Neckline Classifier

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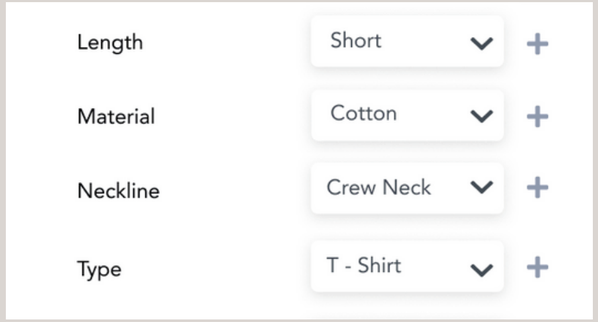
Problem



- In online shopping, large fashion datasets or e-commerce platforms manually tagging and classifiying 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, manufacterers 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

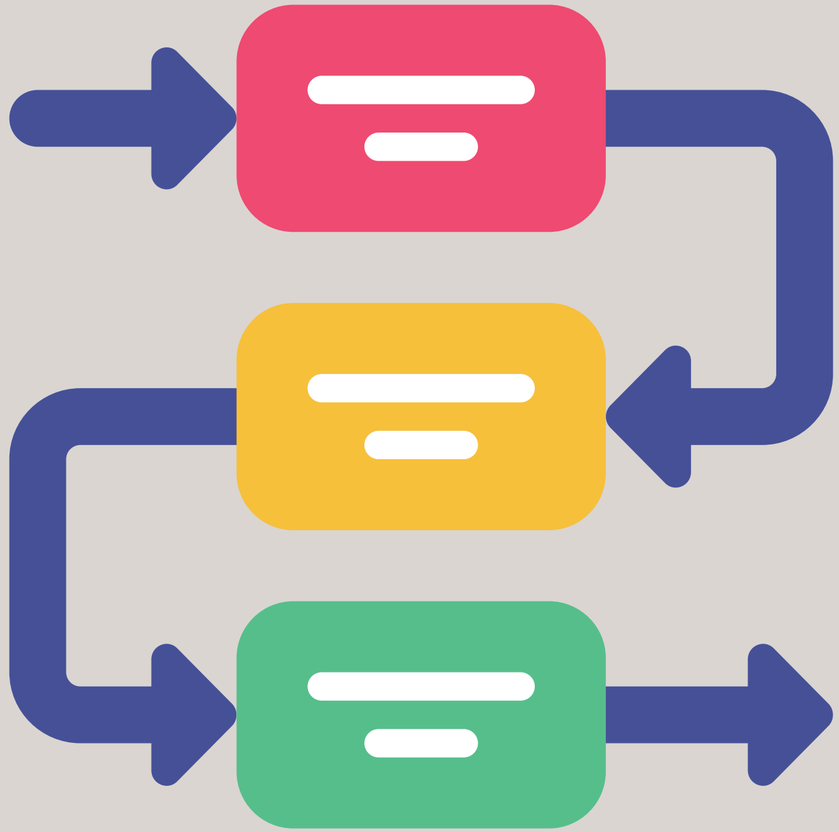
The dataset has been obtained from the Kaggle website. The data contains three types of necklines in clothing.

