

Neckline Classifier

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Problem

- In online shopping, large fashion datasets or e-commerce platforms manually tagging and classifying each clothing can be **a time-consuming task**. Since consumers will have preferences in the neckline styles.
- For marketers and designers, **analyzing the fashion trends** and consumer preferences is an important detail. Also, manufacturers will need **the market demands to produce clothing**.



Solution

- We will build a model using a **labeled dataset** to classify clothing items based on their neckline styles. In the process of creating this model, we will employ various architectures and follow a comparative approach to reach a conclusion. By the end of the project, **we will have categorized the photos as round, V-neck, and scoop neck styles.**



Dataset

The dataset has been obtained from the Kaggle website. The data contains three types of necklines in clothing.

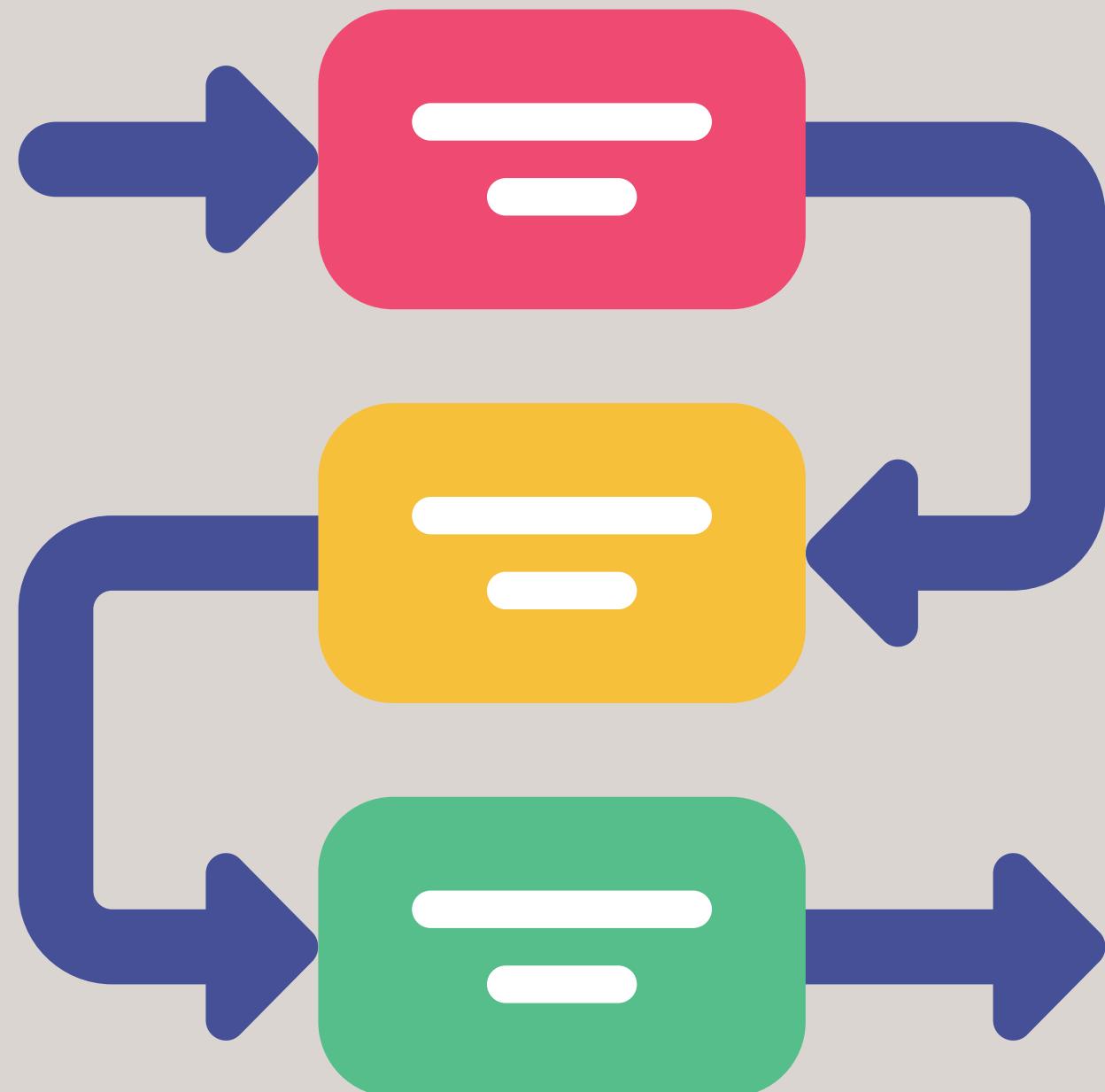
The dataset contains **flatlay images (images without human models) of upper/full body clothes**. We are required to classify if the cloth's region around the neck falls under one of these three categories i.e. **round, scoop or v-neck**.

The following image gives **an understanding of the three different types of necklines mentioned above**.



