Deep learning Lab Assignment

```
Name: Ayush Rewatkar
Div: A
Batch: DL-1
Roll No: 12
PRN No: 202201040033
```

Binary Classification

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import cifar10
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# Selecting class "Airplane" (label 0) and merging others into "Not Airplane" (label 1) y_train_binary = np.where(y_train == 0, 0, 1) y_test_binary = np.where(y_test == 0, 0, 1)
# Normalize pixel values
x_train, x_test = x_train / 255.0, x_test / 255.0
# Build CNN model
model = keras.Sequential([
     layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)),
     layers.MaxPooling2D((2,2)),
layers.Conv2D(64, (3,3), activation='relu'),
layers.MaxPooling2D((2,2)),
     layers.Conv2D(128, (3,3), activation='relu'),
layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dense(128, activation='relu')
layers.Dense(1, activation='sigmoid') # Binary classification
1)
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Train model
\label{eq:history} \textbf{history = model.fit}(x\_train, y\_train\_binary, epochs=5, validation\_data=(x\_test, y\_test\_binary), batch\_size=64)
# Model summary
model.summary()
# Evaluate model
test_loss, test_acc = model.evaluate(x_test, y_test_binary, verbose=2)
print(f"Test Accuracy: {test_acc:.4f}")
 `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Ir \alpha
```

Laver (type)		 Outnut Shan	_		Daran			
Model: "sequential"								
782/782	— 5s 5ms/ste	p - accuracy:	0.9508 - los	s: 0.1	.295 - val_acc	uracy: 0.9	468 - val_los	s: 0.1452
Epoch 5/5								
782/782	- 3s 4ms/ste	p - accuracy:	0.9461 - los	s: 0.1	.453 - val_acc	uracy: 0.9	354 - val_los	s: 0.1656
Epoch 4/5								
782/782	- 5s 4ms/ste	p - accuracy:	0.9361 - los	s: 0.1	.724 - val_acc	uracy: 0.9	368 - val_los	s: 0.1701
Epoch 3/5								
782/782	- 6s 5ms/ste	p - accuracy:	0.9260 - los	s: 0.1	.979 - val_acc	uracy: 0.9	356 - val_los	s: 0.1754
Epoch 2/5								
782/782	- 10s 7ms/st	ep - accuracy	: 0.9063 - lo	ss: 0.	2780 - val_ac	curacy: 0.	9180 - val_lo	ss: 0.232
Epoch 1/5								
super()init(activit	_regularizer	activity_reg	ularizer, **k	wargs)				
/usr/local/lib/python3.11/	ist-packages	/ Kel. 92/ 21.C/ 19	yers/convoiut	TOLIGT/	base_conv.py:	TOY. USEIW	arming. Do no	t pass an

Layer (type)	Output Shape	Param #	
conv2d (Conv2D)	(None, 30, 30, 32)	896	
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0	
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496	
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0	
conv2d_2 (Conv2D)	(None, 4, 4, 128)	73,856	
flatten (Flatten)	(None, 2048)	0	
dense (Dense)	(None, 128)	262,272	
dense_1 (Dense)	(None, 1)	129	

Total params: 1,066,949 (4.07 MB)
Trainable params: 355,649 (1.36 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 711,300 (2.71 MB)
313/313 - 15 - 4ms/step - accuracy: 0.9468 - loss: 0.1452
Test Accuracy: 0.9468

Multiclass Classification

```
import tensorflow as tf
from tensorflow import keras
from tensorflow import keras
from tensorflow keras import layers
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import cifar10

# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize pixel values to [0,1]
x_train, x_test = x_train / 255.0, x_test / 255.0

# Convert labels to categorical (one-hot encoding)
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)

# Build CNN model
model = keras.Sequential([
layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)),
layers.MaxPooling2D((2,2)),
layers.Conv2D(64, (3,3), activation='relu'),
layers.MaxPooling2D((2,2)),
layers.Conv2D(128, (3,3), activation='relu'),
```

