```
import time
start_time = time.time()
import tensorflow as tf
print("Num GPUs Available:", len(tf.config.list_physical_devices('GPU')))
→ Num GPUs Available: 1
# Install necessary packages
!pip install kagglehub -q
!pip install imutils -q
!pip install tensorflow -q
import os
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import kagglehub
from imutils import paths
from \ tensorflow. keras. preprocessing. image \ import \ ImageDataGenerator
from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.layers import MaxPooling2D, Dropout, Flatten, Dense, Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.inception_v3 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array, load_img
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,accuracy_score
# Download Datasets and Get Paths
print("Downloading datasets...")
# Path for the training dataset
damage_dataset_path = kagglehub.dataset_download("anujms/car-damage-detection")
print(f"Damage dataset downloaded to: {damage_dataset_path}")
# Path for an example prediction image
coco_dataset_path = kagglehub.dataset_download("lplenka/coco-car-damage-detection-dataset")
print(f"COCO dataset downloaded to: {coco_dataset_path}")
→ Downloading datasets...
     Damage dataset downloaded to: /kaggle/input/car-damage-detection
     COCO dataset downloaded to: /kaggle/input/coco-car-damage-detection-dataset
# Configuration
INIT_LR = 1e-4
HEAD_EPOCHS = 20
FINE_TUNE_EPOCHS = 80
TOTAL_EPOCHS = HEAD_EPOCHS + FINE_TUNE_EPOCHS
BS = 64
CATEGORIES = ["00-damage", "01-whole"]
# Correctly Define Directories using the downloaded path
DIRECTORY_TRAIN = os.path.join(damage_dataset_path, "data1a", "training")
DIRECTORY_VAL = os.path.join(damage_dataset_path, "data1a", "validation")
# Load Data
print("Loading images...")
data = []
labels = []
# Function to load images from a directory
def load images from dir(directory):
    for category in CATEGORIES:
        path = os.path.join(directory, category)
        if not os.path.exists(path):
            print(f"Directory not found: {path}. Skipping.")
            continue
        for img_file in os.listdir(path):
```

```
img_path = os.path.join(path, img_file)
            image = load_img(img_path, target_size=(224, 224))
            image = img_to_array(image)
            image = preprocess_input(image)
            data.append(image)
            labels.append(category)
# Load training and validation images
load images from dir(DIRECTORY TRAIN)
load_images_from_dir(DIRECTORY_VAL)
# Preprocess Labels and Data
print("Preprocessing data...")
lb = LabelBinarizer()
labels = lb.fit_transform(labels)
labels = to_categorical(labels)
data = np.array(data, dtype="float32")
labels = np.array(labels)
# Split Data
(trainX, testX, trainY, testY) = train_test_split(data, labels,
                                                 test_size=0.20, stratify=labels, random_state=42)
print(f"Training samples: {len(trainX)}, Testing samples: {len(testX)}")
# Data Augmentation
aug = ImageDataGenerator(
    rotation_range=20,
    zoom_range=0.15,
    width shift range=0.2,
    height_shift_range=0.2,
    shear range=0.15.
    horizontal_flip=True,
    fill_mode="nearest"

→ Loading images...
     Preprocessing data...
     Training samples: 1840, Testing samples: 460
# Build Model
print("Initializing InceptionV3 model...")
baseModel = InceptionV3(weights="imagenet", include_top=False,
                       input tensor=Input(shape=(224, 224, 3)))
# Construct the head of the model
headModel = baseModel.output
headModel = MaxPooling2D(pool_size=(2, 2))(headModel)
headModel = Flatten(name="flatten")(headModel)
headModel = Dense(256, activation="relu")(headModel)
headModel = Dropout(0.5)(headModel)
headModel = Dense(2, activation="softmax")(headModel)
# Place the head FC model on top of the base model(Inceptionv3)
model = Model(inputs=baseModel.input, outputs=headModel)
# Freeze all layers in the base model
for layer in baseModel.layers:
    layer.trainable = False
# Callbacks
early_stopping = EarlyStopping(
    monitor='val_accuracy',
    patience=10, # Stop if val_accuracy doesn't improve for 10 epochs
    verbose=1,
    restore_best_weights=True
)
→ Initializing InceptionV3 model...
# Phase 1: Train the Head
print("Compiling and training head layers...")
opt = Adam(learning_rate=INIT_LR)
model.compile(loss="binary crossentropy", optimizer=opt, metrics=["accuracy"])
```

```
H1 = model.fit(
    aug.flow(trainX, trainY, batch size=BS),
    validation_data=(testX, testY),
    epochs=HEAD_EPOCHS,
    callbacks=[early_stopping]
)
# Phase 2: Fine-Tuning
print("\nUnfreezing top layers for fine-tuning...")
# Unfreeze the top layers of the model
for layer in baseModel.layers[-50:]:
    layer.trainable = True
# Re-compile the model for fine-tuning with a lower learning rate
opt = Adam(learning_rate=INIT_LR / 10) # Use a 10x smaller learning rate
model.compile(loss="binary_crossentropy", optimizer=opt, metrics=["accuracy"])
print(" Starting fine-tuning phase...")
# We check if the first training phase completed all epochs or stopped early
initial_epoch = H1.epoch[-1] + 1
