



VIT – CHENNAI CAMPUS
BCSE332P – DEEP LEARNING LAB
21BAI1364 – VITTA VISHNU DATTA
DEEP LEARNING LAB ASSESSMENT – 6

1. Simple Transfer Learning with Keras

```
import matplotlib.pyplot as plt
import numpy as np
import os
import tensorflow as tf

_URL = 'https://storage.googleapis.com/mledu-
datasets/cats_and_dogs_filtered.zip'
path_to_zip = tf.keras.utils.get_file('cats_and_dogs.zip', origin=_URL,
extract=True)
PATH = os.path.join(os.path.dirname(path_to_zip),
'cats_and_dogs_filtered')

train_dir = os.path.join(PATH, 'train')
validation_dir = os.path.join(PATH, 'validation')

BATCH_SIZE = 32
IMG_SIZE = (160, 160)

train_dataset = tf.keras.utils.image_dataset_from_directory(train_dir,
                                                               shuffle=True,
                                                               batch_size=BATCH_SIZE,
                                                               image_size=IMG_SIZE)
validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir, shuffle=True, batch_size=BATCH_SIZE,
    image_size=IMG_SIZE
)
class_names = train_dataset.class_names

plt.figure(figsize=(10, 10))
for images, labels in train_dataset.take(1):
    for i in range(9):
```

```

        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
val_batches = tf.data.experimental.cardinality(validation_dataset)
test_dataset = validation_dataset.take(val_batches // 5)
validation_dataset = validation_dataset.skip(val_batches // 5)
print(
    "Number of validation batches: %d"
    % tf.data.experimental.cardinality(validation_dataset)
)
print("Number of test batches: %d" %
tf.data.experimental.cardinality(test_dataset))
AUTOTUNE = tf.data.AUTOTUNE

train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)
data_augmentation = tf.keras.Sequential(
    [
        tf.keras.layers.RandomFlip("horizontal"),
        tf.keras.layers.RandomRotation(0.2),
    ]
)
for image, _ in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image,
0))
        plt.imshow(augmented_image[0] / 255)
        plt.axis("off")
preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
rescale = tf.keras.layers.Rescaling(1.0 / 127.5, offset=-1)
# Create the base model from the pre-trained model MobileNet V2
IMG_SHAPE = IMG_SIZE + (3,)
base_model = tf.keras.applications.MobileNetV2(
    input_shape=IMG_SHAPE, include_top=False, weights="imagenet"
)
image_batch, label_batch = next(iter(train_dataset))
feature_batch = base_model(image_batch)
print(feature_batch.shape)
base_model.trainable = False
# Let's take a look at the base model architecture
base_model.summary()
global_average_layer = tf.keras.layers.GlobalAveragePooling2D()

```

```

feature_batch_average = global_average_layer(feature_batch)
print(feature_batch_average.shape)
prediction_layer = tf.keras.layers.Dense(1)
prediction_batch = prediction_layer(feature_batch_average)
print(prediction_batch.shape)
inputs = tf.keras.Input(shape=(160, 160, 3))
x = data_augmentation(inputs)
x = preprocess_input(x)
x = base_model(x, training=False)
x = global_average_layer(x)
x = tf.keras.layers.Dropout(0.2)(x)
outputs = prediction_layer(x)
model = tf.keras.Model(inputs, outputs)
base_learning_rate = 0.0001
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=base_learning_rate),
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    metrics=["accuracy"],
)
len(model.trainable_variables)
initial_epochs = 10

loss0, accuracy0 = model.evaluate(validation_dataset)
print("initial loss: {:.2f}".format(loss0))
print("initial accuracy: {:.2f}".format(accuracy0))
history = model.fit(
    train_dataset, epochs=initial_epochs,
    validation_data=validation_dataset
)
base_model.trainable = True
model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    optimizer=tf.keras.optimizers.RMSprop(learning_rate=base_learning_rate / 10),
    metrics=["accuracy"],
)
len(model.trainable_variables)
fine_tune_epochs = 10
total_epochs = initial_epochs + fine_tune_epochs

history_fine = model.fit(
    train_dataset,
    epochs=total_epochs,
    initial_epoch=history.epoch[-1],
    validation_data=validation_dataset,
)

```

```

# Retrieve a batch of images from the test set
image_batch, label_batch = test_dataset.as_numpy_iterator().next()
predictions = model.predict_on_batch(image_batch).flatten()

# Apply a sigmoid since our model returns logits
predictions = tf.nn.sigmoid(predictions)
predictions = tf.where(predictions < 0.5, 0, 1)

print("Predictions:\n", predictions.numpy())
print("Labels:\n", label_batch)

plt.figure(figsize=(10, 10))
for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(image_batch[i].astype("uint8"))
    plt.title(class_names[predictions[i]])
    plt.axis("off")

# Save the model
model_name = "cat-dog-tuned"
model.save(model_name)

```

The screenshot shows a Google Colab notebook titled '21BAI1364 BCSE332P LAB ASSIGN.6.ipynb'. The code cell [2] contains Python code for loading a dataset of cats and dogs. The output shows the download of the dataset from a Google Cloud Storage URL. The sidebar on the right displays the user's profile information: 'vittavishnu.datta2021@vitstudent.ac.in' (Managed by vitstudent.ac.in), a profile picture, and a greeting 'Hi, Vitta Vishnu Datta!'. It also includes links for 'Manage your Google Account', 'Add account', and 'Sign out'. The bottom status bar shows the notebook was completed at 11:23PM on 19-03-2024.

```

[2] _URL = 'https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip'
path_to_zip = tf.keras.utils.get_file('cats_and_dogs.zip', origin=_URL, extract=True)
PATH = os.path.dirname(path_to_zip) + '/cats_and_dogs_filtered'

train_dir = os.path.join(PATH, 'train')
validation_dir = os.path.join(PATH, 'validation')

BATCH_SIZE = 32
IMG_SIZE = (160, 160)

train_dataset = tf.keras.utils.image_dataset_from_directory(train_dir,
                                                        shuffle=True,
                                                        batch_size=BATCH_SIZE,
                                                        image_size=IMG_SIZE)

Downloading data from https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip
68606236/68606236 [=====] - 0s 0us/step
Found 2000 files belonging to 2 classes.

[3] validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir, shuffle=True, batch_size=BATCH_SIZE, image_size=IMG_SIZE
)

```

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```
[3]: validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir, shuffle=True, batch_size=BATCH_SIZE, image_size=IMG_SIZE
)
```

Found 1000 files belonging to 2 classes.