Methodology

1. Data Collection
2. Deciding libraries we will use
3. Reviewing Architectures
4. Model Setup



Data Collection

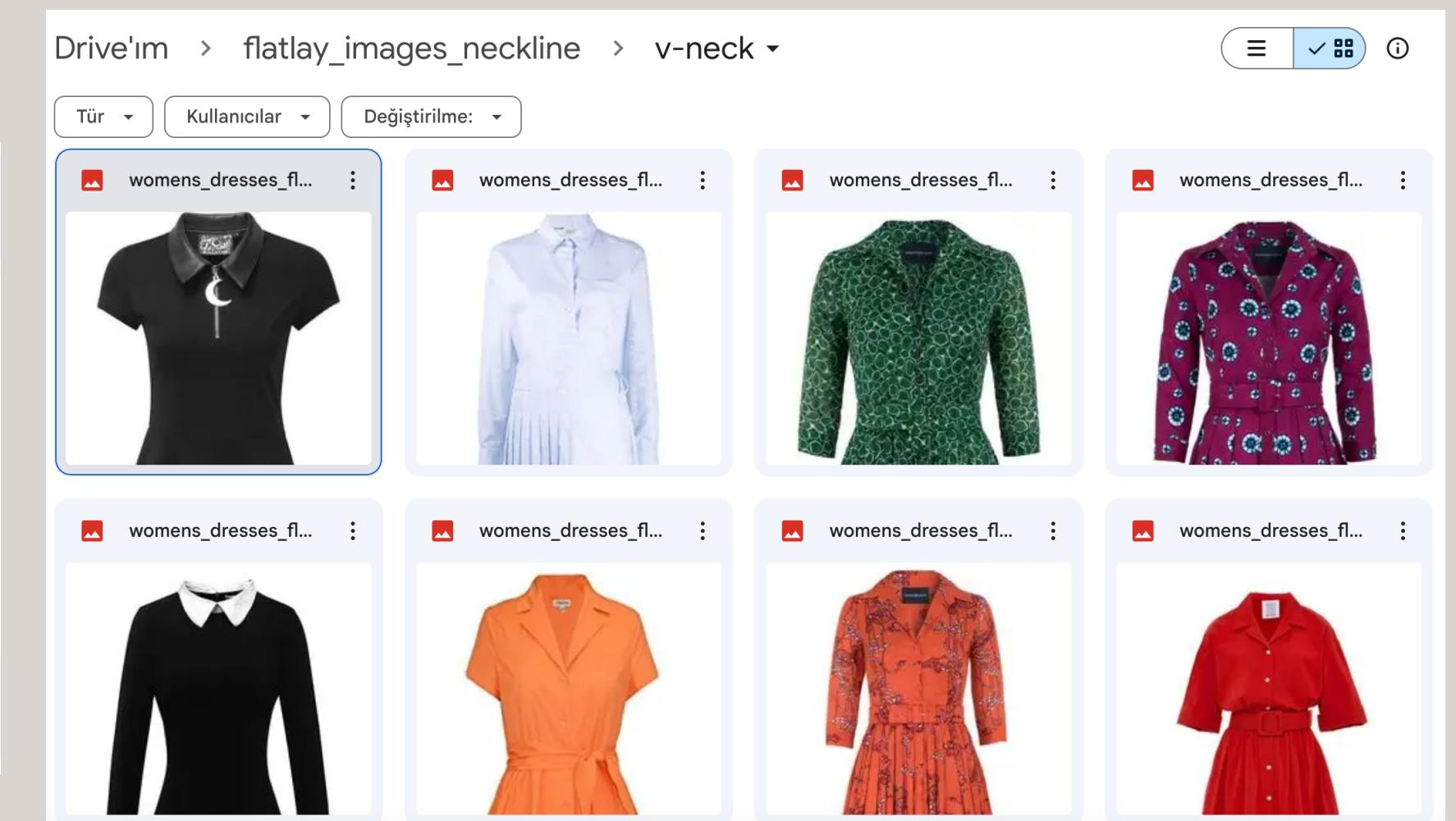
Drive'da arayın

Drive'ım > flatlay_images_neckline

Tür Kullanıcılar Değiştirilme:

Klasörler

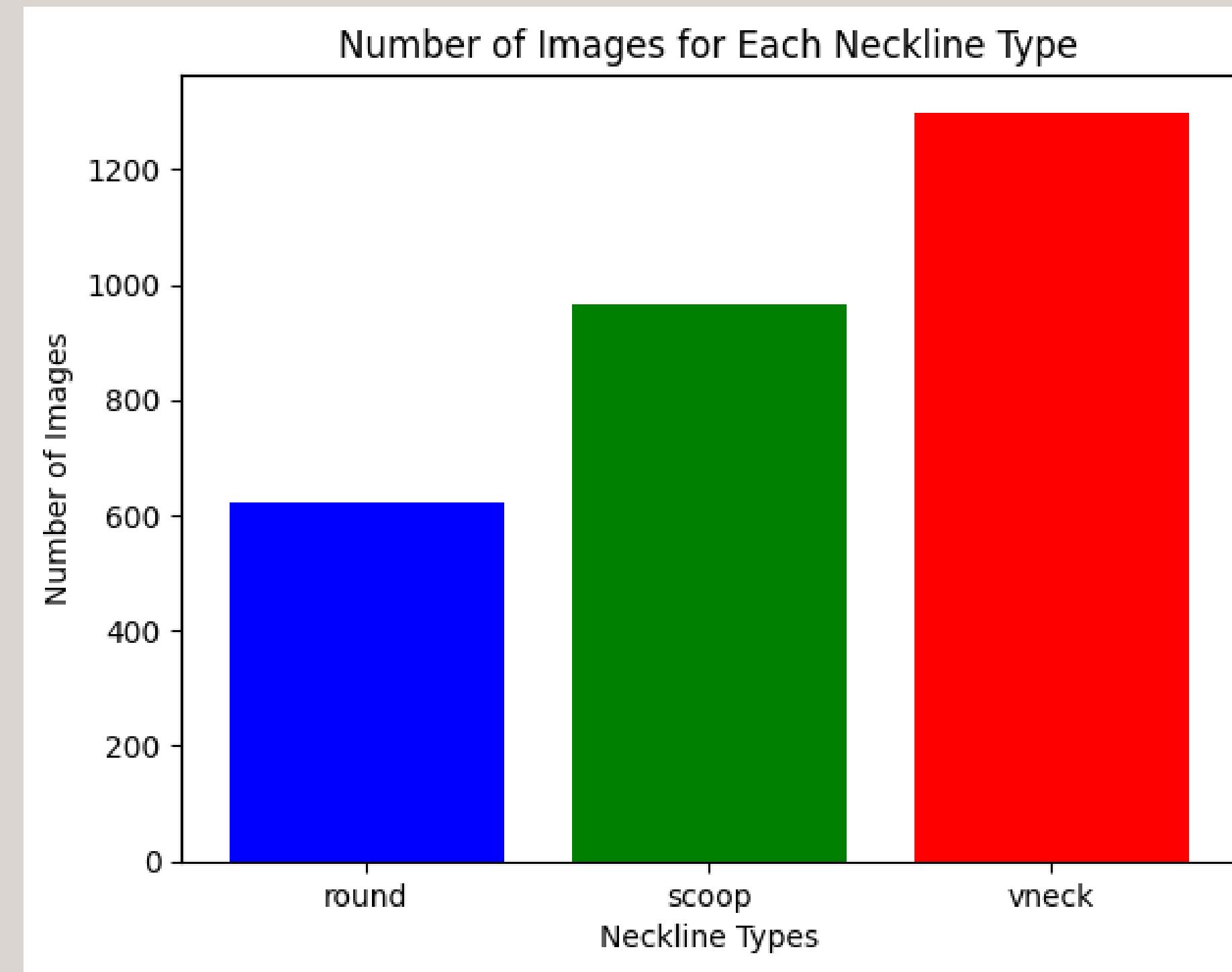
- v-neck
- scoop



```
[ ] from google.colab import drive  
drive.mount('/content/drive')
```

