Step 1: Project Details

Title: Covid-19 Chest XRay Image Recognition

Description: The project aims to build an image classification model that can identify Covid-19 positive patients by analyzing their chest X-ray images. By utilizing computer vision techniques, the model will be able to distinguish between healthy and Covid-19 infected lungs based on visual patterns present in the X-ray images

Dataset and Description: The dataset you will be using for this project is available on Kaggle, and it is called "Covid19 Image Dataset" by Pranav Raikokte. It presumably contains chest X-ray images of both Covid-19 positive and negative patients. You can use this dataset to train and evaluate your image classification model

Tags: Image Processing, Computer Vision (CV)

Dataset Source: https://www.kaggle.com/datasets/pranavraikokte/covid19-image-dataset

This project involves building a model to analyze medical images, which can have significant real-world applications in healthcare, especially during the ongoing Covid-19 pandemic. If you have any specific questions or need further assistance regarding your project, feel free to ask!

Step 2: Importing Libraries

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import cv2
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import of
```

Step 3: Data Preprocessing

```
# Load and preprocess a sample image
img = cv2.imread("/content/drive/MyDrive/Capstone project/archive/Covid19-dataset/train/Normal/011.jpeg")
img = cv2.resize(img, (256, 256))
img = img / 255.0
# Data Augmentation
train_data = '/content/drive/MyDrive/Capstone project/archive/Covid19-dataset/train'
test_data = '/content/drive/MyDrive/Capstone project/archive/Covid19-dataset/test'
target_size = (256, 256)
batch_size = 16
train_datagen = ImageDataGenerator(
    rescale=1 / 255,
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
   shear_range=0.2,
   zoom_range=0.2,
    horizontal_flip=True,
    fill mode='nearest'
test_datagen = ImageDataGenerator(rescale=1 / 255)
```

Step 4: Model Building

```
# Step 4: Model Building
model = keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Dropout(0.23),

layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
```

```
layers.Dropout(0.25),
   layers.Conv2D(128, (3, 3), activation='relu'),
   layers.MaxPooling2D(pool size=(2, 2)),
   layers.Dropout(0.25),
   lavers.Flatten().
   layers.Dense(64, activation='relu'),
   layers.Dropout(0.4),
   layers.Dense(3, activation='softmax') # 3 classes: Covid-19 Positive, Covid-19 Negative, and Virus
# Step 4: Model Compilation
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
Step 5: Model Training
train_generator = train_datagen.flow_from_directory(
   train data,
   target_size=target_size,
   batch_size=batch_size,
   class_mode='categorical'
test generator = test datagen.flow from directory(
   test_data,
   target_size=target_size,
   batch_size=batch_size,
   class_mode='categorical'
history = model.fit(
   train_generator,
   epochs=20,
   steps_per_epoch=len(train_generator),
   validation_data=test_generator,
   validation_steps=len(test_generator)
)
    Found 251 images belonging to 3 classes.
    Found 66 images belonging to 3 classes.
    Epoch 1/20
    16/16 [============= ] - 78s 4s/step - loss: 2.2652 - accuracy: 0.4064 - val_loss: 1.0963 - val_accuracy: 0.4394
    Epoch 2/20
    Epoch 3/20
    16/16 [============ ] - 60s 4s/step - loss: 0.7743 - accuracy: 0.6494 - val_loss: 0.6662 - val_accuracy: 0.7273
    Epoch 4/20
                     =========] - 60s 4s/step - loss: 0.6285 - accuracy: 0.7649 - val_loss: 0.5904 - val_accuracy: 0.6818
    16/16 [====
    Epoch 5/20
    16/16 [======
                 Epoch 6/20
                     ==========] - 59s 4s/step - loss: 0.5671 - accuracy: 0.7331 - val loss: 0.5286 - val accuracy: 0.7121
    16/16 [====
    Epoch 7/20
    16/16 [============ ] - 57s 4s/step - loss: 0.6929 - accuracy: 0.7052 - val_loss: 0.5908 - val_accuracy: 0.7576
    Epoch 8/20
    16/16 [====
                      :========] - 66s 4s/step - loss: 0.6131 - accuracy: 0.7610 - val_loss: 0.5572 - val_accuracy: 0.7273
    Epoch 9/20
    16/16 [=====
                    =========] - 60s 4s/step - loss: 0.6308 - accuracy: 0.7689 - val_loss: 0.6967 - val_accuracy: 0.6515
    Epoch 10/20
    16/16 [=====
                    ========] - 62s 4s/step - loss: 0.6755 - accuracy: 0.7131 - val_loss: 0.6766 - val_accuracy: 0.7424
    Epoch 11/20
    16/16 [============= ] - 59s 4s/step - loss: 0.5311 - accuracy: 0.7769 - val_loss: 0.6344 - val_accuracy: 0.7273
    Epoch 12/20
    16/16 [============ ] - 58s 4s/step - loss: 0.5618 - accuracy: 0.7610 - val_loss: 0.6061 - val_accuracy: 0.7273
    Epoch 13/20
    16/16 [============= - 57s 4s/step - loss: 0.4438 - accuracy: 0.8088 - val_loss: 0.6419 - val_accuracy: 0.7273
    Epoch 14/20
    16/16 [=====
                    =========] - 59s 4s/step - loss: 0.4618 - accuracy: 0.7809 - val_loss: 0.6347 - val_accuracy: 0.7576
    Epoch 15/20
    16/16 [=====
                    =========] - 59s 4s/step - loss: 0.5029 - accuracy: 0.7928 - val_loss: 0.6828 - val_accuracy: 0.7879
    Epoch 16/20
    16/16 [============= ] - 65s 4s/step - loss: 0.4531 - accuracy: 0.8247 - val_loss: 0.7910 - val_accuracy: 0.7121
    Epoch 17/20
                  :============] - 59s 4s/step - loss: 0.5123 - accuracy: 0.7809 - val_loss: 0.7972 - val_accuracy: 0.7424
    16/16 [======
    Epoch 18/20
    Epoch 19/20
                      =========] - 58s 4s/step - loss: 0.4279 - accuracy: 0.8406 - val_loss: 0.6890 - val_accuracy: 0.7576
    16/16 [==
    Epoch 20/20
    16/16 [=============] - 57s 4s/step - loss: 0.4062 - accuracy: 0.8127 - val_loss: 0.8700 - val_accuracy: 0.6818
```

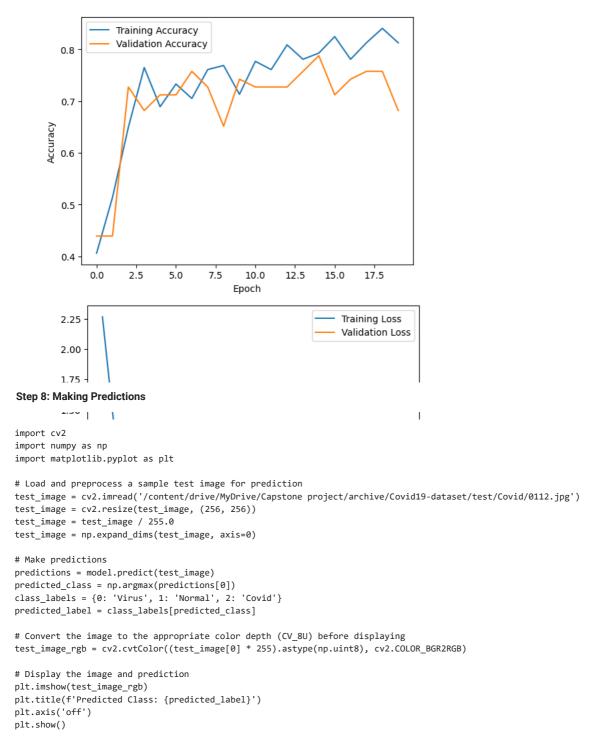
Step 6: Model Evaluation

Step 7: Model Visualization

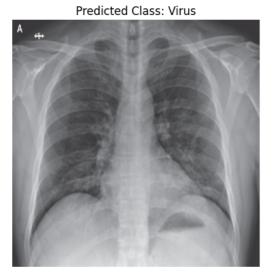
```
# Plot training and validation accuracy/loss curves
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Print model summary
model.summary()
```

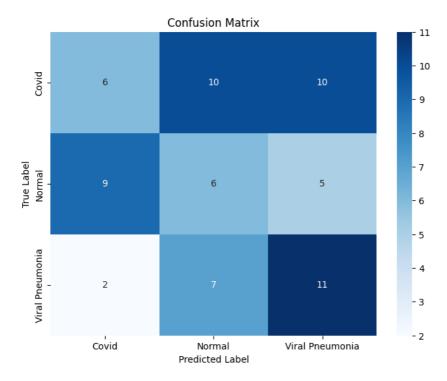


1/1 [======] - 0s 111ms/step



Data Analysis