```
[3]: class_names = train_dataset.class_names
```

```
plt.figure(figsize=(10, 10))
for images, labels in train_dataset.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

cats

cats

cats

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```
[3]: validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir, shuffle=True, batch_size=BATCH_SIZE, image_size=IMG_SIZE
)
```

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```
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```

```
[3]: class_names = train_dataset.class_names
```

```
plt.figure(figsize=(10, 10))
for images, labels in train_dataset.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

cats

dogs

cats

dogs

cats

cats

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```
[6] val_batches = tf.data.experimental.cardinality(validation_dataset)
    test_dataset = validation_dataset.take(val_batches // 5)
    validation_dataset = validation_dataset.skip(val_batches // 5)

[7] print(
    "Number of validation batches: %d"
    % tf.data.experimental.cardinality(validation_dataset)
)
print("Number of test batches: %d" % tf.data.experimental.cardinality(test_dataset))

Number of validation batches: 26
Number of test batches: 6

[8] AUTOTUNE = tf.data.AUTOTUNE

train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)

[9] data_augmentation = tf.keras.Sequential(
    [
        tf.keras.layers.RandomFlip("horizontal"),
        tf.keras.layers.RandomRotation(0.2),
    ]
)

[18] for image, _ in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image, 0))
        plt.imshow(augmented_image[0] / 255)
        plt.axis("off")
```

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```
[18] for image, _ in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image, 0))
        plt.imshow(augmented_image[0] / 255)
        plt.axis("off")
```



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```
[19] preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
[20] rescale = tf.keras.layers.Rescaling(1.0 / 127.5, offset=-1)
```

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```
[19] preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
[20] rescale = tf.keras.layers.Rescaling(1.0 / 127.5, offset=-1)
[21] # Create the base model from the pre-trained model MobileNet V2
    IMG_SHAPE = IMG_SIZE + (3,)
    base_model = tf.keras.applications.MobileNetV2(
        input_shape=IMG_SHAPE, include_top=False, weights="imagenet"
    )
    Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_160_no_top.h5
    9406464/9406464 [=====] - 0s @ 0us/step
```

```
[22] image_batch, label_batch = next(iter(train_dataset))
    feature_batch = base_model(image_batch)
    print(feature_batch.shape)
    (32, 5, 5, 1280)
[23] base_model.trainable = False
[24] # Let's take a look at the base model architecture
    base_model.summary()
    normalization
    block_15_expand_relu (ReLU (None, 5, 5, 960)
    )
```

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```
[24] # Let's take a look at the base model architecture
base_model.summary()

```

(x)	normalization)	
	block_15_expand_relu (ReLU (None, 5, 5, 960)	0 ['block_15_expand_BN[0][0]']
☛)	
	block_15_depthwise (DepthwiseConv2D (None, 5, 5, 960)	8640 ['block_15_expand_relu[0][0]']
☛	iseConv2D)	
	block_15_depthwise_BN (BatchNormalization (None, 5, 5, 960))	3840 ['block_15_depthwise[0][0]']
	block_15_depthwise_relu (ReLU (None, 5, 5, 960) eLU)	0 ['block_15_depthwise_BN[0][0]']
	block_15_project (Conv2D (None, 5, 5, 160))	153600 ['block_15_depthwise_relu[0][0]']
	block_15_project_BN (BatchNormalization (None, 5, 5, 160))	640 ['block_15_project[0][0]']
	block_15_add (Add (None, 5, 5, 160))	0 ['block_14_add[0][0]', 'block_15_project_BN[0][0]']
☛	block_16_expand (Conv2D (None, 5, 5, 960))	153600 ['block_15_add[0][0]']
☛	block_16_expand_BN (BatchNormalization (None, 5, 5, 960))	3840 ['block_16_expand[0][0]']
☛	block_16_expand_relu (ReLU (None, 5, 5, 960))	0 ['block_16_expand_BN[0][0]']

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```
[24] block_16_expand_BN (BatchNormalization (None, 5, 5, 960))

```

(x)	normalization)	3840 ['block_16_expand[0][0]']
	block_16_expand_relu (ReLU (None, 5, 5, 960))	0 ['block_16_expand_BN[0][0]']
☛	block_16_depthwise (DepthwiseConv2D (None, 5, 5, 960))	8640 ['block_16_expand_relu[0][0]']
☛	iseConv2D)	
	block_16_depthwise_BN (BatchNormalization (None, 5, 5, 960))	3840 ['block_16_depthwise[0][0]']
	block_16_depthwise_relu (ReLU (None, 5, 5, 960) eLU)	0 ['block_16_depthwise_BN[0][0]']
	block_16_project (Conv2D (None, 5, 5, 320))	307200 ['block_16_depthwise_relu[0][0]']
	block_16_project_BN (BatchNormalization (None, 5, 5, 320))	1280 ['block_16_project[0][0]']
	Conv_1 (Conv2D (None, 5, 5, 1280))	409600 ['block_16_project_BN[0][0]']
	Conv_1_bn (BatchNormalization (None, 5, 5, 1280))	5120 ['Conv_1[0][0]']
	out_relu (ReLU (None, 5, 5, 1280))	0 ['Conv_1_bn[0][0]']

```
Total params: 2257984 (8.61 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 2257984 (8.61 MB)
```

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```
[25] global_average_layer = tf.keras.layers.GlobalAveragePooling2D()
feature_batch_average = global_average_layer(feature_batch)
print(feature_batch_average.shape)
(x)
(32, 1280)

[26] prediction_layer = tf.keras.layers.Dense(1)
prediction_batch = prediction_layer(feature_batch_average)
print(prediction_batch.shape)
(32, 1)

[27] inputs = tf.keras.Input(shape=(160, 160, 3))
x = data_augmentation(inputs)
x = preprocess_input(x)
x = base_model(x, training=False)
x = global_average_layer(x)
x = tf.keras.layers.Dropout(0.2)(x)
outputs = prediction_layer(x)
model = tf.keras.Model(inputs, outputs)

[28] base_learning_rate = 0.0001
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=base_learning_rate),
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    metrics=["accuracy"],
)
```

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```
[29] len(model.trainable_variables)
(x)
2

[30] initial_epochs = 10
loss0, accuracy0 = model.evaluate(validation_dataset)
26/26 [=====] - 4s 52ms/step - loss: 0.8174 - accuracy: 0.4332

[31] print("initial loss: {:.2f}".format(loss0))
print("initial accuracy: {:.2f}".format(accuracy0))

initial loss: 0.82
initial accuracy: 0.43

[32] history = model.fit(
    train_dataset, epochs=initial_epochs, validation_data=validation_dataset
)
Epoch 1/10
63/63 [=====] - 11s 94ms/step - loss: 0.7200 - accuracy: 0.5725 - val_loss: 0.5437 - val_accuracy: 0.6510
Epoch 2/10
63/63 [=====] - 4s 53ms/step - loss: 0.5401 - accuracy: 0.7060 - val_loss: 0.3999 - val_accuracy: 0.7636
Epoch 3/10
63/63 [=====] - 4s 60ms/step - loss: 0.4165 - accuracy: 0.7890 - val_loss: 0.3043 - val_accuracy: 0.8515
Epoch 4/10
63/63 [=====] - 3s 51ms/step - loss: 0.3553 - accuracy: 0.8265 - val_loss: 0.2586 - val_accuracy: 0.8738
Epoch 5/10
63/63 [=====] - 4s 61ms/step - loss: 0.3113 - accuracy: 0.8570 - val_loss: 0.2074 - val_accuracy: 0.9183
```