```
model.compile(optimizer='adam', loss='categorical crossentropy', metrics=['accuracy'])
history = model.fit(x_train, y_train, epochs=5, validation_data=(x_test, y_test), batch_size=64)
model.summary()
# Evaluate model
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f"Test Accuracy: {test_acc:.4f}")
Epoch 1/5
782/782 -
                                  — 8s 8ms/step - accuracy: 0.3391 - loss: 1.7926 - val_accuracy: 0.5580 - val_loss: 1.2403
     Epoch 2/5
                                  - 6s 4ms/step - accuracy: 0.5636 - loss: 1.2243 - val accuracy: 0.6192 - val loss: 1.0659
      782/782
      Fnoch 3/5
     782/782 —
Epoch 4/5
782/782 —
                                 --- 4s 5ms/step - accuracy: 0.6304 - loss: 1.0470 - val_accuracy: 0.6467 - val_loss: 1.0078
                                  — 5s 4ms/step - accuracy: 0.6755 - loss: 0.9257 - val_accuracy: 0.6814 - val_loss: 0.9158
     Epoch 5/5
                                  - 3s 4ms/step - accuracy: 0.7091 - loss: 0.8285 - val accuracy: 0.6904 - val loss: 0.8840
     782/782 -
     Model: "sequential_2"
       Layer (type)
                                                 Output Shape
                                                                                         Param #
        conv2d_6 (Co
        max_pooling2d_4 (MaxPooling2D)
                                                 (None, 15, 15, 32)
        conv2d_7 (Conv2D)
                                                 (None, 13, 13, 64)
                                                                                           18,496
                                                (None, 6, 6, 64)
       max_pooling2d_5 (MaxPooling2D)
                                                                                                a
        conv2d_8 (Conv2D)
                                                 (None, 4, 4, 128)
                                                                                           73,856
        flatten_2 (Flatten)
                                                 (None, 2048)
       dense 4 (Dense)
                                                 (None, 128)
                                                                                         262.272
```

Total params: 1,070,432 (4.08 MB)
Trainable params: 356,810 (1.36 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 713,622 (2.72 MB)
313/313 - 1s - 3ms/step - accuracy: 0.6904 - loss: 0.8840

dense_5 (Dense)

import tensorflow as tf
from tensorflow import keras

from tensorflow.keras import lavers, applications

layers.Flatten(),

layers.Dense(128, activation='relu'),

layers.Dense(10, activation='softmax') # Multiclass classification (10 classes)

Pretrained Model (VGG16,ResNet50,MoblieNet)

(None, 10)

```
from tensorflow.keras.datasets import cifar10
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
# Convert labels to categorical (one-hot encoding)
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
# Function to create a model with Transfer Learning
# Total transfer teaching def create_pretrained_model(base_model):

base_model.trainable = False # Freeze base model layers model = keras.Sequential([
           layers.GlobalAveragePooling2D(),
           layers.Dense(128, activation='relu'),
layers.Dense(10, activation='softmax') # 10 classes
       odel.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Load pre-trained models (without top layers)
vgg16_base = applications.VGG16(weights='imagenet', include_top=False, input_shape=(32,32,3))
resnet50_base = applications.ResNet50(weights='imagenet', include_top=False, input_shape=(32,32,3))
mobilenet_base = applications.MobileNetV2(weights='imagenet', include_top=False, input_shape=(32,32,3))
vgg16_model = create_pretrained_model(vgg16_base)
resnet50 model = create pretrained model(resnet50 base)
mobilenet_model = create_pretrained_model(mobilenet_base)
# Train models (only showing VGG16, repeat for others)
history_vgg16 = vgg16_model.fit(x_train, y_train, epochs=5, validation_data=(x_test, y_test), batch_size=64) history_resnet50 = resnet50_model.fit(x_train, y_train, epochs=5, validation_data=(x_test, y_test), batch_size=64)
history_mobilenet = mobilenet_model.fit(x_train, y_train, epochs=5, validation_data=(x_test, y_test), batch_size=64)
# Model summaries
print("\nVGG16 Model Summary:")
vgg16_model.summary()
print("\nResNet50 Model Summary:")
resnet50_model.summary()
print("\nMobileNetV2 Model Summary:")
mobilenet_model.summary()
print("\nVGG16 Accuracy:")
vgg16_model.evaluate(x_test, y_test)
print("\nResNet50 Accuracy:")
 resnet50_model.evaluate(x_test, y_test)
print("\nMobileNetV2 Accuracy:")
mobilenet_model.evaluate(x_test, y_test)
```