```
# Count the number of images in each class
train_counts = train_generator.classes
test_counts = test_generator.classes
class_labels = train_generator.class_indices
class_labels = {v: k for k, v in class_labels.items()}
train_class_counts = {class_labels[i]: np.count_nonzero(train_counts == i) for i in range(len(class_labels))}
test_class_counts = {class_labels[i]: np.count_nonzero(test_counts == i) for i in range(len(class_labels))}
print("Train Class Counts:", train_class_counts)
print("Test Class Counts:", test_class_counts)
     Train Class Counts: {'Covid': 111, 'Normal': 70, 'Viral Pneumonia': 70} Test Class Counts: {'Covid': 26, 'Normal': 20, 'Viral Pneumonia': 20}
from sklearn.metrics import classification_report, confusion_matrix
# Get true labels and predicted labels for the test data
y_true = test_generator.classes
y_pred = np.argmax(model.predict(test_generator), axis=1)
# Generate the classification report
print("Classification Report:")
\verb|print(classification_report(y_true, y_pred, target_names=list(class_labels.values()))||
cm = confusion_matrix(y_true, y_pred)
print("Confusion Matrix:")
print(cm)
     5/5 [=======] - 3s 580ms/step
     Classification Report:
                     precision recall f1-score
                                                       support
                           0.35
                                     0.23
                                                0.28
                                                             26
               Covid
                           0.26
                                                0.28
              Normal
                                      0.30
                                                             20
     Viral Pneumonia
                           0.42
                                     0.55
                                                0.48
                                                            20
            accuracy
                                                0.35
                                                            66
           macro avg
                           0.35
                                      0.36
                                                0.35
                                                            66
        weighted avg
                           0.35
                                      0.35
                                                0.34
                                                            66
     Confusion Matrix:
     [[ 6 10 10]
      [965]
      [ 2 7 11]]
# Plot the confusion matrix
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=list(class_labels.values())), yticklabels=list(class_labels.values()))
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



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