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```
[32]: Epoch 5/10
63/63 [=====] - 4s 61ms/step - loss: 0.3113 - accuracy: 0.8570 - val_loss: 0.2074 - val_accuracy: 0.9183
Epoch 6/10
63/63 [=====] - 3s 50ms/step - loss: 0.2756 - accuracy: 0.8715 - val_loss: 0.1902 - val_accuracy: 0.9171
Epoch 7/10
63/63 [=====] - 3s 50ms/step - loss: 0.2620 - accuracy: 0.8810 - val_loss: 0.1688 - val_accuracy: 0.9245
Epoch 8/10
63/63 [=====] - 4s 66ms/step - loss: 0.2448 - accuracy: 0.8915 - val_loss: 0.1500 - val_accuracy: 0.9307
Epoch 9/10
63/63 [=====] - 3s 51ms/step - loss: 0.2287 - accuracy: 0.9020 - val_loss: 0.1358 - val_accuracy: 0.9443
Epoch 10/10
63/63 [=====] - 3s 49ms/step - loss: 0.2180 - accuracy: 0.9070 - val_loss: 0.1287 - val_accuracy: 0.9431

[33]: base_model.trainable = True

[34]: model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    optimizer=tf.keras.optimizers.RMSprop(learning_rate=base_learning_rate / 10),
    metrics=["accuracy"],
)

[35]: len(model.trainable_variables)
158

<>
[36]: fine_tune_epochs = 10
total_epochs = initial_epochs + fine_tune_epochs

history_fine = model.fit(
    train_dataset,
```

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```
[36]: fine_tune_epochs = 10
total_epochs = initial_epochs + fine_tune_epochs

[X]
history_fine = model.fit(
    train_dataset,
    epochs=total_epochs,
    initial_epoch=history.epoch[-1],
    validation_data=validation_dataset,
)

Epoch 10/20
63/63 [=====] - 28s 149ms/step - loss: 0.1418 - accuracy: 0.9375 - val_loss: 0.0512 - val_accuracy: 0.9876
Epoch 11/20
63/63 [=====] - 7s 101ms/step - loss: 0.1161 - accuracy: 0.9515 - val_loss: 0.0433 - val_accuracy: 0.9839
Epoch 12/20
63/63 [=====] - 7s 102ms/step - loss: 0.0932 - accuracy: 0.9660 - val_loss: 0.0533 - val_accuracy: 0.9839
Epoch 13/20
63/63 [=====] - 7s 108ms/step - loss: 0.0884 - accuracy: 0.9685 - val_loss: 0.0376 - val_accuracy: 0.9864
Epoch 14/20
63/63 [=====] - 7s 108ms/step - loss: 0.0743 - accuracy: 0.9695 - val_loss: 0.0445 - val_accuracy: 0.9839
Epoch 15/20
63/63 [=====] - 7s 101ms/step - loss: 0.0701 - accuracy: 0.9740 - val_loss: 0.0578 - val_accuracy: 0.9740
Epoch 16/20
63/63 [=====] - 7s 107ms/step - loss: 0.0594 - accuracy: 0.9705 - val_loss: 0.0397 - val_accuracy: 0.9827
Epoch 17/20
63/63 [=====] - 7s 113ms/step - loss: 0.0825 - accuracy: 0.9690 - val_loss: 0.0414 - val_accuracy: 0.9839
Epoch 18/20
63/63 [=====] - 7s 102ms/step - loss: 0.0572 - accuracy: 0.9765 - val_loss: 0.0420 - val_accuracy: 0.9827
Epoch 19/20
63/63 [=====] - 7s 108ms/step - loss: 0.0556 - accuracy: 0.9770 - val_loss: 0.0831 - val_accuracy: 0.9790
Epoch 20/20
63/63 [=====] - 7s 113ms/step - loss: 0.0427 - accuracy: 0.9845 - val_loss: 0.0346 - val_accuracy: 0.9827
```

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```
[37] # Retrieve a batch of images from the test set
image_batch, label_batch = test_dataset.as_numpy_iterator().next()
predictions = model.predict_on_batch(image_batch).flatten()

# Apply a sigmoid since our model returns logits
predictions = tf.nn.sigmoid(predictions)
predictions = tf.where(predictions < 0.5, 0, 1)

print("Predictions:\n", predictions.numpy())
print("Labels:\n", label_batch)

plt.figure(figsize=(10, 10))
for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(image_batch[i].astype("uint8"))
    plt.title(class_names[predictions[i]])
    plt.axis("off")
```

Predictions:
[1 0 0 1 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 1 1 0 1 0 1 0 0]
Labels:
[1 0 0 1 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 1 1 0 1 0 1 0 0]

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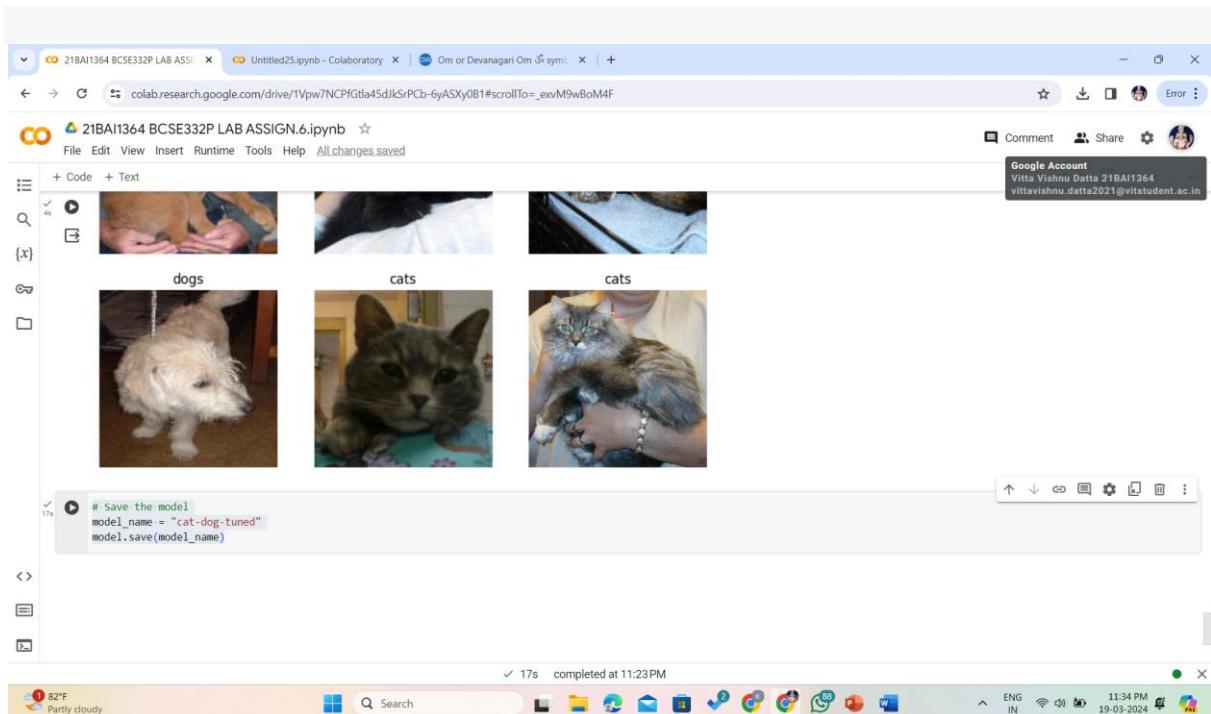
```
[38] Predictions:
[1 0 0 1 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 1 1 0 1 0 1 0 0]
Labels:
[1 0 0 1 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 1 1 0 1 0 1 0 0]
```

dogs cats cats

dogs cats cats

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Exploratory model structure analysis