Mounted at /content/drive

Visualization

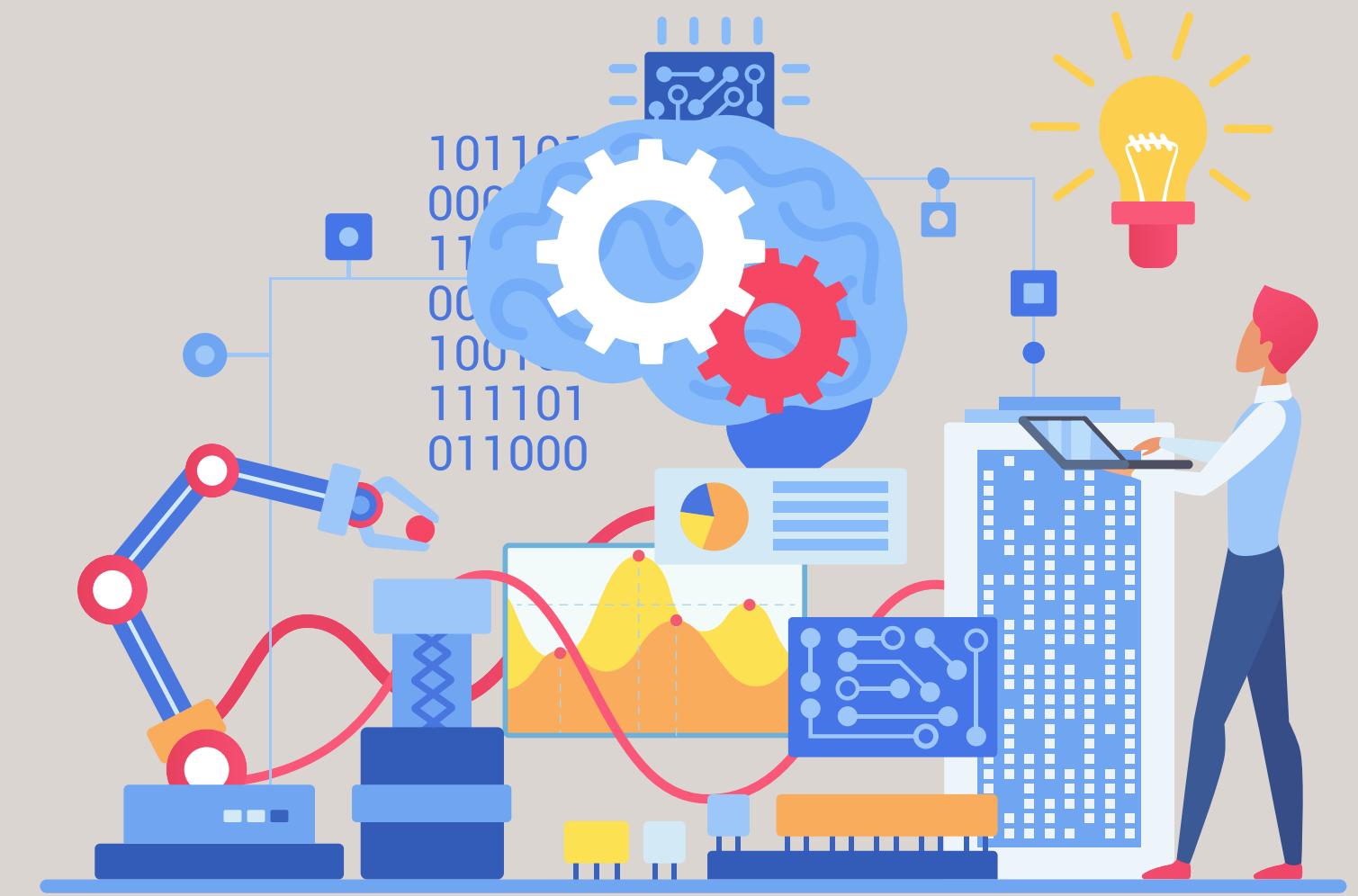


Importing Libraries

```
[ ] import numpy as np
import pandas as pd
import cv2
from google.colab.patches import cv2_imshow
from skimage import io
from PIL import Image
import matplotlib.pyplot as plt
import os
from os.path import isfile, join
from os import listdir
```