if initial_epoch < HEAD_EPOCHS:</pre>
    print(f"Early stopping occurred. Starting fine-tuning from epoch {initial_epoch}.")
H2 = model.fit(
    aug.flow(trainX, trainY, batch_size=BS),
    validation_data=(testX, testY),
    epochs=TOTAL_EPOCHS,
    initial_epoch=initial_epoch, # Continue from where we left off
    callbacks=[early_stopping]
)
<del>→</del> 29/29 −
                            —— 23s 769ms/step - accuracy: 0.8109 - loss: 0.4042 - val_accuracy: 0.9000 - val_loss: 0.2660
     Epoch 7/20
     29/29
                               – 22s 746ms/step - accuracy: 0.8513 - loss: 0.3432 - val_accuracy: 0.8913 - val_loss: 0.2637
     Epoch 8/20
                               - 22s 761ms/step - accuracy: 0.8588 - loss: 0.3432 - val_accuracy: 0.8935 - val_loss: 0.2518
     29/29
     Epoch 9/20
     29/29
                               — 21s 736ms/step - accuracy: 0.8526 - loss: 0.3532 - val_accuracy: 0.8891 - val_loss: 0.2782
     Epoch 10/20
     29/29
                               - 41s 751ms/step - accuracy: 0.8679 - loss: 0.3227 - val accuracy: 0.8848 - val loss: 0.2663
     Epoch 11/20
                               – 22s 766ms/step - accuracy: 0.8705 - loss: 0.3073 - val_accuracy: 0.8957 - val_loss: 0.2369
     29/29
     Epoch 12/20
     29/29
                               - 21s 734ms/step - accuracy: 0.8702 - loss: 0.3106 - val_accuracy: 0.8870 - val_loss: 0.2605
     Epoch 13/20
     29/29 -
                               <mark>- 42s</mark> 761ms/step - accuracy: 0.8584 - loss: 0.3006 - val_accuracy: 0.8696 - val_loss: 0.2870
     Epoch 14/20
     29/29
                               – 22s 771ms/step - accuracy: 0.8907 - loss: 0.2807 - val_accuracy: 0.9043 - val_loss: 0.2280
     Epoch 15/20
     29/29
                               - 21s 712ms/step - accuracy: 0.8864 - loss: 0.2867 - val_accuracy: 0.9152 - val_loss: 0.2254
     Epoch 16/20
     29/29
                               — 21s 727ms/step - accuracy: 0.8876 - loss: 0.2769 - val_accuracy: 0.9109 - val_loss: 0.2238
     Epoch 17/20
     29/29
                               - 22s 743ms/step - accuracy: 0.8927 - loss: 0.2844 - val accuracy: 0.9130 - val loss: 0.2322
     Epoch 18/20
     29/29
                               - 22s 753ms/step - accuracy: 0.8924 - loss: 0.2698 - val_accuracy: 0.9022 - val_loss: 0.2426
     Epoch 19/20
                               - 21s 720ms/step - accuracy: 0.8975 - loss: 0.2757 - val_accuracy: 0.9065 - val_loss: 0.2295
     29/29
     Epoch 20/20
                               - 22s 763ms/step - accuracy: 0.8778 - loss: 0.2892 - val_accuracy: 0.9087 - val_loss: 0.2396
     Restoring model weights from the end of the best epoch: 15.
```

```
29/29
                              — 21s 742ms/step - accuracy: 0.9229 - loss: 0.2166 - val_accuracy: 0.9109 - val_loss: 0.2064
     Epoch 29/100
                               <mark>— 22s</mark> 750ms/step - accuracy: 0.9127 - loss: 0.2219 - val_accuracy: 0.9043 - val_loss: 0.2233
     29/29
     Epoch 30/100
     29/29
                               <mark>- 22s</mark> 773ms/step - accuracy: 0.9006 - loss: 0.2298 - val_accuracy: 0.9130 - val_loss: 0.1989
     Epoch 31/100
     29/29
                                - 22s 755ms/step - accuracy: 0.9085 - loss: 0.2199 - val_accuracy: 0.9109 - val_loss: 0.1969
     Epoch 31: early stopping
     Restoring model weights from the end of the best epoch: 21.
# Evaluate Network
predictions = model.predict(testX, batch_size=BS)
y_pred = np.argmax(predictions, axis=1)
y_true = np.argmax(testY, axis=1)
# Calculate and Print Accuracy
accuracy = accuracy_score(y_true, y_pred)
print(f"\nOverall Accuracy: {accuracy * 100:.2f}%")
print("-" * 60) # Separator line
# Classification Report
print("Classification Report:")
print(classification_report(y_true, y_pred, target_names=lb.classes_))
print("-" * 60) # Separator line
# Plot Confusion Matrix as a Heatmap
cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(5, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=lb.classes_, yticklabels=lb.classes_)
plt.title('Confusion Matrix', fontsize=16)
plt.ylabel('Actual Label', fontsize=12)
plt.xlabel('Predicted Label', fontsize=12)
plt.tight_layout()
plt.show()
# Plot Training History
history_dict = H1.history
if 'H2' in locals():
    for key in H1.history.keys():
        history_dict[key].extend(H2.history[key])
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
loss = history dict['loss']
val_loss = history_dict['val_loss']
epochs_range = range(1, len(acc) + 1)
plt.style.use("ggplot")
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label="Training Accuracy")
plt.plot(epochs_range, val_acc, label="Validation Accuracy")
plt.legend(loc="lower right")
plt.title("Training and Validation Accuracy")
plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label="Training Loss")
plt.plot(epochs_range, val_loss, label="Validation Loss")
plt.legend(loc="upper right")
plt.title("Training and Validation Loss")
plt.tight_layout()
plt.show()
# Save the Model
model.save('car_damage_classifier.h5')
print("\nModel saved as car_damage_classifier.h5")
```