```

import torch
from torch import nn
import torchvision
import os
from typing import List, Any, Tuple
pip install torchinfo
from torchinfo import summary
from torchvision.datasets import VisionDataset

classification_models =
torchvision.models.list_models(module=torchvision.models)
print(len(classification_models), "classification models:",
classification_models)

alexnet = torchvision.models.alexnet(weights=None)
alexnet
convnext_base = torchvision.models.convnext_base(weights=None)
convnext_base
dict(alexnet.named_children()).keys()
layer_count = dict()

for model_name in classification_models:
    m = getattr(torchvision.models, model_name)(weights=None)
    layer_names = dict(m.named_children()).keys()
    for ln in layer_names:

```

```

        layer_count[ln] = layer_count.get(ln, 0) + 1
    # end for
# end for

print(layer_count)
vgg16 = torchvision.models.vgg16_bn(weights=None)
resnet50 = torchvision.models.resnet50(weights=None)
resnet152 = torchvision.models.resnet152(weights=None)
print("vgg16\n", vgg16.classifier)
print("resnet50\n", resnet50.fc)
print("resnet152\n", resnet152.fc)

```

In this notebook, we shall explore the structure of pre-trained torchvision image classification models, and develop an understanding of how the models are structured (using which layer names). This will help us determine how to extract the name of the 'classification head' for each model, and replace it with a custom classification head for our task.

```

import torch
from torch import nn
import torchvision
import os
from typing import List, Any, Tuple
pip install torchinfo
from torchinfo import summary
from torchvision.datasets import VisionDataset

```

▼ List all pre-trained classification models in torchvision

There are 80 pre-trained classification models provided by torchvision. We shall use the [list_models](#) API for this purpose. The [pre-trained models page](#) shows pre-trained models for other image tasks such as segmentation, object detection, and keypoint detection. Also included are pre-trained video classification models.

```
[ ] classification_models = torchvision.models.list_models(module=torchvision.models)
print(len(classification_models), "classification models:")

```

```

80 classification models: ['alexnet', 'convnext_base', 'convnext_large', 'convnext_small', 'convnext_tiny', 'densenet121', 'densenet161', 'densenet169', 'densenet201', 'efficientnet_b4', 'efficientnet_b5', 'efficientnet_b6', 'efficientnet_b7', 'efficientnet_v2_b0', 'efficientnet_v2_b1', 'efficientnet_v2_b2', 'efficientnet_v2_b3', 'efficientnet_v2_l', 'efficientnet_v2_s', 'efficientnet_v3_b0', 'efficientnet_v3_b1', 'efficientnet_v3_b2', 'efficientnet_v3_b3', 'efficientnet_v3_l', 'efficientnet_v3_s', 'efficientnet_v3_xl', 'mnasnet1_0', 'mnasnet1_1', 'mobilenet_v2', 'resnet18', 'resnet34', 'resnet50', 'resnet101', 'resnet152', 'resnet200', 'shufflenet_v2_x0_5', 'shufflenet_v2_x1_0', 'shufflenet_v2_x2_0', 'swin_base_patch4_window7_224', 'swin_medium_patch4_window7_224', 'swin_large_patch4_window7_224', 'swin_tiny_patch4_window7_224', 'vit_base_patch16_224', 'vit_base_patch16_384', 'vit_base_patch4_window12_384', 'vit_base_patch4_window7_224', 'vit_base_patch4_window7_384', 'vit_base_patch8_224', 'vit_base_patch8_384', 'vit_medium_patch4_window12_384', 'vit_medium_patch4_window7_224', 'vit_medium_patch4_window7_384', 'vit_small_patch4_window12_384', 'vit_small_patch4_window7_224', 'vit_small_patch4_window7_384', 'vit_tiny_patch4_window12_384', 'vit_tiny_patch4_window7_224', 'vit_tiny_patch4_window7_384']

```

▼ View the alexnet model structure

```
[ ] alexnet = torchvision.models.alexnet(weights=None)
alexnet
```

```

AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(

```

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```
[ ] (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
[ ] (11): ReLU(inplace=True)
[ ] (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
[x] (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
(classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```

View the ConvNeXt Base model

[ConvNeXt](#) (and other pre-trained) models come in different variants (sizes). Typically, author(s) names these with a suffix like `base`, `small`, `tiny`, `large`, or `huge` to indicate their size.

```
[ ] convnext_base = torchvision.models.convnext_base(weights=None)
convnext_base
```

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```
[ ] (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
[ ] (11): ReLU(inplace=True)
[ ] (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
[x] (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
(classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```

View the ConvNeXt Base model

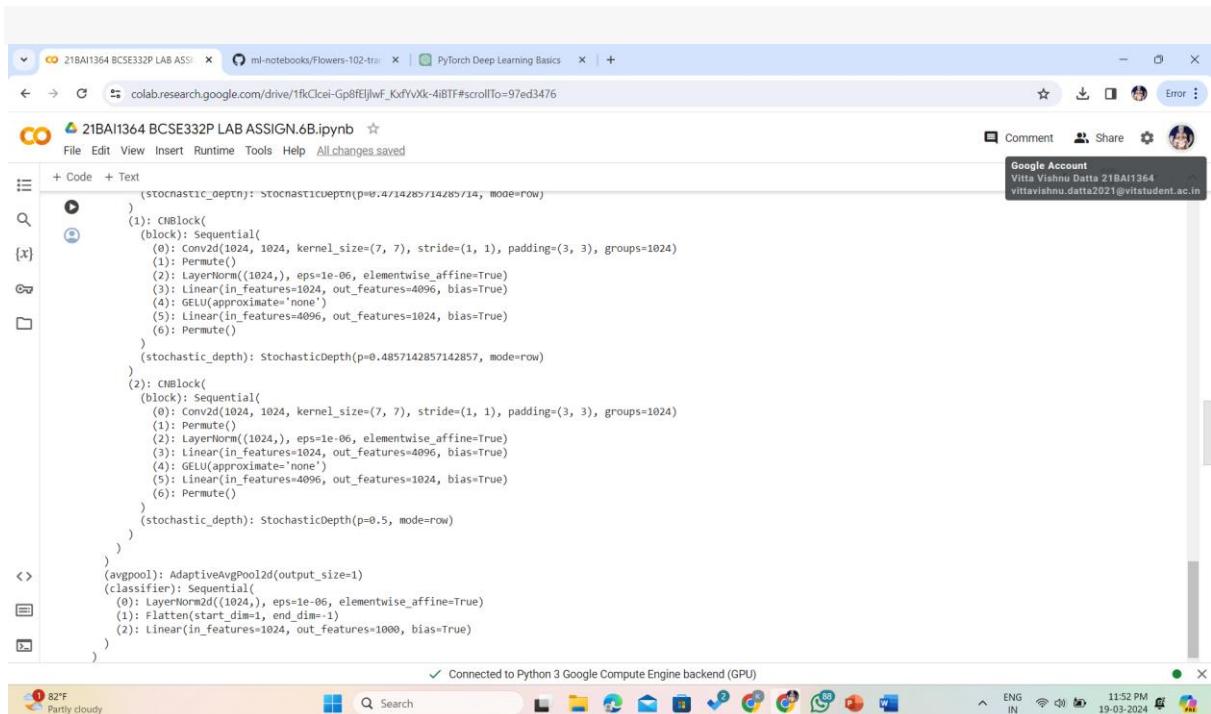
[ConvNeXt](#) (and other pre-trained) models come in different variants (sizes). Typically, author(s) names these with a suffix like `base`, `small`, `tiny`, `large`, or `huge` to indicate their size.