Reviewing Architectures

1. VGG16
2. ResNet
3. Mobilenet



1. VGG16

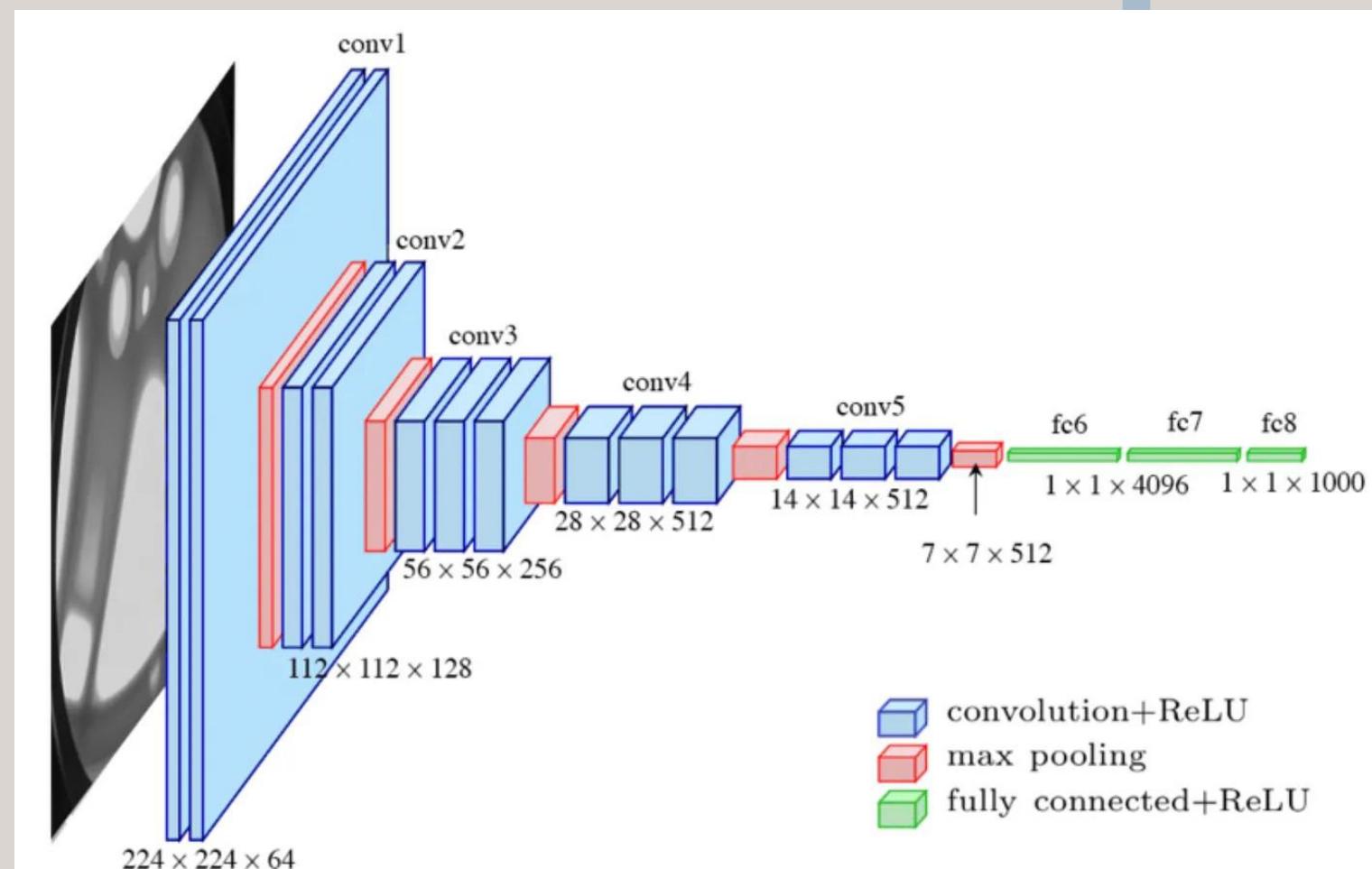


- VGG is a deep convolutional neural network that was proposed by Karen Simonyan and Andrew Zisserman.
- The VGG model investigates the depth of layers with a very small convolutional filter size (3×3) to deal with large-scale images.