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.**

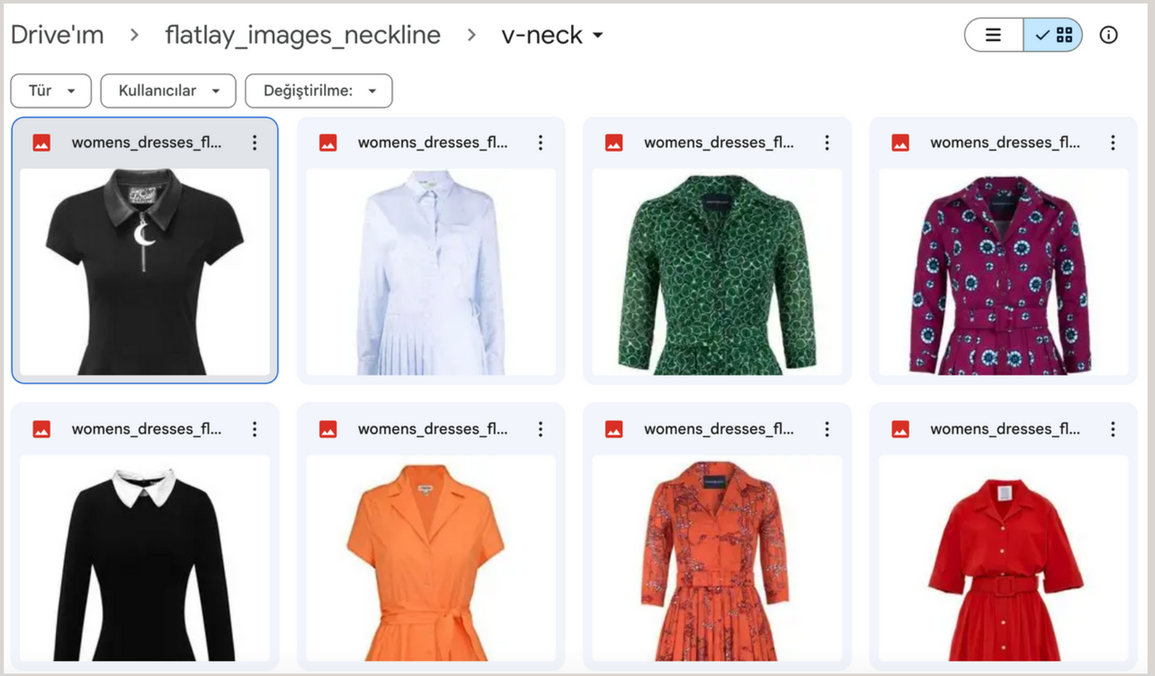
Methodology

1. **Data Collection**
2. **Data Balancing**
3. **Reviewing Architectures**
4. **Model Setup**