```
Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16-weights-tf-dim-ordering-tf-kernels-notop.h5">https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16-weights-tf-dim-ordering-tf-kernels-notop.h5</a>
Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50-weights-tf-dim-ordering-tf-kernels-notop.h5-94765736/94765736">https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50-weights-tf-dim-ordering-tf-kernels-notop.h5-94765736/94765736</a>
So Ous/step
          94765736 — 58 @us/step
cipython-input-4-c451b73e33e9>:31: UserWarning: 'input_shape' is undefined or non-square, or 'rows' is not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.
mobilenet_base = applications.MobileNetV2(weights='imagenet', include_top=False, input_shape=(32,32,3))
Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilene
                                                                        - 19s 20ms/step - accuracy: 0.4562 - loss: 1.5775 - val_accuracy: 0.5576 - val_loss: 1.2756
           782/782 -
           Fnoch 2/5
           782/782 —
Epoch 3/5
782/782 —
                                                              ----- 13s 13ms/step - accuracy: 0.5712 - loss: 1.2223 - val_accuracy: 0.5739 - val_loss: 1.2186
                                                            ----- 11s 14ms/step - accuracy: 0.5986 - loss: 1.1496 - val_accuracy: 0.5869 - val_loss: 1.1790
           Epoch 4/5
782/782 -
                                                                          - 11s 14ms/step - accuracy: 0.6120 - loss: 1.1139 - val accuracy: 0.5881 - val loss: 1.1906
           Epoch 5/5
           782/782
                                                                      -- 33s 29ms/step - accuracy: 0.2061 - loss: 2.1756 - val_accuracy: 0.3169 - val_loss: 1.9253
           Epoch 2/5
                                                                      --- 9s 11ms/step - accuracy: 0.3113 - loss: 1.9058 - val accuracy: 0.3192 - val loss: 1.8599
           782/782
           Epoch 3/5
           782/782
                                                                ——— 10s 11ms/step - accuracy: 0.3346 - loss: 1.8356 - val_accuracy: 0.3626 - val_loss: 1.7834
           Epoch 4/5
782/782 —
                                                                    —— 10s 11ms/step - accuracy: 0.3497 - loss: 1.7982 - val_accuracy: 0.3629 - val_loss: 1.7702
           Epoch 5/5
                                                                        — 8s 10ms/step - accuracy: 0.3571 - loss: 1.7786 - val accuracy: 0.3854 - val loss: 1.7330
           782/782
           782/782
                                                                       --- 6s 8ms/step - accuracy: 0.3276 - loss: 1.8568 - val_accuracy: 0.3358 - val_loss: 1.8438
           Epoch 3/5
```

VGG16 Model Summary: Model: "sequential 3"

782/782 Epoch 4/5 782/782

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 1, 1, 512)	14,714,688
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense_6 (Dense)	(None, 128)	65,664
dense_7 (Dense)	(None, 10)	1,290

— 10s 7ms/step - accuracy: 0.3550 - loss: 1.7841 - val_accuracy: 0.3431 - val_loss: 1.8180 -- 6s 8ms/step - accuracy: 0.3637 - loss: 1.7558 - val_accuracy: 0.3537 - val_loss: 1.8020

Total params: 14,915,552 (56.90 MB) Trainable params: 66,954 (261.54 KB) Non-trainable params: 14,714,688 (56.13 MB) Optimizer params: 133,910 (523.69 KB)

ResNet50 Model Summary: Model: "sequential_4"

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 1, 1, 2048)	23,587,712
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0
dense_8 (Dense)	(None, 128)	262,272
dense_9 (Dense)	(None, 10)	1,290

Total params: 24,378,400 (93.00 MB) Trainable params: 263,562 (1.01 MB) Non-trainable params: 23,587,712 (89.98 MB) Optimizer params: 527,126 (2.01 MB)

MobileNetV2 Model Summary: Model: "sequential_5"

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Functional)	(None, 1, 1, 1280)	2,257,984
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0
dense_10 (Dense)	(None, 128)	163,968
dense_11 (Dense)	(None, 10)	1,290

Total params: 2,753,760 (10.50 MB)
Trainable params: 165,258 (645.54 KB)
Non-trainable params: 2,257,984 (8.61 MB)
Optimizer params: 330,518 (1.26 MB)

VGG16 Accuracy: 313/313 -- 4s 8ms/step - accuracy: 0.6005 - loss: 1.1550 ResNet50 Accuracy:

- 5s 7ms/step - accuracy: 0.3878 - loss: 1.7277 313/313

MobileNetV2 Accuracy:

— **4s** 7ms/step - accuracy: 0.3579 - loss: 1.7961

Fine Tuning

vgg16_base,