```
[ ] convnext_base = torchvision.models.convnext_base(weights=None)
convnext_base
```

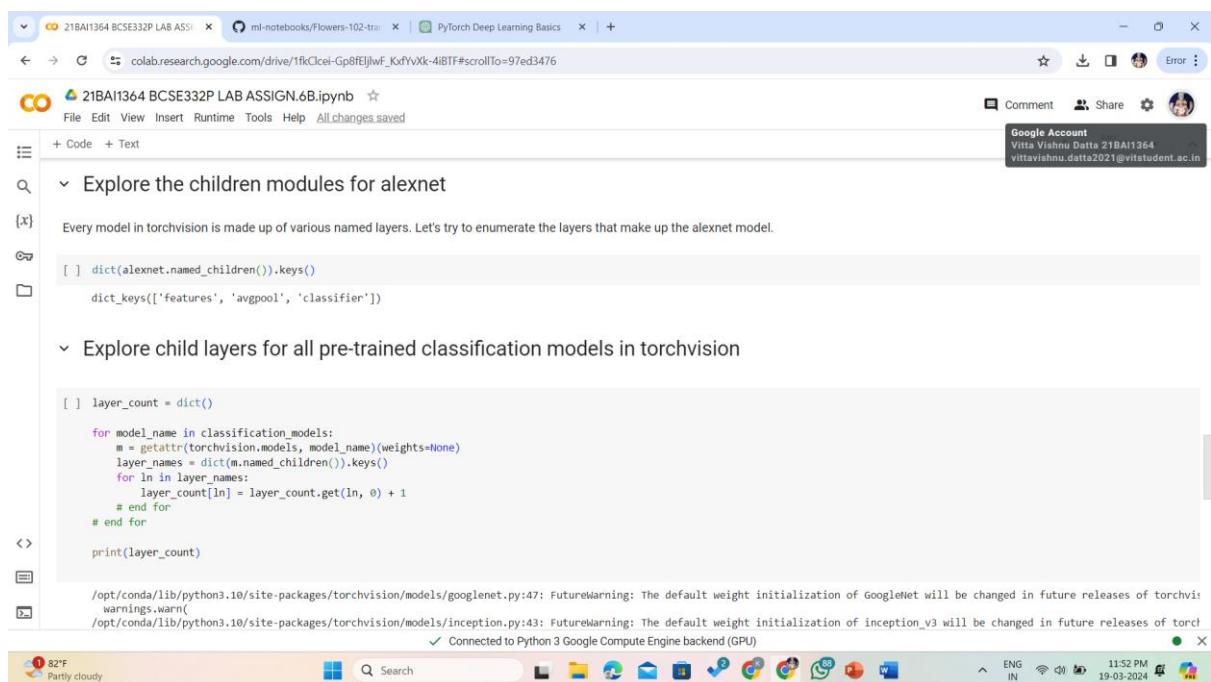
ConvNeXt(
 (features): Sequential(
 (0): Conv2dNormActivation(
 (0): Conv2d(3, 128, kernel_size=(4, 4), stride=(4, 4))
 (1): LayerNorm2d((128), eps=1e-06, elementwise_affine=True)
 (1): Sequential(
 (0): Conv2dNormActivation(
 (0): Conv2d(128, 128, kernel_size=(4, 4), stride=(4, 4))
 (1): LayerNorm2d((128), eps=1e-06, elementwise_affine=True)
 (1): Sequential(
 (0): CHBNBlock(
 (block): Sequential(
 (0): Conv2d(128, 128, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3), groups=128)
 (1): Permute()
 (2): LayerNorm((128), eps=1e-06, elementwise_affine=True)
 (3): Linear(in_features=128, out_features=512, bias=True)
 (4): GELU(approximate='none')
 (5): Linear(in_features=512, out_features=128, bias=True)
 (6): Permute()
)
 (stochastic_depth): StochasticDepth(p=0.0, mode=row)
)
 (1): CHBNBlock(
 (block): Sequential(
 (0): Conv2d(128, 128, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3), groups=128)
 (1): Permute()
)
)

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```
(stochastic_depth): StochasticDepth(p=0.4/14285/14285/14, mode=row)
)
(1): CMBlock(
    (block): Sequential(
        (0): Conv2d(1024, 1024, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3), groups=1024)
        (1): Permute()
        (2): LayerNorm((1024,), eps=1e-06, elementwise_affine=True)
        (3): Linear(in_features=1024, out_features=4096, bias=True)
        (4): GELU(approximate='none')
        (5): Linear(in_features=4096, out_features=1024, bias=True)
        (6): Permute()
    )
    (stochastic_depth): StochasticDepth(p=0.4857142857142857, mode=row)
)
(2): CMBlock(
    (block): Sequential(
        (0): Conv2d(1024, 1024, kernel_size=(7, 7), stride=(1, 1), padding=(3, 3), groups=1024)
        (1): Permute()
        (2): LayerNorm((1024,), eps=1e-06, elementwise_affine=True)
        (3): Linear(in_features=1024, out_features=4096, bias=True)
        (4): GELU(approximate='none')
        (5): Linear(in_features=4096, out_features=1024, bias=True)
        (6): Permute()
    )
    (stochastic_depth): StochasticDepth(p=0.5, mode=row)
)
)
)
(avppool): AdaptiveAvgPool2d(output_size=1)
(classifier): Sequential(
    (0): LayerNorm2d((1024,), eps=1e-06, elementwise_affine=True)
    (1): Flatten(start_dim=1, end_dim=-1)
    (2): Linear(in_features=1024, out_features=1000, bias=True)
)
)
```



```
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[ ] dict(alexnet.named_children()).keys()
dict_keys(['features', 'avgpool', 'classifier'])

[ ] layer_count = dict()
for model_name in classification_models:
    m = getattr(torchvision.models, model_name)(weights=None)
    layer_names = dict(m.named_children()).keys()
    for ln in layer_names:
        layer_count[ln] = layer_count.get(ln, 0) + 1
# end for
# end for
print(layer_count)

/opt/conda/lib/python3.10/site-packages/torchvision/models/googlenet.py:47: FutureWarning: The default weight initialization of GoogleNet will be changed in future releases of torchvis
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/torchvision/models/inception.py:43: FutureWarning: The default weight initialization of inception_v3 will be changed in future releases of torchvis
```

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Focus on classification layer for vgg16, resnet50, resnet152

[x] Since we'll be using these pre-trained models for our custom Flowers 102 classification task, let's focus on the classification heads of these models.