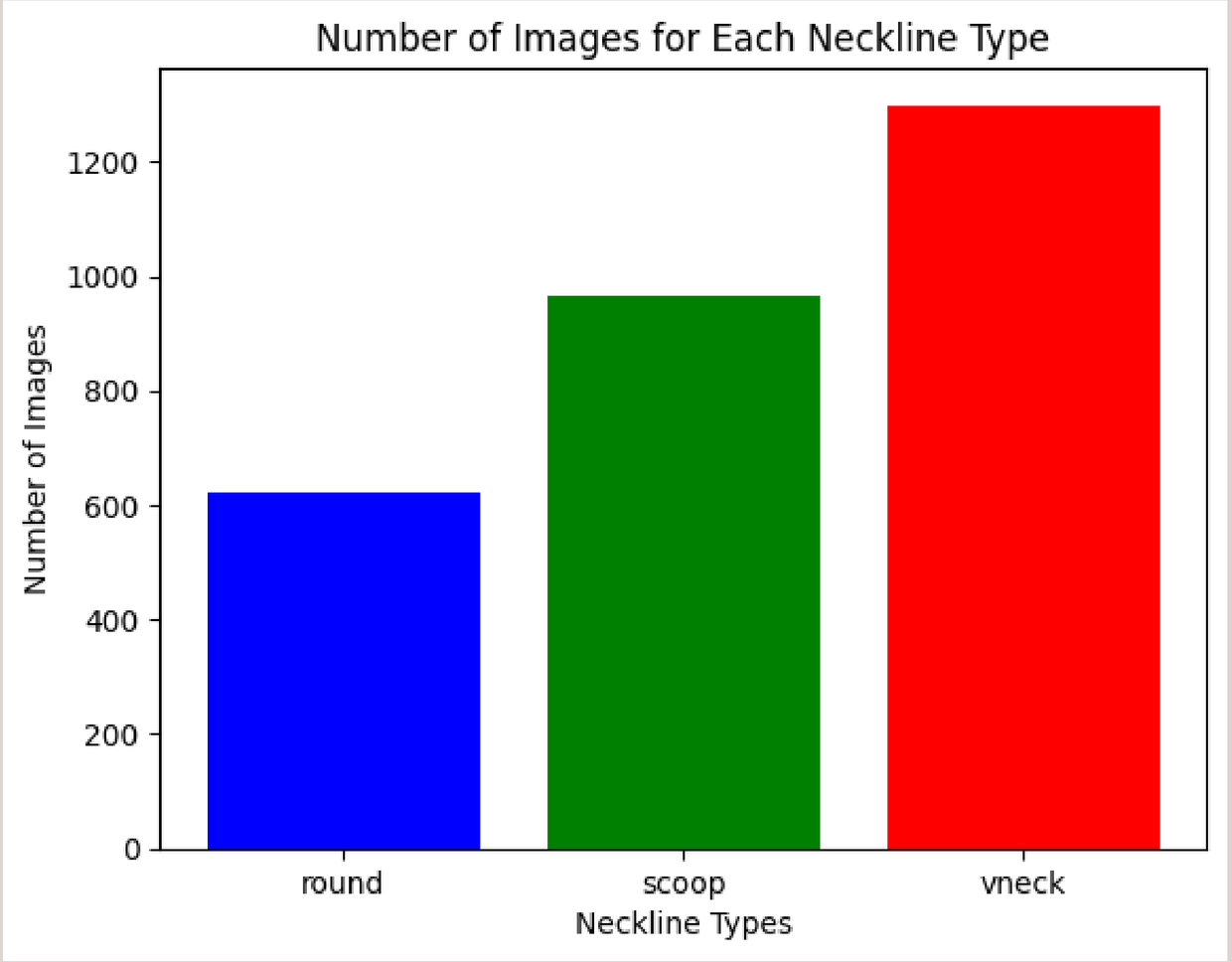
Data Collection


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

     Mounted at /content/drive
```



Visualization of Dataset

Visualization of “Unbalanced Data”



Round = 621

Scoup = 966

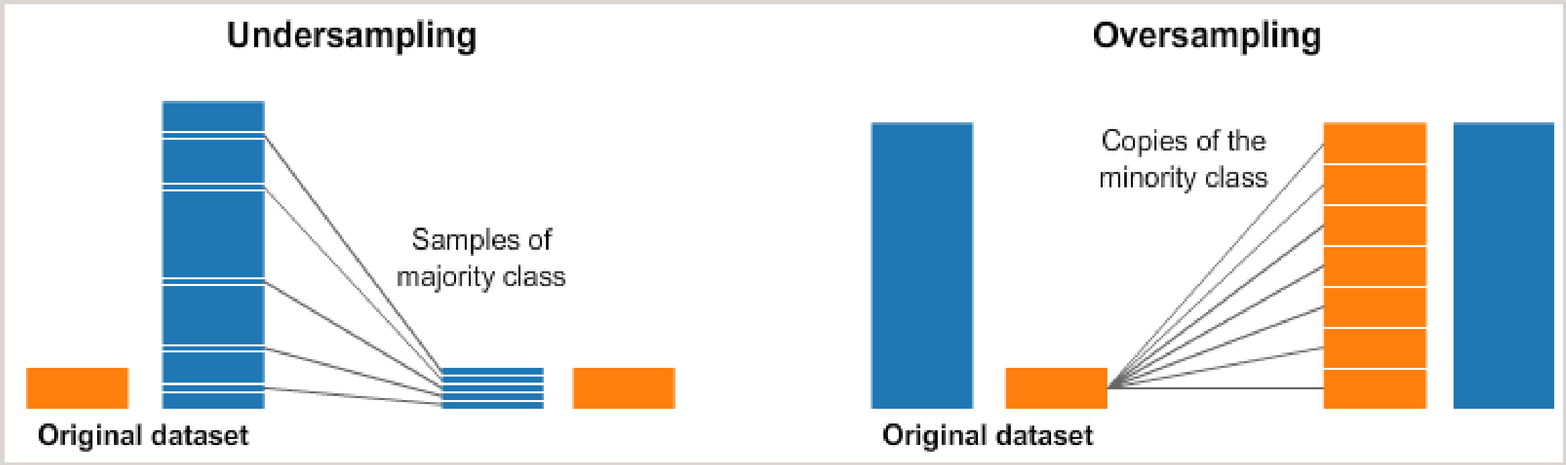
V-Neck = 1298

Data Balancing

Resampling

→ Undersampling : Remove samples from the majority class until the class distribution is balanced.

→ Oversampling: Duplicate or generate synthetic samples for the minority class until the class distribution is balanced.



Data Balancing

Weighted Classes

Assigning different weights to different classes during training.
This way, the model pays more attention to the minority class.

1