```
from tensorflow import keras
from tensorflow.keras import layers, applications from tensorflow.keras.datasets import cifar10
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# Normalize pixel values
x_train, x_test = x_train / 255.0, x_test / 255.0
# Convert labels to categorical (one-hot encoding)
y train = keras.utils.to categorical(y train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
# Load pre-trained VGG16 model
vgg16_base = applications.VGG16(weights='imagenet', include_top=False, input_shape=(32,32,3))
# Freeze the first few layers and unfreeze the last few layers for fine-tuning
for layer in vgg16_base.layers[:10]: # Freeze first 10 layers
layer.trainable = False
# Build fine-tuned model
model = keras.Sequential([
```

```
layers.GlobalAveragePooling2D(),
    layers.Dense(256, activation='relu'),
layers.Dropout(0.5), # Dropout for regularization
layers.Dense(10, activation='softmax') # 10 classes
1)
# Compile model with a lower learning rate for fine-tuning
model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0001), loss='categorical_crossentropy',
                metrics=['accuracy'])
# Train model
\label{eq:model.fit}  \text{history = model.fit}(x\_\text{train, y\_train, epochs=10, validation\_data=}(x\_\text{test, y\_test}), \ \text{batch\_size=64}) \\
# Model summary
print("\nFine-Tuned VGG16 Model Summary:")
model.summary()
# Evaluate model
print("\nFine-Tuned VGG16 Accuracy:")
model.evaluate(x_test, y_test)
→ Epoch 1/10
      782/782
                                     - 46s 50ms/step - accuracy: 0.5473 - loss: 1.3172 - val accuracy: 0.7556 - val loss: 0.7164
     Epoch 2/10
782/782 —
Epoch 3/10
782/782 —
                                 ---- 71s 42ms/step - accuracy: 0.7765 - loss: 0.6726 - val_accuracy: 0.7810 - val_loss: 0.6569
                                     - 32s 41ms/step - accuracy: 0.8336 - loss: 0.5079 - val_accuracy: 0.7977 - val_loss: 0.6181
      Epoch 4/10
      782/782
                                    — 33s 42ms/step - accuracy: 0.8819 - loss: 0.3565 - val_accuracy: 0.8047 - val_loss: 0.6156
      Epoch 5/10
782/782 —
                                    -- 41s 41ms/step - accuracy: 0.9216 - loss: 0.2403 - val_accuracy: 0.8105 - val_loss: 0.6503
      Epoch 6/10
                                     - 41s 41ms/step - accuracy: 0.9465 - loss: 0.1664 - val_accuracy: 0.7957 - val_loss: 0.7841
      782/782 --
Epoch 7/10
                                    --- 32s 41ms/step - accuracy: 0.9634 - loss: 0.1201 - val_accuracy: 0.7899 - val_loss: 0.8604
      782/782
      Epoch 8/10
782/782 —
                                   --- 33s 42ms/step - accuracy: 0.9715 - loss: 0.0908 - val_accuracy: 0.7968 - val_loss: 0.8241
     Epoch 9/10
782/782 —
                                     - 41s 43ms/step - accuracy: 0.9767 - loss: 0.0746 - val_accuracy: 0.8032 - val_loss: 0.9243
      Epoch 10/10
                                     - 32s 41ms/step - accuracy: 0.9774 - loss: 0.0746 - val accuracy: 0.7927 - val loss: 0.9759
      782/782
     Fine-Tuned VGG16 Model Summary: Model: "sequential_6"
       Layer (type)
                                                                                                  Param #
                                                     Output Shape
                                                                                               14,714,688
        vgg16 (Functional)
                                                     (None, 1, 1, 512)
       global_average_pooling2d_3
(GlobalAveragePooling2D)
                                                     (None, 512)
        dense_12 (Dense)
                                                      (None, 256)
                                                                                                  131,328
```

dropout (Dropout) (None, 256) dense_13 (Dense) (None, 10) 2,570

```
Total params: 41,074,784 (156.69 MB)
Trainable params: 13,113,098 (50.02 MB)
Non-trainable params: 1,735,488 (6.62 MB)
 Optimizer params: 26,226,198 (100.05 MB)
Fine-Tuned VGG16 Accuracy:
                                        - 3s 8ms/step - accuracy: 0.7895 - loss: 0.9812
```

Comparative Analysis

