model.keras
219/219 - 265s - 1s/step - accuracy: 0.9627 - loss: 0.2976 -
val_accuracy: 0.9704 - val_loss: 0.2582 - learning_rate: 1.0000e-04
Epoch 16/20

Epoch 16: val_loss improved from 0.25823 to 0.22746, saving model to
best_model.keras
219/219 - 274s - 1s/step - accuracy: 0.9687 - loss: 0.2654 -
val_accuracy: 0.9755 - val_loss: 0.2275 - learning_rate: 1.0000e-04
Epoch 17/20

Epoch 17: val_loss did not improve from 0.22746
219/219 - 275s - 1s/step - accuracy: 0.9687 - loss: 0.2537 -
val_accuracy: 0.9717 - val_loss: 0.2303 - learning_rate: 1.0000e-04
```

```
Epoch 18/20

Epoch 18: val_loss did not improve from 0.22746
219/219 - 255s - 1s/step - accuracy: 0.9657 - loss: 0.2406 -
val_accuracy: 0.9292 - val_loss: 0.3614 - learning_rate: 1.0000e-04
Epoch 19/20

Epoch 19: val_loss did not improve from 0.22746
219/219 - 263s - 1s/step - accuracy: 0.9707 - loss: 0.2244 -
val_accuracy: 0.9601 - val_loss: 0.2423 - learning_rate: 1.0000e-04
Epoch 20/20

Epoch 20: val_loss improved from 0.22746 to 0.22445, saving model to
best_model.keras
219/219 - 260s - 1s/step - accuracy: 0.9672 - loss: 0.2140 -
val_accuracy: 0.9588 - val_loss: 0.2245 - learning_rate: 1.0000e-04
Restoring model weights from the end of the best epoch: 20.
```

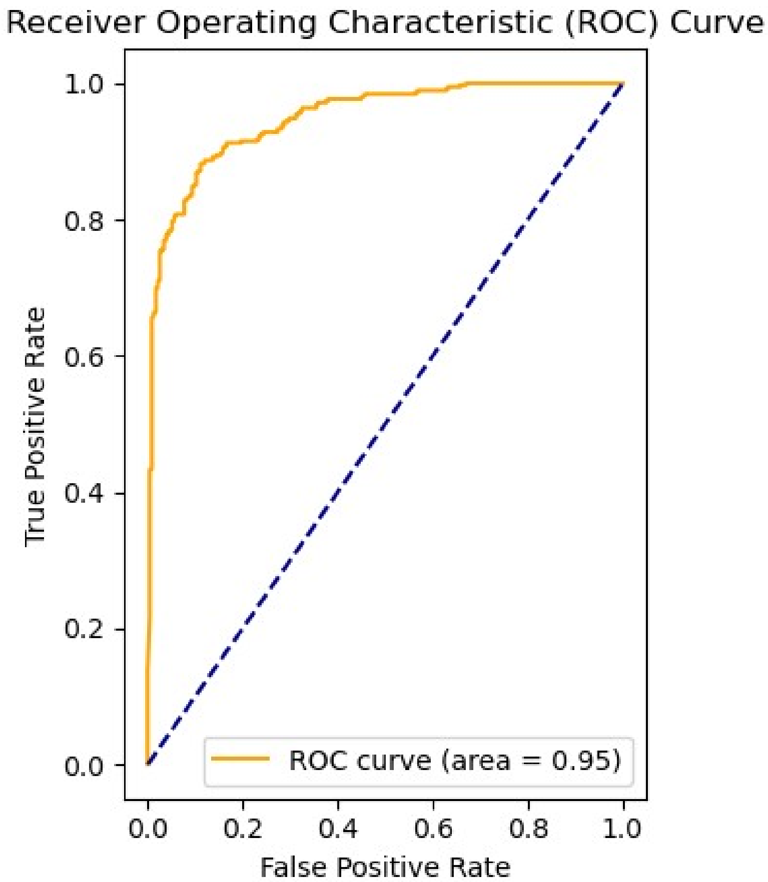
Evaluating Training Model

```
predictions = model.predict(X_test)