1. VGG16

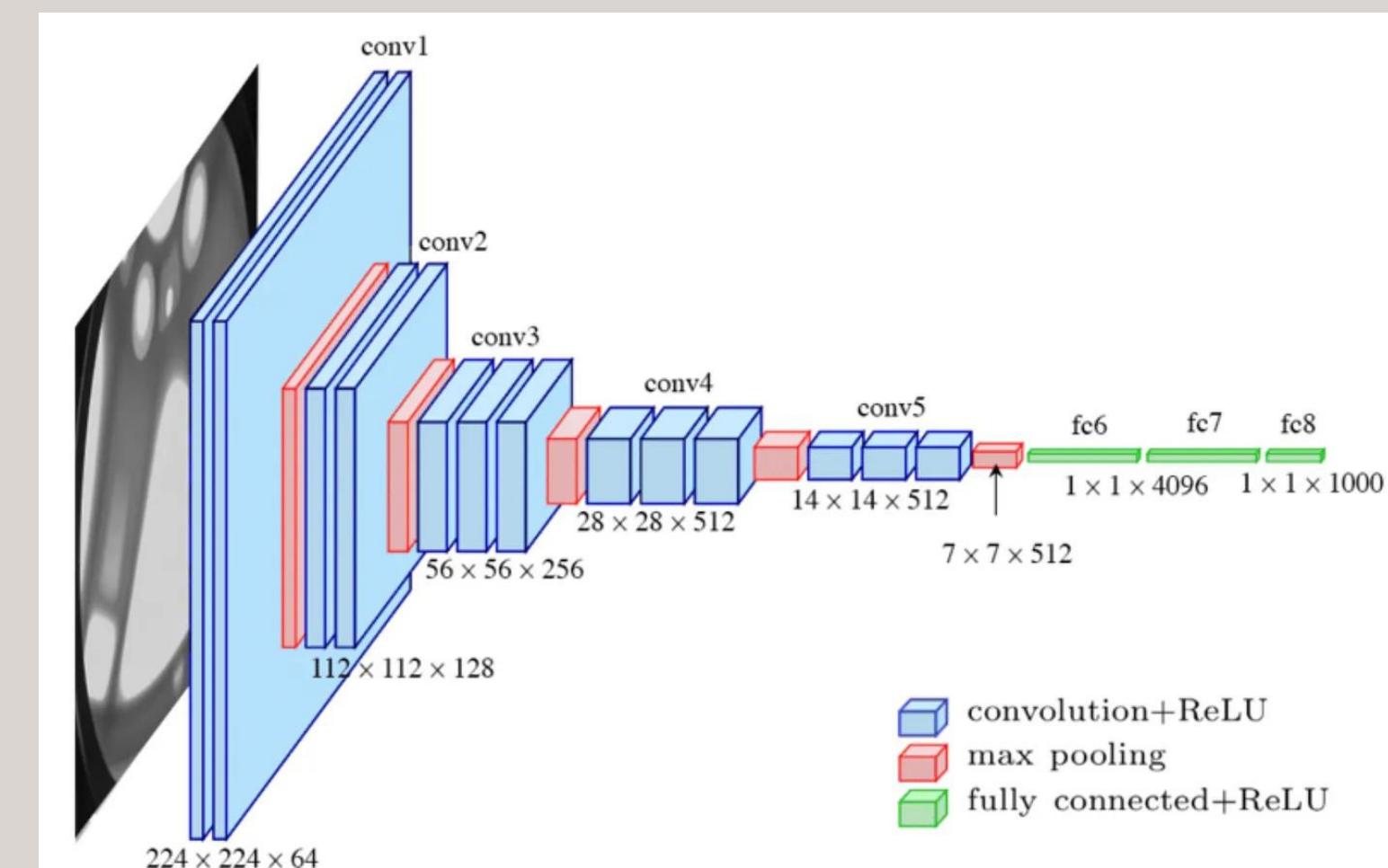
VGG16 is composed of

- **13 convolutional layers,**
- **5 max-pooling layers,**
- **3 fully connected layers.**
- The number of layers having **tunable parameters is 16** (13 convolutional layers and 3 fully connected layers).



1. VGG16

- The number of filters **in the first block is 64**, then this number **is doubled in the later blocks until it reaches 512**.
- This model is finished by two fully connected hidden layers and one output layer. The two fully connected layers have **the same neuron numbers which are 4096**.
- **The output layer consists of 1000 neurons** corresponding to the number of categories of the Imagenet dataset.



```
▶ model.summary()
```

```
● Model: "model"
```

| Layer (type) | Output Shape | Param # |
|---|-----------------------|---------|
| <hr/> | | |
| input_2 (InputLayer) | [(None, 224, 224, 3)] | 0 |
| block1_conv1 (Conv2D) | (None, 224, 224, 64) | 1792 |
| block1_conv2 (Conv2D) | (None, 224, 224, 64) | 36928 |
| block1_pool (MaxPooling2D) | (None, 112, 112, 64) | 0 |
| block2_conv1 (Conv2D) | (None, 112, 112, 128) | 73856 |
| block2_conv2 (Conv2D) | (None, 112, 112, 128) | 147584 |
| block2_pool (MaxPooling2D) | (None, 56, 56, 128) | 0 |
| block3_conv1 (Conv2D) | (None, 56, 56, 256) | 295168 |
| block3_conv2 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_conv3 (Conv2D) | (None, 56, 56, 256) | 590080 |
| block3_pool (MaxPooling2D) | (None, 28, 28, 256) | 0 |
| block4_conv1 (Conv2D) | (None, 28, 28, 512) | 1180160 |
| block4_conv2 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_conv3 (Conv2D) | (None, 28, 28, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (None, 14, 14, 512) | 0 |
| block5_conv1 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv2 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_conv3 (Conv2D) | (None, 14, 14, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (None, 7, 7, 512) | 0 |
| flatten (Flatten) | (None, 25088) | 0 |
| dense (Dense) | (None, 3) | 75267 |
| <hr/> | | |
| Total params: 14789955 (56.42 MB) | | |
| Trainable params: 75267 (294.01 KB) | | |
| Non-trainable params: 14714688 (56.13 MB) | | |