```
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import applications
from tensorflow.keras.datasets import cifar10
# Load CTEAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
# Normalize pixel values
x_train, x_test = x_train / 255.0, x_test / 255.0
# Convert labels to categorical (one-hot encoding)
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
# Function to build, train, and evaluate models
def evaluate_model(model, name, epochs=5):
    start_time = time.time()
     history = model.fit(x_train, y_train, epochs=epochs, validation_data=(x_test, y_test), batch_size=64, verbose=1) end_time = time.time()
      # Evaluate model performance
      loss, accuracy = model.evaluate(x_test, y_test, verbose=0)
      # Store model details
            "Model": name,
            "Accuracy": round(accuracy * 100, 2), # Convert to percentage "Loss": round(loss, 4),
            "Parameters": model.count_params(),
            "Training Time (s)": round(end_time - start_time, 2)
# CNN from Scratch (Multiclass)
cnn_model = keras.Sequential([
     keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)), keras.layers.MaxPooling2D((2,2)),
      keras.layers.Conv2D(64, (3,3), activation='relu'),
      keras.layers.MaxPooling2D((2,2)),
keras.layers.Conv2D(128, (3,3), activation='relu'),
     keras.layers.Flatten(),
keras.layers.Dense(128, activation='relu'),
keras.layers.Dense(10, activation='softmax')
1//
cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
cnn_results = evaluate_model(cnn_model, "CNN from Scratch")
# VGG16 (Pretrained)
vgg16 base = applications.VGG16(weights='imagenet', include top=False, input shape=(32,32,3))
vgg16_base = applications.VGG16(weights='imagenet', include_top=False, input_shape=(32,32,3))
vgg16_base.trainable = False  # Freeze all layers
vgg16_model = keras.Sequential([vgg16_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
vgg16_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
vgg16_results = evaluate_model(vgg16_model, "VGG16 (Pretrained)")
# ResNet50 (Pretrained)
```