[x] Note that when the classification head is made up of multiple Linear layers, it's called classifier (like in VGG16), and when it's made up of a single Linear layer, it's simply called fc. If you wish to use a model from one of the 80 models above, you'll have to manually list out the layers and determine what the **classification head** for that model is and how it is structured.

```
[ ] vgg16 = torchvision.models.vgg16_bn(weights=None)
resnet50 = torchvision.models.resnet50(weights=None)
resnet152 = torchvision.models.resnet152(weights=None)
print("vgg16\n", vgg16.classifier)
print("resnet50\n", resnet50.fc)
print("resnet152\n", resnet152.fc)

vgg16
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
resnet50
Linear(in_features=2048, out_features=1000, bias=True)
resnet152
```

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Focus on classification layer for vgg16, resnet50, resnet152

[x] Since we'll be using these pre-trained models for our custom Flowers 102 classification task, let's focus on the classification heads of these models.

[x] Note that when the classification head is made up of multiple Linear layers, it's called classifier (like in VGG16), and when it's made up of a single Linear layer, it's simply called fc. If you wish to use a model from one of the 80 models above, you'll have to manually list out the layers and determine what the **classification head** for that model is and how it is structured.

```
[ ] vgg16 = torchvision.models.vgg16_bn(weights=None)
resnet50 = torchvision.models.resnet50(weights=None)
resnet152 = torchvision.models.resnet152(weights=None)
print("vgg16\n", vgg16.classifier)
print("resnet50\n", resnet50.fc)
print("resnet152\n", resnet152.fc)

vgg16
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
resnet50
Linear(in_features=2048, out_features=1000, bias=True)
resnet152
Linear(in_features=2048, out_features=1000, bias=True)
```

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Implement transfer learning with vgg16, resnet50, resnet152

Implementing Transfer Learning with VGG16

```
from tensorflow.keras.applications import VGG16

vgg_base = VGG16(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))

for layer in vgg_base.layers:
    layer.trainable = False
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Flatten, Dense

x = Flatten()(vgg_base.output)
x = Dense(256, activation='relu')(x)
predictions = Dense(num_classes, activation='softmax')(x)  #
num_classes is the number of classes in your dataset

model = Model(inputs=vgg_base.input, outputs=predictions)
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
from keras.applications import VGG16
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras import layers
from keras import models

# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) =
cifar10.load_data()

# Preprocess the data
train_images = train_images.astype('float32') / 255
test_images = test_images.astype('float32') / 255

# Convert labels to categorical
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

# Load the VGG16 network, ensuring the head FC layer sets are left off
base_model = VGG16(weights='imagenet', include_top=False,
input_shape=(32, 32, 3))

# Freeze the layers except the last 4 layers
for layer in base_model.layers[:-4]:
```

```

        layer.trainable = False

# Create the model
model = models.Sequential()

# Add the VGG16 convolutional base model
model.add(base_model)

# Add new layers
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(10, activation='softmax')) # CIFAR-10 has 10
classes

# Compile the model
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(train_images, train_labels, epochs=5, batch_size=64,
validation_data=(test_images, test_labels))

base_model.summary()

test_loss, test_acc = model.evaluate(test_images, test_labels)
print('Test accuracy:', test_acc)

```

```

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colab.research.google.com/drive/1fkClel-Gp8fIJwf_KxJYvXk-4iBT#scrollTo=y4SezpeMnrQ
File Edit View Insert Runtime Tools Help All changes saved
Comment Share Settings
+ Code + Text
Implementing Transfer Learning with VGG16
[6] from tensorflow.keras.applications import VGG16
      vgg_base = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

[7] for layer in vgg_base.layers:
      layer.trainable = False

[8] from tensorflow.keras.models import Model
      from tensorflow.keras.layers import Flatten, Dense
      x = Flatten()(vgg_base.output)
      x = Dense(256, activation='relu')(x)
      predictions = Dense(num_classes, activation='softmax')(x) # num_classes is the number of classes in your dataset
      model = Model(inputs=vgg_base.input, outputs=predictions)

[9] model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

[12] from keras.applications import VGG16
      from keras.datasets import cifar10
      from keras.utils import to_categorical
      from keras import layers
      from keras import models

```

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```
from keras.applications import VGG16
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras import layers
from keras import models

# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

# Preprocess the data
train_images = train_images.astype('float32') / 255
test_images = test_images.astype('float32') / 255

# Convert labels to categorical
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

# Load the VGG16 network, ensuring the head FC layer sets are left off
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))

# Freeze the layers except the last 4 layers
for layer in base_model.layers[:-4]:
    layer.trainable = False

# Create the model
model = models.Sequential()

# Add the VGG16 convolutional base model
model.add(base_model)

# Add new layers
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(10, activation='softmax')) # CIFAR-10 has 10 classes
```

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```
[12] # Add new layers
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(10, activation='softmax')) # CIFAR-10 has 10 classes

# Compile the model
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(train_images, train_labels, epochs=5, batch_size=64, validation_data=(test_images, test_labels))

Epoch 1/5
782/782 [=====] - 45s 53ms/step - loss: 2.3098 - accuracy: 0.0994 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 2/5
782/782 [=====] - 17s 21ms/step - loss: 2.3028 - accuracy: 0.0989 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 3/5
782/782 [=====] - 17s 22ms/step - loss: 2.3028 - accuracy: 0.0963 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 4/5
782/782 [=====] - 16s 20ms/step - loss: 2.3027 - accuracy: 0.0987 - val_loss: 2.3026 - val_accuracy: 0.1000
Epoch 5/5
782/782 [=====] - 16s 20ms/step - loss: 2.3027 - accuracy: 0.0967 - val_loss: 2.3026 - val_accuracy: 0.1000
<keras.sr.callbacks.History at 0x7e6aa37e9b0>

[14] base_model.summary()
```

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	[None, 32, 32, 3]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792

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```
[14] base_model.summary()
```

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	[None, 32, 32, 3]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808

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```
[14] base_model.summary()
```

Layer (type)	Output Shape	Param #
block3_pool (MaxPooling2D)	(None, 8, 8, 256)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0

```
Total params: 14714688 (56.13 MB)
Trainable params: 7079424 (27.01 MB)
Non-trainable params: 7635264 (29.13 MB)
```

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
print("Test accuracy:", test_acc)
```

```
313/313 [=====] - 3s 8ms/step - loss: 2.3026 - accuracy: 0.1000
Test accuracy: 0.10000000149011612
```

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Implementing Transfer Learning with ResNet50

```
from keras.applications import ResNet50
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
from keras import layers
```

```
from keras import models
from keras import optimizers

# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) =
cifar10.load_data()

# Preprocess the data
train_images = train_images.astype('float32') / 255
test_images = test_images.astype('float32') / 255

# Convert labels to categorical
train_labels = to_categorical(train_labels, 10)
test_labels = to_categorical(test_labels, 10)