Model Setup

- VGG16

▼ VGG16 Model

```
[ ] from keras.models import Model
from keras.layers import Flatten, Dense
from keras.applications import VGG16

IMAGE_SIZE = [224, 224]

vgg = VGG16(input_shape = IMAGE_SIZE + [3], weights = 'imagenet', include_top = False)

for layer in vgg.layers:
    layer.trainable = False

x = Flatten()(vgg.output)

x = Dense(3, activation = 'softmax')(x)

model = Model(inputs = vgg.input, outputs = x)

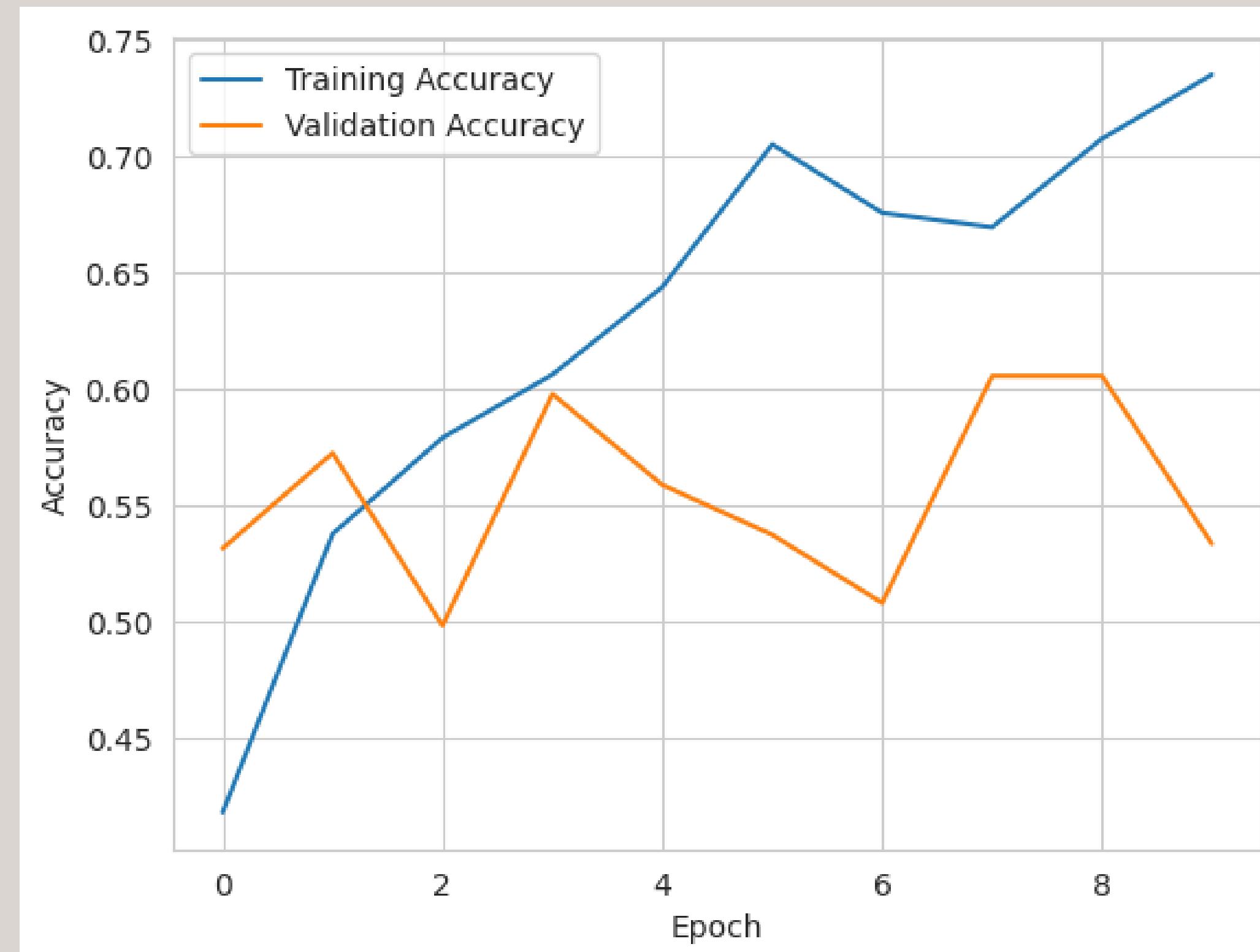
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Model Setup

- VGG16

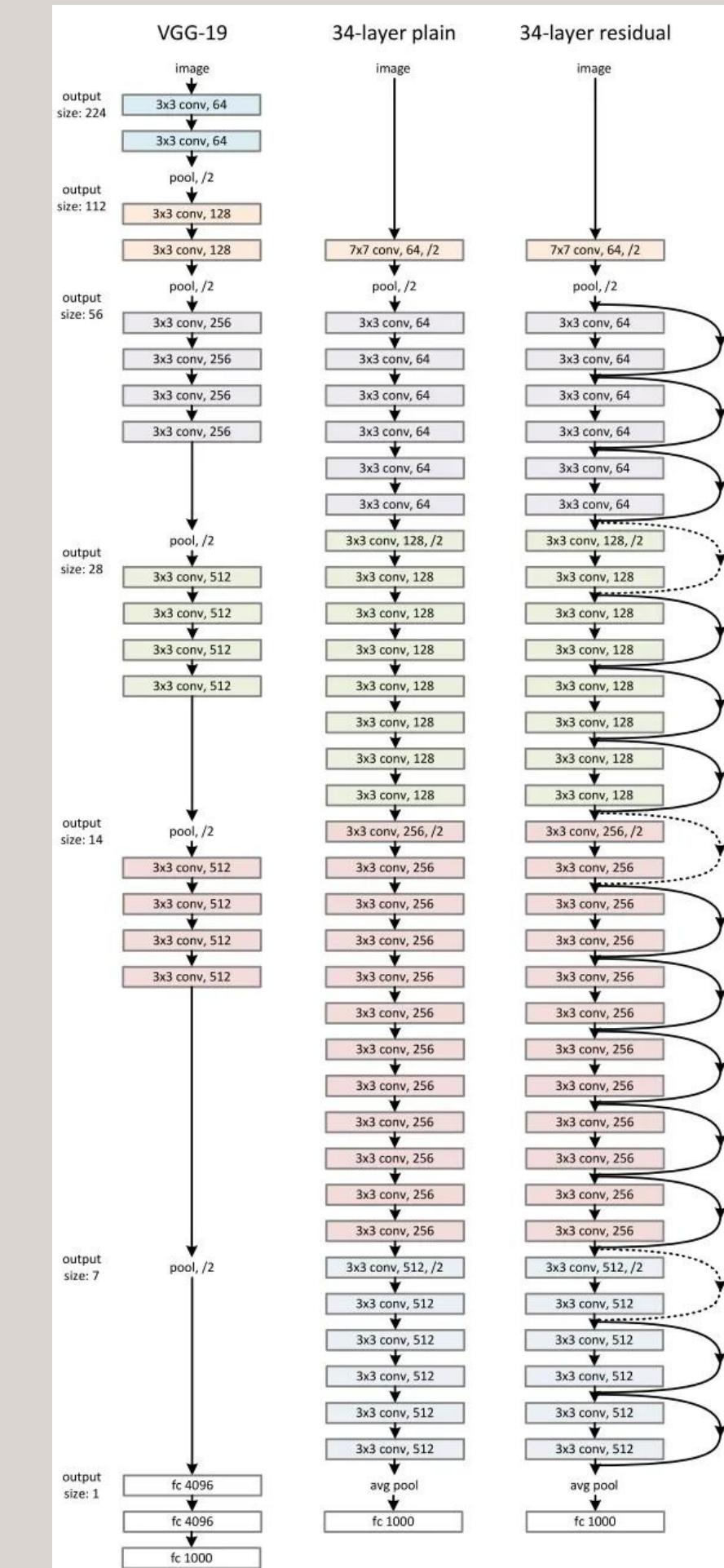
```
⌚ <ipython-input-7-bfe12322dac2>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use
      history = model.fit_generator(training_generator,
Epoch 1/10
20/20 [=====] - 319s 15s/step - loss: 1.5331 - accuracy: 0.4177 - val_loss: 1.0582 - val_accuracy: 0.5312
Epoch 2/10
20/20 [=====] - 108s 5s/step - loss: 0.9657 - accuracy: 0.5375 - val_loss: 0.9058 - val_accuracy: 0.5723
Epoch 3/10
20/20 [=====] - 54s 3s/step - loss: 0.8930 - accuracy: 0.5789 - val_loss: 1.0563 - val_accuracy: 0.4980
Epoch 4/10
20/20 [=====] - 36s 2s/step - loss: 0.9091 - accuracy: 0.6061 - val_loss: 0.8805 - val_accuracy: 0.5977
Epoch 5/10