```
resnet50_model = keras.Sequential([resnet50_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
resnet50_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
resnet50_results = evaluate_model(resnet50_model, "ResNet50 (Pretrained)")
# MobileNetV2 (Pretrained)
mobilenet_base = applications.MobileNetV2(weights='imagenet', include_top=False, input_shape=(32,32,3))
mobilenet_base.trainable = False
mobilenet_model = keras.Sequential([mobilenet_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
mobilenet_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
mobilenet_results = evaluate_model(mobilenet_model, "MobileNetV2 (Pretrained)")
for layer in vgg16 base.layers[:10]: # Unfreeze last few layers
    laver.trainable = True
fine_tuned_vgg16 = keras.Sequential([vgg16_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(256, activation='relu'), keras.layers.Dropout(0.5), keras.layers.Dense(10, activation='softmax')])
fine_tuned_vgg16.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
fine_tuned_vgg16_results = evaluate_model(fine_tuned_vgg16, "Fine-Tuned VGG16")
# Create DataFrame for results
df = pd.DataFrame([cnn_results, vgg16_results, resnet50_results, mobilenet_results, fine_tuned_vgg16_results])
# Print results
print("\nComparative Analysis of Models (Accuracy & Loss):\n")
print(df)
Epoch 3/5
782/782 -
                                     - 3s 4ms/step - accuracy: 0.6433 - loss: 1.0037 - val_accuracy: 0.6652 - val_loss: 0.9602
      Epoch 4/5
      782/782
                                    — 5s 4ms/step - accuracy: 0.6970 - loss: 0.8659 - val_accuracy: 0.6741 - val_loss: 0.9314
                                   — 5s 5ms/step - accuracy: 0.7230 - loss: 0.7899 - val accuracy: 0.6761 - val loss: 0.9245
                                     - 14s 16ms/step - accuracy: 0.3637 - loss: 1.8536 - val accuracy: 0.5122 - val loss: 1.4288
      782/782
      Epoch 2/5
      782/782
                                     18s 14ms/step - accuracy: 0.5330 - loss: 1.3751 - val accuracy: 0.5427 - val loss: 1.3356
      Epoch 3/5
      782/782 —
Epoch 4/5
782/782 —
                                      - 11s 14ms/step - accuracy: 0.5580 - loss: 1.2991 - val_accuracy: 0.5534 - val_loss: 1.2957
                                     - 11s 15ms/step - accuracy: 0.5691 - loss: 1.2644 - val_accuracy: 0.5615 - val_loss: 1.2694
      Epoch 5/5
      782/782
                                    — 21s 15ms/step - accuracy: 0.5781 - loss: 1.2321 - val_accuracy: 0.5664 - val_loss: 1.2529
                                    -- 26s 21ms/step - accuracy: 0.1972 - loss: 2.1879 - val_accuracy: 0.2952 - val_loss: 1.9652
                                   --- 8s 11ms/step - accuracy: 0.2948 - loss: 1.9568 - val_accuracy: 0.3312 - val_loss: 1.8848
      782/782
      Epoch 3/5
      782/782
                                    --- 11s 12ms/step - accuracy: 0.3205 - loss: 1.8938 - val accuracy: 0.3466 - val loss: 1.8394
      Epoch 4/5
782/782 —
                                    — 10s 12ms/step - accuracy: 0.3375 - loss: 1.8599 - val_accuracy: 0.3639 - val_loss: 1.8121
                                       10s 12ms/step - accuracy: 0.3485 - loss: 1.8319 - val_accuracy: 0.3550 - val_loss: 1.7938
      782/782
        mobilenet_base = applications.MobileNetV2(weights='imagenet', include_top=False, input_shape(32,32,3))
      <ipython-input-7-0157f30ddf09>:65: UserWarning:
      782/782
                                    — 20s 17ms/step - accuracy: 0.2375 - loss: 2.1684 - val_accuracy: 0.2931 - val_loss: 1.9944
                                    — 11s 8ms/step - accuracy: 0.3024 - loss: 1.9710 - val_accuracy: 0.3030 - val_loss: 1.9419
      782/782
      Epoch 3/5
      782/782
                                ----- 5s 7ms/step - accuracy: 0.3107 - loss: 1.9264 - val_accuracy: 0.3063 - val_loss: 1.9214
      782/782
                               ----- 6s 7ms/step - accuracy: 0.3142 - loss: 1.9042 - val_accuracy: 0.3079 - val_loss: 1.9111
      Epoch 5/5
782/782 -
                                      - 10s 8ms/step - accuracy: 0.3184 - loss: 1.8924 - val_accuracy: 0.3119 - val_loss: 1.9046
      Epoch 1/5
      782/782
                                    -- 32s 34ms/step - accuracy: 0.3565 - loss: 1.7916 - val_accuracy: 0.6703 - val_loss: 0.9263
      Epoch 2/
782/782
                                   --- 24s 31ms/step - accuracy: 0.6754 - loss: 0.9421 - val_accuracy: 0.7347 - val_loss: 0.7611
                                    -- 40s 30ms/step - accuracy: 0.7477 - loss: 0.7402 - val_accuracy: 0.7733 - val_loss: 0.6516
      Epoch 4/5
      782/782
                                    --- 41s 30ms/step - accuracy: 0.7945 - loss: 0.6080 - val accuracy: 0.8063 - val loss: 0.5671
                                   --- 41s 30ms/step - accuracy: 0.8200 - loss: 0.5279 - val_accuracy: 0.8158 - val_loss: 0.5423
     Comparative Analysis of Models (Accuracy & Loss):
                               Model Accuracy Loss
cratch 67.61 0.9245
                                                     Loss Parameters Training Time (s)
                  CNN from Scratch
                                                                 356810
                                                                                        28 68
         VGG16 (Pretrained)
ResNet50 (Pretrained)
MobileNetV2 (Pretrained)
                                           56.64 1.2529
35.50 1.7938
                                                               14719818
23608202
                                                                2270794
                                           31.19
                  Fine-Tuned VGG16
                                          81.58 0.5423
                                                               14848586
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import applications
from tensorflow.keras.datasets import cifar10
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
# Function to build, train, and store training history
def train_model(model, name, epochs=5):
    history = model.fit(x_train, y_train, epochs=epochs, validation_data=(x_test, y_test), batch_size=64, verbose=1)
    return {"name": name, "history": history}
# CNN from Scratch
cnn_model = keras.Sequential([
    keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)),
     keras.layers.MaxPooling2D((2,2)),
    keras.layers.Conv2D(64, (3,3), activation='relu'),
keras.layers.MaxPooling2D((2,2)),
    keras.layers.Conv2D(128, (3,3), activation='relu'),
    keras.layers.Flatten(),
keras.layers.Dense(128, activation='relu')
    keras.layers.Dense(10, activation='softmax')
cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
cnn_history = train_model(cnn_model, "CNN from Scratch")
# VGG16 (Pretrained)
vgg16_base = applications.VGG16(weights='imagenet', include_top=False, input_shape=(32,32,3))
vgg16_base.trainable = False
vgg16_model = keras.Sequential([vgg16_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
vgg16_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
vgg16_history = train_model(vgg16_model, "VGG16 (Pretrained)")
resnet50 base = applications.ResNet50(weights='imagenet', include top=False, input shape=(32,32,3))
resnet50_base.trainable = False
resnet50_model = keras.Sequential([resnet50_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
resnet50_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
resnet50_history = train_model(resnet50_model, "ResNet50 (Pretrained)")
```

resnet50_base = applications.ResNet50(weights='imagenet', include_top=False, input_shape=(32,32,3))

resnet50 base.trainable = False