# Load the ResNet152 network
base_model = ResNet152(weights='imagenet', include_top=False,
input_shape=(32, 32, 3))

# Freeze the layers of the base model
for layer in base_model.layers:
    layer.trainable = False

# Create the model
model = models.Sequential()
model.add(base_model)
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(10, activation='softmax')) # CIFAR-10 has 10
classes

# Compile the model
model.compile(optimizer=optimizers.RMSprop(lr=2e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(train_images, train_labels,
                     epochs=5,
                     batch_size=20,
                     validation_data=(test_images, test_labels))

base_model.summary()
test_loss, test_acc = model.evaluate(test_images, test_labels)
print('Test accuracy:', test_acc)
```

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```
[18] from keras.applications import ResNet152
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
from keras import layers
from keras import models
from keras import optimizers

# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

# Preprocess the data
train_images = train_images.astype('float32') / 255
test_images = test_images.astype('float32') / 255

# Convert labels to categorical
train_labels = to_categorical(train_labels, 10)
test_labels = to_categorical(test_labels, 10)

# Load the ResNet152 network
base_model = ResNet152(weights='imagenet', include_top=False, input_shape=(32, 32, 3))

# Freeze the layers of the base model
for layer in base_model.layers:
    layer.trainable = False

# Create the model
model = models.Sequential()
model.add(base_model)
model.add(layers.Flatten())
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

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```
[18] for layer in base_model.layers:
    layer.trainable = False

    # Create the model
    model = models.Sequential()
    model.add(base_model)
    model.add(layers.Flatten())
    model.add(layers.Dense(256, activation='relu'))
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    # Compile the model
    model.compile(optimizer=optimizers.RMSprop(lr=2e-5),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

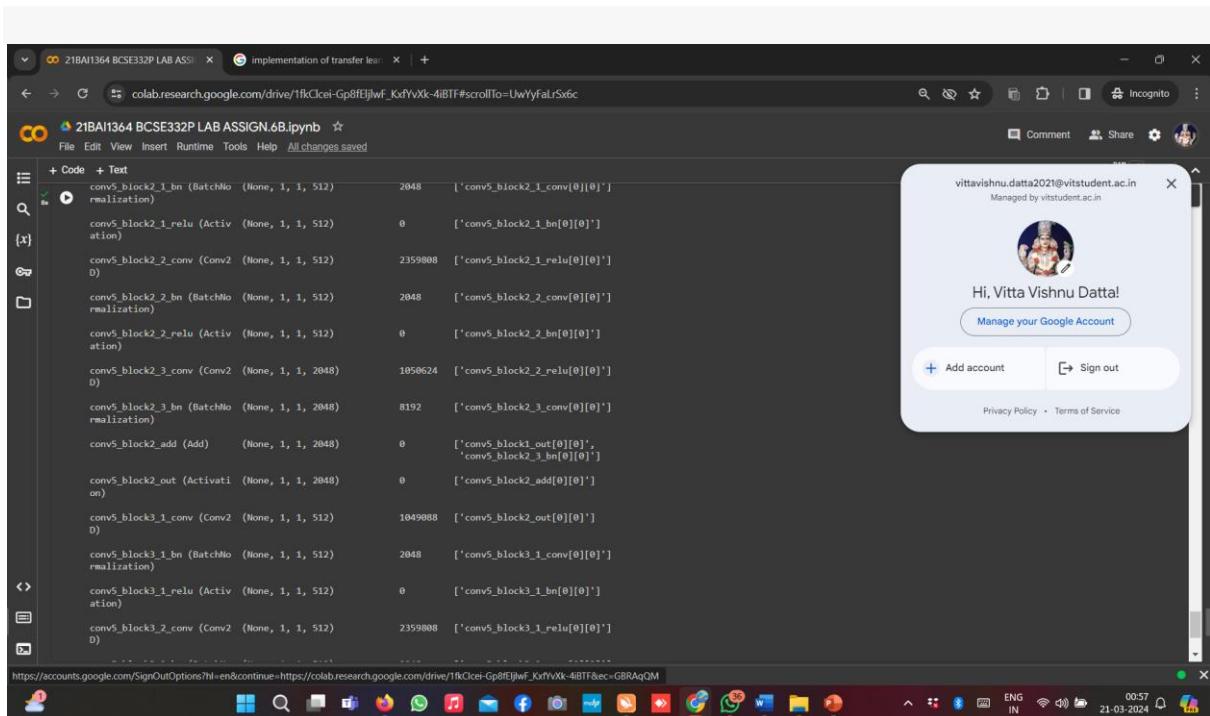
    # Train the model
    history = model.fit(train_images, train_labels,
                        epochs=5,
                        batch_size=20,
                        validation_data=(test_images, test_labels))

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet152_weights_tf_dim_ordering_tf_kernels_notop.h5
234698864 [=====] - 6s 0us/step
WARNING:absl: 'lr' is deprecated in Keras optimizer, please use 'learning_rate' or use the legacy optimizer, e.g., tf.keras.optimizers.legacy.RMSprop.
Epoch 1/5
2500/2500 [=====] - 92s 32ms/step - loss: 2.2446 - accuracy: 0.1514 - val_loss: 2.1579 - val_accuracy: 0.2271
Epoch 2/5
2500/2500 [=====] - 85s 30ms/step - loss: 2.1761 - accuracy: 0.1896 - val_loss: 2.0999 - val_accuracy: 0.2272
Epoch 3/5
2500/2500 [=====] - 82s 33ms/step - loss: 2.1498 - accuracy: 0.2032 - val_loss: 2.0821 - val_accuracy: 0.2413
Epoch 4/5
2500/2500 [=====] - 72s 29ms/step - loss: 2.1356 - accuracy: 0.2096 - val_loss: 2.0682 - val_accuracy: 0.2316
Epoch 5/5
2500/2500 [=====] - 81s 33ms/step - loss: 2.1274 - accuracy: 0.2146 - val_loss: 2.0675 - val_accuracy: 0.2515
```

13s completed at 12:49 AM

```
[19] base_model.summary()
    conv4_block36_2_relu (Activ (None, 2, 2, 2048)
                           activation)
    conv4_block36_3_conv (Conv (None, 2, 2, 1024)
                           2048)
    conv4_block36_3_bn (BatchN (None, 2, 2, 1024)
                           4096)
    conv4_block36_3_add (Add (None, 2, 2, 1024)
                           0)
    conv4_block36_out (Activat (None, 2, 2, 1024)
                           ion)
    conv5_block1_1_conv (Conv2 (None, 1, 1, 512)
                           524800)
    conv5_block1_1_bn (BatchMo (None, 1, 1, 512)
                           rmalization)
    conv5_block1_1_relu (Activ (None, 1, 1, 512)
                           ation)
    conv5_block1_2_conv (Conv2 (None, 1, 1, 512)
                           2359808)
    conv5_block1_2_bn (BatchMo (None, 1, 1, 512)
                           rmalization)
    conv5_block1_2_relu (Activ (None, 1, 1, 512)
                           ation)
    conv5_block1_0_conv (Conv2 (None, 1, 1, 2048)
                           2099200)
```