20/20 [=====] - 32s 2s/step - loss: 0.7817 - accuracy: 0.6437 - val_loss: 0.9527 - val_accuracy: 0.5586
Epoch 6/10
20/20 [=====] - 31s 2s/step - loss: 0.7005 - accuracy: 0.7052 - val_loss: 0.9837 - val_accuracy: 0.5371
Epoch 7/10
20/20 [=====] - 27s 1s/step - loss: 0.7446 - accuracy: 0.6757 - val_loss: 1.1000 - val_accuracy: 0.5078
Epoch 8/10
20/20 [=====] - 28s 1s/step - loss: 0.7382 - accuracy: 0.6695 - val_loss: 0.8845 - val_accuracy: 0.6055
Epoch 9/10
20/20 [=====] - 28s 1s/step - loss: 0.6726 - accuracy: 0.7076 - val_loss: 0.9102 - val_accuracy: 0.6055
Epoch 10/10
20/20 [=====] - 29s 1s/step - loss: 0.6114 - accuracy: 0.7352 - val_loss: 1.1217 - val_accuracy: 0.5332
```

Validation Train Graph



1. ResNet

- The fundamental feature of ResNet is the inclusion of a connection type known as "residual learning" or "skip connection." These connections directly add the input from the previous layer to the next layer. As a result, it prevents information loss in deeper layers of the network, making training easier.



Model Setup

- ResNet

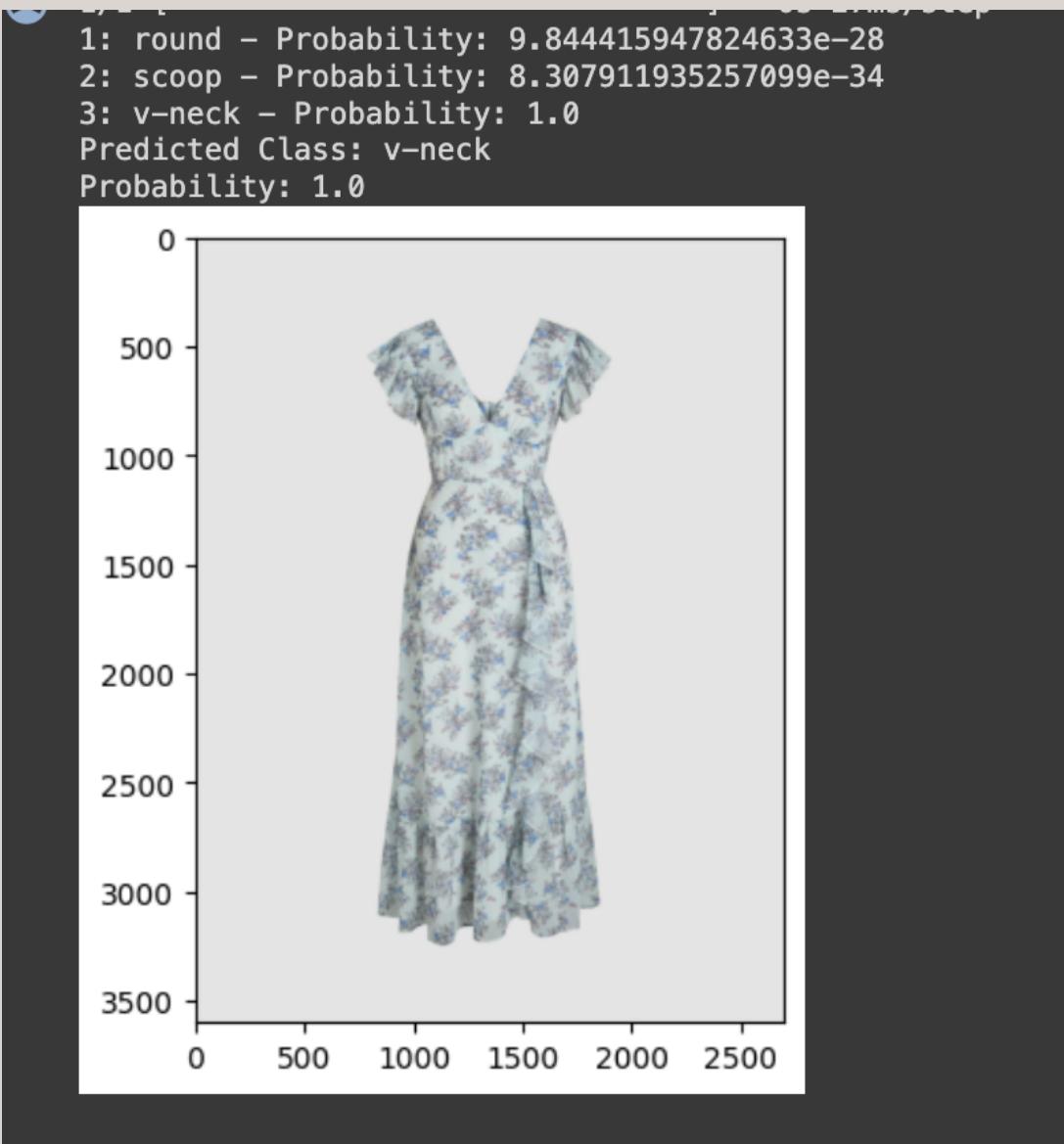
```
▶ history = model.fit_generator(  
    training_generator,  
    epochs= 10,  
    validation_data = validation_generator,  
    validation_steps = 10,  
    steps_per_epoch = 20,  
    class_weight=class_weights)  
  