```
# MobileNetV2 (Pretrained)
mobilenet_base = applications.MobileNetV2(weights='imagenet', include_top=False, input_shape=(32,32,3))
mobilenet base.trainable = False
mobilenet_model = keras.Sequential([mobilenet_base, keras.layers.GlobalAveragePooling2D(), keras.layers.Dense(10, activation='softmax')])
mobilenet_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
mobilenet_history = train_model(mobilenet_model, "MobileNetV2 (Pretrained)")
# Fine-Tuned VGG16
for layer in vgg16_base.layers[:10]:
    layer.trainable = True
fine_tuned_vgg16 = keras.Sequential([
     vgg16_base,
keras.layers.GlobalAveragePooling2D(),
     keras.layers.Dense(256, activation='relu'),
     keras.layers.Dropout(0.5),
keras.layers.Dense(10, activation='softmax')
fine_tuned_vgg16.compile(optimizer=keras.optimizers.Adam(learning_nate=0.0001), loss='categorical_crossentropy', metrics=['accuracy']) fine_tuned_vgg16_history = train_model(fine_tuned_vgg16, "Fine-Tuned VGG16")
models = [cnn history, vgg16 history, resnet50 history, mobilenet history, fine tuned vgg16 history]
# Plot Accuracy and Loss Graphs
plt.figure(figsize=(12, 5))
Show hidden output
# Plot Accuracy
plt.figure(figsize=(8, 5)) for model in models:
     plt.plot(model["history"].history["accuracy"], label=f"{model['name']} (Train)")
plt.plot(model["history"].history["val_accuracy"], linestyle="dashed", label=f"{model['name']} (Val)")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title("Model Accuracy Comparison")
plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
plt.tight_layout()
plt.show()
₹
                                    Model Accuracy Comparison
                                                                                                          CNN from Scratch (Train)
            0.8
                                                                                                          CNN from Scratch (Val)
                                                                                                          VGG16 (Pretrained) (Train)
                                                                                                         VGG16 (Pretrained) (Val)
ResNet50 (Pretrained) (Train)
            0.7
                                                                                                          ResNet50 (Pretrained) (Val)
                                                                                                          MobileNetV2 (Pretrained) (Train)
            0.6
                                                                                                          MobileNetV2 (Pretrained) (Val)
                                                                                                          Fine-Tuned VGG16 (Train)
                                                                                                    --- Fine-Tuned VGG16 (Val)
            0.5
            0.4
            0.3
                                               1.5
                                                      2.0
                                                                         3.0
                                                                                  3.5
                                                                                           4.0
                                                     Epochs
# Plot Loss
plt.figure(figsize=(8, 5))
for model in models:
     mouer in mouels:
plt.plot(model["history"].history["loss"], label=f"{model['name']} (Train)")
plt.plot(model["history"].history["val_loss"], linestyle="dashed", label=f"{model['name']} (Val)")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Model Loss Comparison")
plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
plt.tight_layout()
plt.show()
<del>____</del>*
                                        Model Loss Comparison
```

CNN from Scratch (Train) CNN from Scratch (Val)

VGG16 (Pretrained) (Train) VGG16 (Pretrained) (Val)

ResNet50 (Pretrained) (Train) ResNet50 (Pretrained) (Val)

Fine-Tuned VGG16 (Val)

MobileNetV2 (Pretrained) (Train) MobileNetV2 (Pretrained) (Val) Fine-Tuned VGG16 (Train)

2.0

1.8

1.6

ssoj 1.

1.0

0.0 0.5

1.0 1.5 2.0

2.5 3.0 3.5 4.0