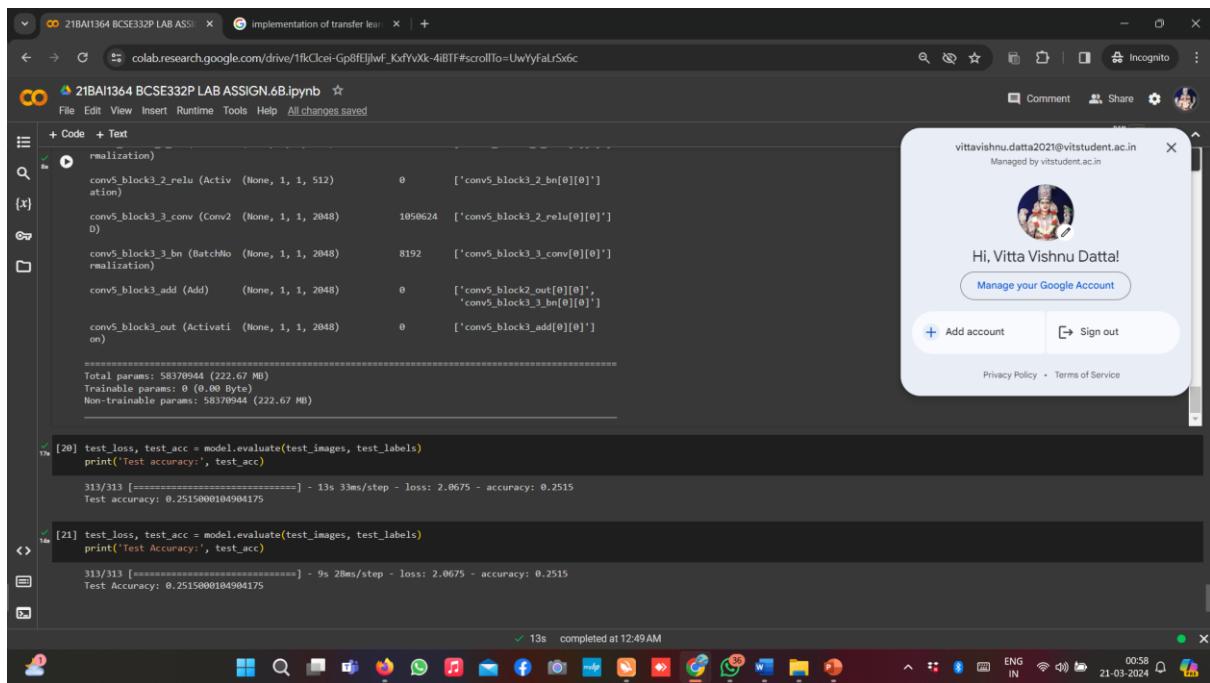
```
[19] base_model.summary()
    conv5_block2_3_conv (Conv2 (None, 1, 1, 512)
                           1049088)
    conv5_block2_1_bn (BatchMo (None, 1, 1, 512)
                           2048)
    conv5_block2_1_relu (Activ (None, 1, 1, 512)
                           ation)
    conv5_block2_2_conv (Conv2 (None, 1, 1, 512)
                           2359808)
    conv5_block2_2_bn (BatchMo (None, 1, 1, 512)
                           rmalization)
    conv5_block2_2_relu (Activ (None, 1, 1, 512)
                           ation)
    conv5_block2_3_conv (Conv2 (None, 1, 1, 2048)
                           1050624)
    conv5_block2_3_bn (BatchMo (None, 1, 1, 2048)
                           8192)
    conv5_block2_add (Add (None, 1, 1, 2048)
                           0)
    conv5_block2_out (Activati (None, 1, 1, 2048)
                           on)
    conv5_block3_1_conv (Conv2 (None, 1, 1, 512)
                           1049088)
    conv5_block3_1_bn (BatchMo (None, 1, 1, 512)
                           rmalization)
```



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```
File Edit View Insert Runtime Tools Help All changes saved
+ Code + Text
conv5.block2_1_bn (BatchNorm2d (None, 1, 1, 512) 2048 ['conv5.block2_1_conv[0][0]'])
conv5.block2_1_relu (Activation (None, 1, 1, 512) 0 ['conv5.block2_1_bn[0][0]'])
conv5.block2_2_conv (Conv2d (None, 1, 1, 512) 2359808 ['conv5.block2_2_conv[0][0]'])
conv5.block2_2_bn (BatchNorm2d (None, 1, 1, 512) 2048 ['conv5.block2_2_conv[0][0]'])
conv5.block2_2_relu (Activation (None, 1, 1, 512) 0 ['conv5.block2_2_bn[0][0]'])
conv5.block2_3_conv (Conv2d (None, 1, 1, 2048) 1050624 ['conv5.block2_2_relu[0][0]'])
conv5.block2_3_bn (BatchNorm2d (None, 1, 1, 2048) 8192 ['conv5.block2_3_conv[0][0]'])
conv5.block2_3_add (Add) (None, 1, 1, 2048) 0 ['conv5.block1_out[0][0]', 'conv5.block2_3_bn[0][0]']
conv5.block2_out (Activation (None, 1, 1, 2048) 0 ['conv5.block2_add[0][0]'])
conv5.block3_1_conv (Conv2d (None, 1, 1, 512) 1049088 ['conv5.block2_out[0][0]'])
conv5.block3_1_bn (BatchNorm2d (None, 1, 1, 512) 2048 ['conv5.block3_1_conv[0][0]'])
conv5.block3_1_relu (Activation (None, 1, 1, 512) 0 ['conv5.block3_1_bn[0][0]'])
conv5.block3_2_conv (Conv2d (None, 1, 1, 512) 2359808 ['conv5.block3_1_relu[0][0]'])

https://accounts.google.com/SignOutOptions?hl=en&continue=https://colab.research.google.com/drive/1fkClei-Gp8fEjlwf_KxfYvXk-4lBT#scrollTo=UwYyfaLrSx6c
```



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```
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conv5.block3_2_bn (BatchNorm2d (None, 1, 1, 512) 0 ['conv5.block3_2_relu[0][0]'])
conv5.block3_3_conv (Conv2d (None, 1, 1, 2048) 1050624 ['conv5.block3_2_relu[0][0]'])
conv5.block3_3_bn (BatchNorm2d (None, 1, 1, 2048) 8192 ['conv5.block3_3_conv[0][0]'])
conv5.block3_3_add (Add) (None, 1, 1, 2048) 0 ['conv5.block2_out[0][0]', 'conv5.block3_3_bn[0][0]']
conv5.block3_out (Activation (None, 1, 1, 2048) 0 ['conv5.block3_add[0][0]'])

=====
Total params: 58370944 (222.67 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 58370944 (222.67 MB)

[20]: test_loss, test_acc = model.evaluate(test_images, test_labels)
print('Test accuracy:', test_acc)
313/313 [=====] - 1s 33ms/step - loss: 2.0675 - accuracy: 0.2515
Test accuracy: 0.2515000104904175

[21]: test_loss, test_acc = model.evaluate(test_images, test_labels)
print('Test Accuracy:', test_acc)
313/313 [=====] - 9s 28ms/step - loss: 2.0675 - accuracy: 0.2515
Test Accuracy: 0.2515000104904175
```

*****THANK YOU*****