# Calculating Precision and Recall values
precisions, recalls, thresholds = precision_recall_curve(y_test,
predictions)

# Plotting Precision-Recall Curve
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(recalls, precisions, marker='.', label='Precision-Recall
curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall curve')
plt.legend()
```

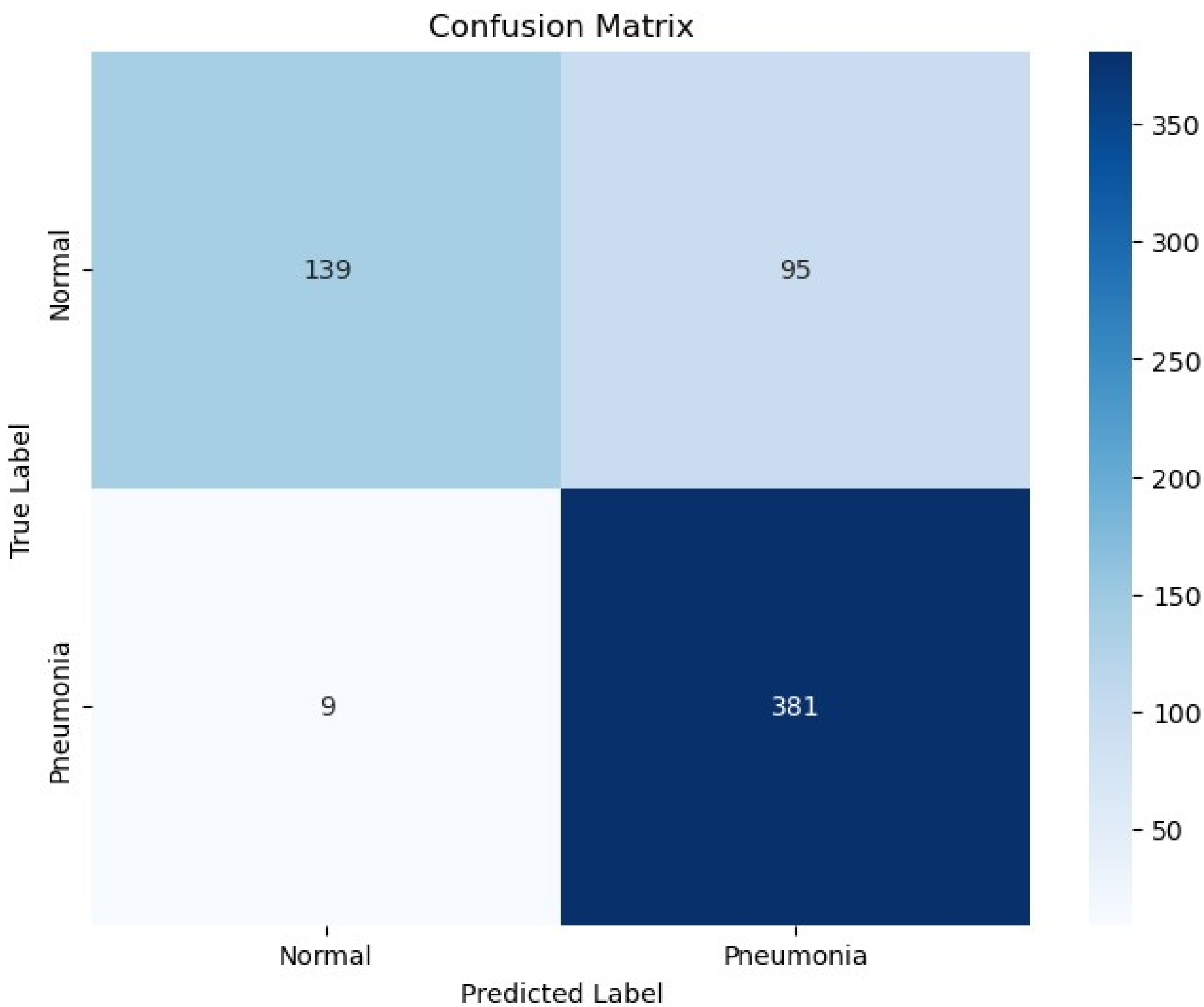
```
20/20 ━━━━━━━━━━━━━━━━━━━━ 4s 179ms/step