❸ <ipython-input-40-16d0f521c88d>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit` instead.  
  history = model.fit_generator(  
Epoch 1/10  
20/20 [=====] - ETA: 0s - loss: 1.4623 - accuracy: 0.3333WARNING:tensorflow:Your input ran out of data;  
20/20 [=====] - 36s 1s/step - loss: 1.4623 - accuracy: 0.3333 - val_loss: 1.2498 - val_accuracy: 0.3351  
Epoch 2/10  
20/20 [=====] - 26s 1s/step - loss: 1.2389 - accuracy: 0.3195  
Epoch 3/10  
20/20 [=====] - 22s 1s/step - loss: 1.1272 - accuracy: 0.3187  
Epoch 4/10  
20/20 [=====] - 24s 1s/step - loss: 1.1183 - accuracy: 0.3516  
Epoch 5/10  
20/20 [=====] - 22s 1s/step - loss: 1.0985 - accuracy: 0.3719  
Epoch 6/10  
20/20 [=====] - 22s 1s/step - loss: 1.1039 - accuracy: 0.3742  
Epoch 7/10  
20/20 [=====] - 22s 1s/step - loss: 1.1022 - accuracy: 0.3079  
Epoch 8/10  
20/20 [=====] - 21s 1s/step - loss: 1.1053 - accuracy: 0.3915  
Epoch 9/10  
20/20 [=====] - 21s 1s/step - loss: 1.0918 - accuracy: 0.3805  
Epoch 10/10  
20/20 [=====] - 21s 1s/step - loss: 1.0867 - accuracy: 0.3867
```

1. MobileNet

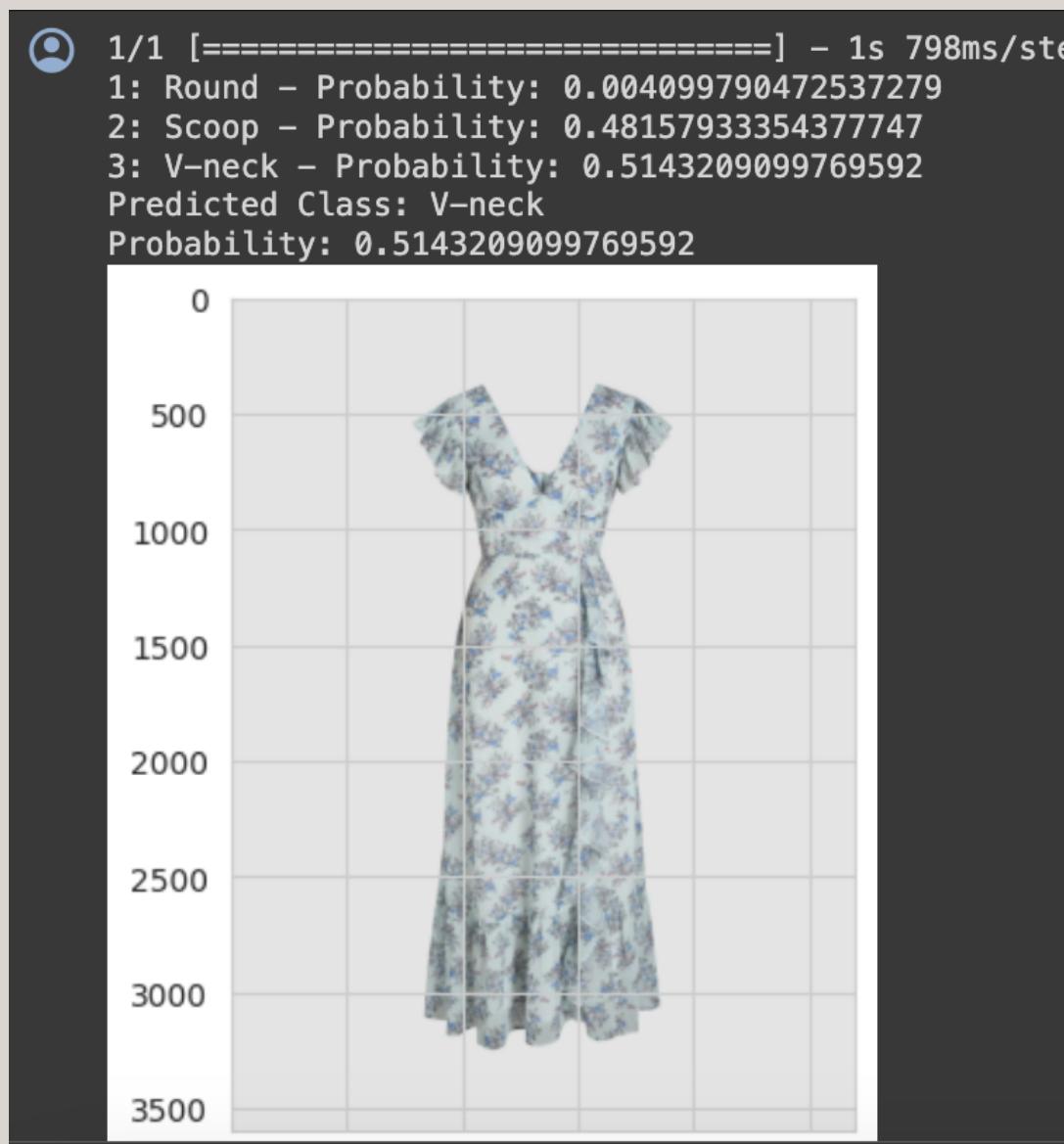
```
▶ history33 = model_mb.fit(training_generator, epochs=10)

❷ Epoch 1/10
73/73 [=====] - 42s 564ms/step - loss: 0.5369 - accuracy: 0.7713
Epoch 2/10
73/73 [=====] - 43s 582ms/step - loss: 0.5129 - accuracy: 0.7839
Epoch 3/10
73/73 [=====] - 40s 545ms/step - loss: 0.4715 - accuracy: 0.8103
Epoch 4/10
73/73 [=====] - 39s 536ms/step - loss: 0.4405 - accuracy: 0.8203
Epoch 5/10
73/73 [=====] - 41s 556ms/step - loss: 0.3992 - accuracy: 0.8372
Epoch 6/10
73/73 [=====] - 39s 540ms/step - loss: 0.3906 - accuracy: 0.8333
Epoch 7/10
73/73 [=====] - 43s 590ms/step - loss: 0.3870 - accuracy: 0.8432
Epoch 8/10
73/73 [=====] - 40s 545ms/step - loss: 0.3770 - accuracy: 0.8445
Epoch 9/10
73/73 [=====] - 41s 555ms/step - loss: 0.3560 - accuracy: 0.8528
Epoch 10/10
73/73 [=====] - 39s 533ms/step - loss: 0.3193 - accuracy: 0.8748
```

VGG16



MobileNet



ResNet