$$wj = \frac{n\_samples}{n\_classes\ x\ n\_class\_samples} = wround = \frac{2885}{3\ x\ 621} = 1{,}54$$

2

$$wj = \frac{n\_samples}{n\_class\_samples} = wround = \frac{2885}{621} = 4{,}65$$

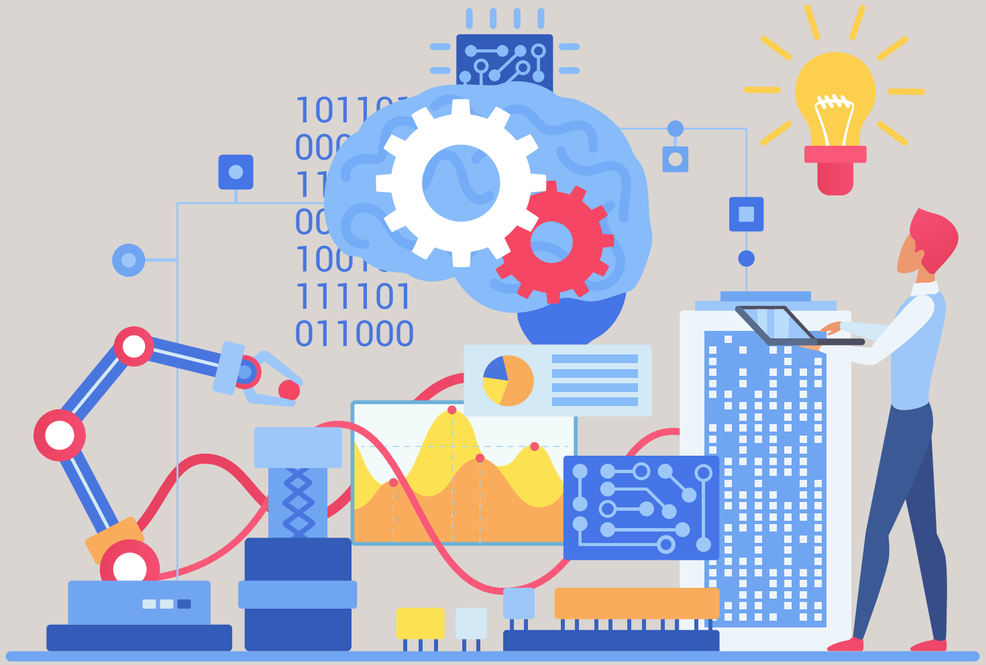
W-Round	W-Scoop	W-V-Neck
1.54	0.99	0.74
4.65	2.22	2.22

Resizing The Images

All images were in different sizes in the base dataset.
We cropped and later resized these images to (224,244)

Reviewing Architectures

1. **VGG16**
2. **ResNet**
3. **Mobilenet**



1. VGG16

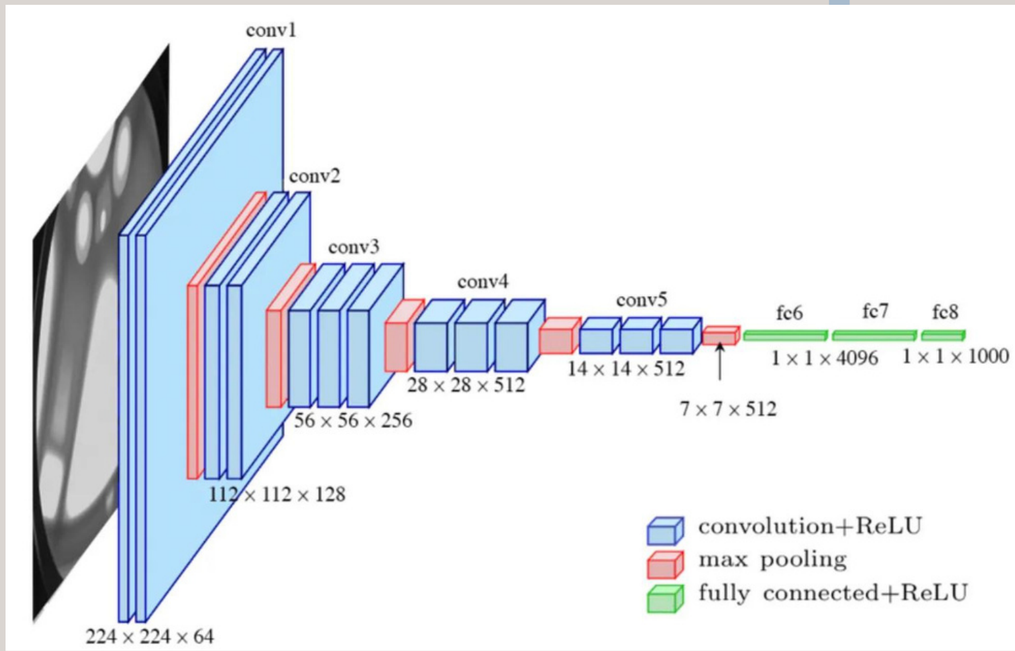
- VGG is a deep convolutional neural network that was proposed by Karen Simonyan and Andrew Zisserman.

- 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