<matplotlib.legend.Legend at 0x259bc090d10>
```




```
from sklearn.metrics import auc

# Calculating the FPR and TPR for the ROC curve
fpr, tpr, roc_thresholds = roc_curve(y_test, predictions)
roc_auc = auc(fpr, tpr)

# Plotting ROC Curve
plt.subplot(1, 2, 2)
plt.plot(fpr, tpr, color='orange', label=f'ROC curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()

plt.tight_layout()
plt.show()
```




```
# Generating binary predictions based on the probability output and a
threshold
binary_predictions = (predictions > 0.5).astype(int)

# Creating the confusion matrix
cm = confusion_matrix(y_test, binary_predictions)
class_labels = ['Normal', 'Pneumonia']

# Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=class_labels, yticklabels=class_labels)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```




```
from sklearn.metrics import classification_report

print(classification_report(y_test, binary_predictions,
target_names=class_labels))
```

```
              precision    recall  f1-score   support

      Normal       0.94      0.59      0.73       234
   Pneumonia       0.80      0.98      0.88       390

    accuracy                           0.83       624
   macro avg       0.87      0.79      0.80       624
weighted avg       0.85      0.83      0.82       624
```

```
train_loss, train_accuracy = model.evaluate(X_train, y_train,
verbose=1)
print(f"Training Accuracy: {train_accuracy*100:.2f}%")
```

```
219/219 ━━━━━━━━━━━━━━━━━━━━ 36s 162ms/step - accuracy: 0.9769 - loss:
0.1918
Training Accuracy: 97.58%
```

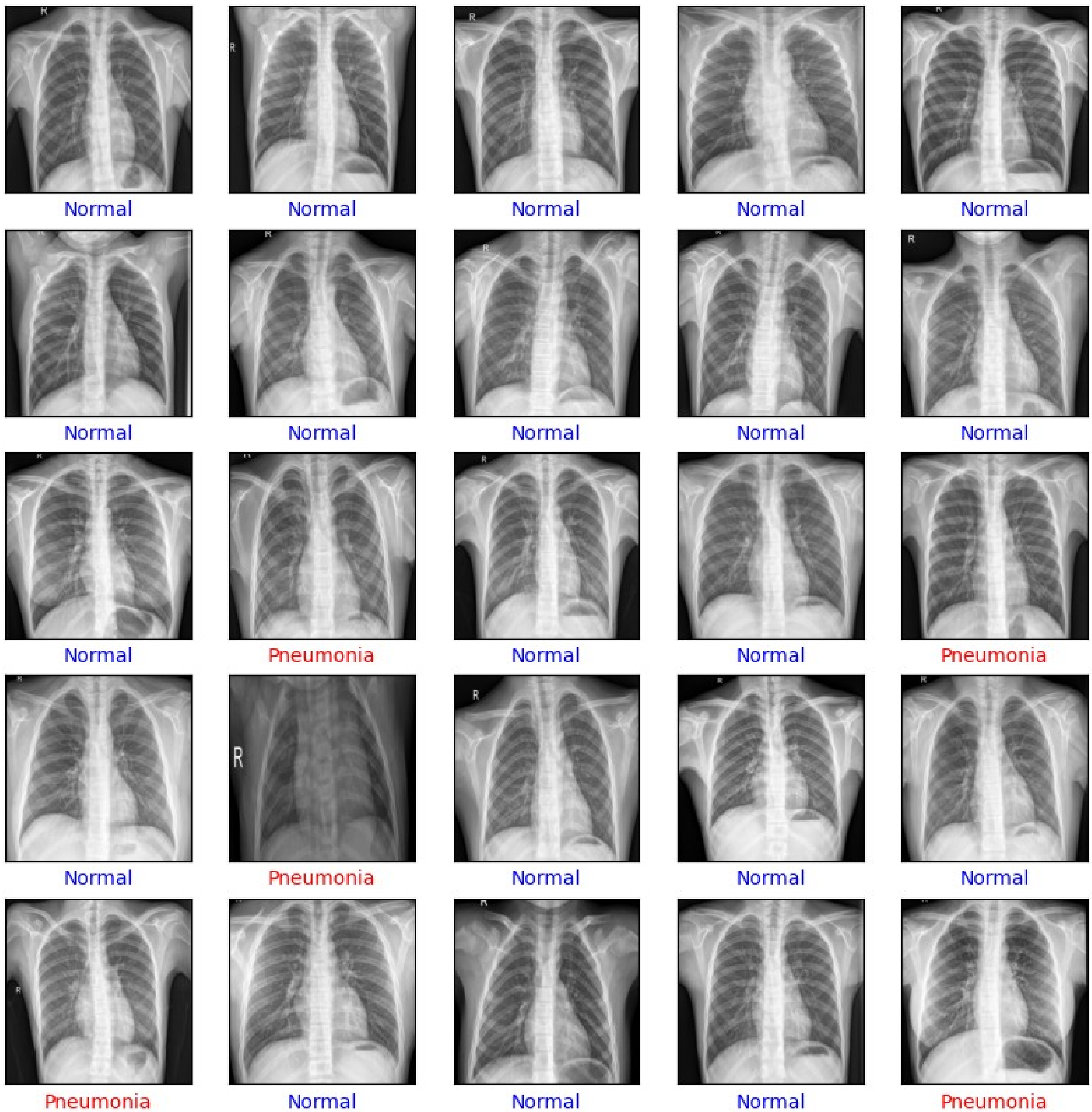
```
print('Accuracy on testing set:', accuracy_score(binary_predictions,
y_test))
print('Precision on testing set:', precision_score(binary_predictions,
y_test))
print('Recall on testing set:', recall_score(binary_predictions,
y_test))
```

```
Accuracy on testing set: 0.8333333333333334
Precision on testing set: 0.9769230769230769
Recall on testing set: 0.8004201680672269
```