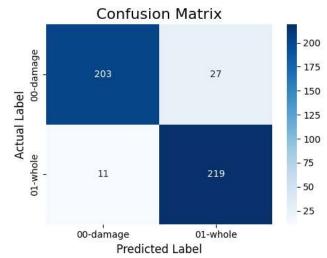
/usr/local/lib/python3.11/dist-packages/keras/src/models/functional.py:237: UserWarning: The structure of `inputs` doesn't match the exp Expected: ['keras_tensor']

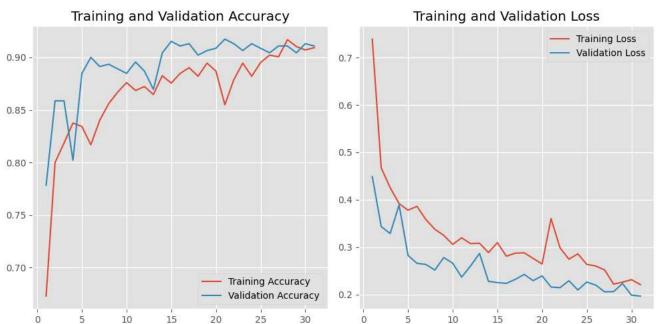
Received: inputs=Tensor(shape=(64, 224, 224, 3))

warnings.warn(msg) 8/8 **- 13s** 983ms/step

Overall Accuracy: 91.74%

Classification Report:					
CIUSSITICUCIO	precision	recall	f1-score	support	
00-damage	0.95	0.88	0.91	230	
01-whole	0.89	0.95	0.92	230	
accuracy			0.92	460	
macro avg	0.92	0.92	0.92	460	
weighted avg	0.92	0.92	0.92	460	





WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is consi

Model saved as car_damage_classifier.h5

```
# Prediction Function
def predict_damage(image_path):
   # Load and preprocess the image
   image = load_img(image_path, target_size=(224, 224))
   image_arr = img_to_array(image)
   image_arr = np.expand_dims(image_arr, axis=0)
```

```
image_arr = preprocess_input(image_arr)
   # Make prediction
   prediction = model.predict(image_arr)
   class_index = np.argmax(prediction)
   label = lb.classes_[class_index]
   confidence = prediction[0][class_index] * 100
   # Display the image and result
   plt.imshow(image)
   plt.title(f"Prediction: {label} ({confidence:.2f}%)")
   plt.axis('off')
   plt.show()
   return label, confidence
# Use the prediction function
example_image_path = os.path.join(coco_dataset_path, "img", "1.jpg")
if os.path.exists(example_image_path):
   predict_damage(example_image_path)
else:
   print(f"Example image not found at: {example_image_path}")
                           — 5s 5s/step
```

Prediction: 00-damage (99.08%)



predict_damage(os.path.join(coco_dataset_path, "train", "4.jpg"))

→ 1/1 ─ 0s 61ms/step

Prediction: 00-damage (97.23%)



(np.str_('00-damage'), np.float32(97.22979))

predict_damage(os.path.join(coco_dataset_path, "test", "28.jpg"))

→ 1/1 Os 48ms/step

Prediction: 01-whole (87.50%)



(np.str_('01-whole'), np.float32(87.50397))

predict_damage(os.path.join(coco_dataset_path, "img", "69.jpg"))

→ 1/1 — 0s 45ms/step

Prediction: 01-whole (99.99%)



(np.str_('01-whole'), np.float32(99.994194))

predict_damage(os.path.join(coco_dataset_path, "train", "37.jpg"))

→ 1/1 Os 48ms/step

Prediction: 01-whole (98.85%)



(1 +22/00 04075))