Printing 25 sample predictions

```
model = keras.models.load_model('pneumonia_detection_v1.keras')

predictions = model.predict(X_test)
# Converting probabilities to binary predictions assuming binary
classification with a threshold of 0.5
binary_predictions = (predictions > 0.5).astype(int)

# Labels for your binary classes
labels = ['Normal', 'Pneumonia']

img_size = 200

# Visualizing the images and their predicted labels
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    # Reshape and display the image, ensure X_train is used if it's
meant to be the training set
    plt.imshow(X_test[i].reshape(img_size, img_size), cmap='gray')
    # Check if prediction matches the true label
    if binary_predictions[i] == y_test[i]:
        plt.xlabel(labels[binary_predictions[i][0]], color='blue')
    else:
        plt.xlabel(labels[binary_predictions[i][0]], color='red')
plt.show()
```

```
20/20 ━━━━━━━━━━━━━━━━━━━━ 4s 177ms/step
```




```
model.save('pneumonia_detection_v1.keras')
```

Predicting with new images

```
def preprocess_image(image_path):
    with open(image_path, 'rb') as f:
        content = f.read()

    image = Image.open(io.BytesIO(content))
    image = image.resize((200, 200)).convert('L')
    image_array = np.array(image) / 255.0
```

```
    image_array = image_array.reshape((1, 200, 200, 1))  # Reshape for
model (adding batch dimension)
    return image_array

def predict_image(image_path, model):
    processed_image = preprocess_image(image_path)
    prediction = model.predict(processed_image)
    return prediction

# Path to the new image
image_path = "C:/Users/affuk/Desktop/GP/normal.jpeg"

prediction = predict_image(image_path, model)

# Output prediction
if prediction[0, 0] >= 0.5:
    print("The image is predicted to be Pneumonia.")
else:
    print("The image is predicted to be Normal.")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
The image is predicted to be Normal.
```

```
def preprocess_image(image_path):
    with open(image_path, 'rb') as f:
        content = f.read()

    image = Image.open(io.BytesIO(content))
    image = image.resize((200, 200)).convert('L')
    image_array = np.array(image) / 255.0
    image_array = image_array.reshape((1, 200, 200, 1))  # Reshape for
model (adding batch dimension)
    return image_array

def predict_image(image_path, model):
    processed_image = preprocess_image(image_path)
    prediction = model.predict(processed_image)
    return prediction

# Path to the new image
image_path = "C:/Users/affuk/Desktop/GP/pneumonia.jpeg"

prediction = predict_image(image_path, model)

# Output prediction
if prediction[0, 0] >= 0.5:
    print("The image is predicted to be Pneumonia.")
else:
    print("The image is predicted to be Normal.")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
The image is predicted to be Pneumonia.
```