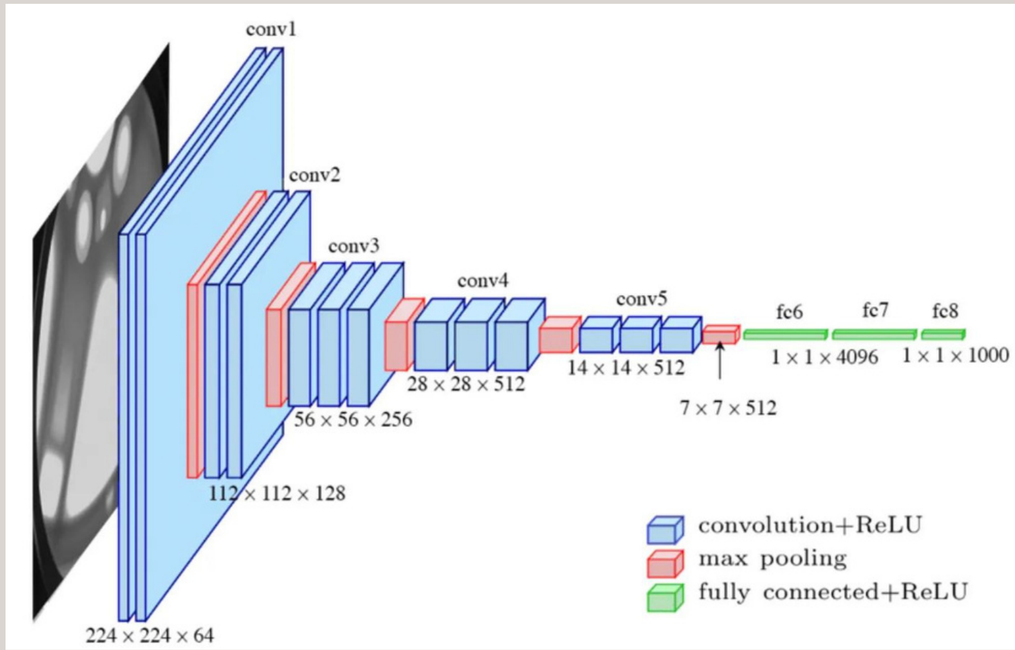
VGG16 is composed of

- **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 #
=================================================================
 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

=================================================================
Total params: 14789955 (56.42 MB)
Trainable params: 75267 (294.01 KB)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

Model Setup

- VGG16

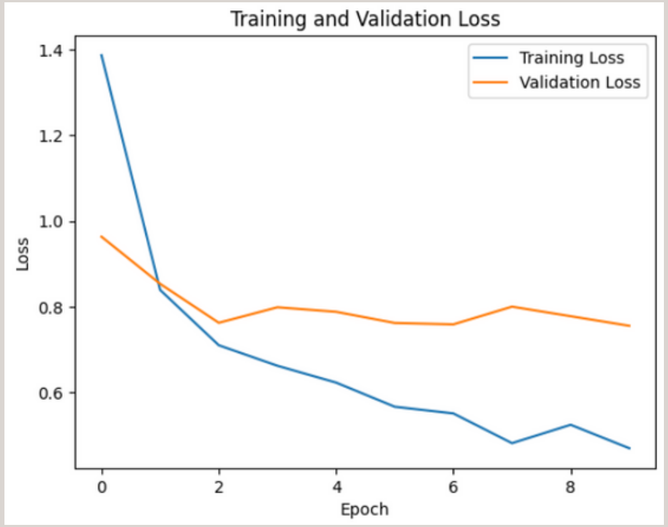
VGG16 Model

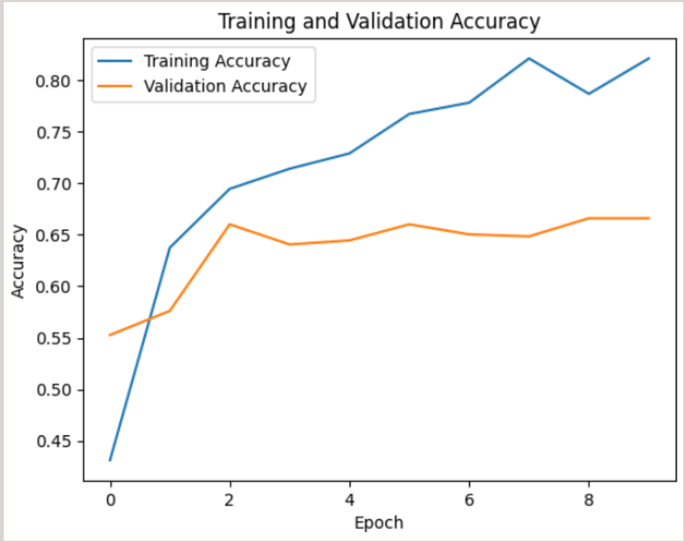
```
[ ]  from keras.models import Model
     from keras.layers import Flatten, Dense
     from keras.applications import VGG16


     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'])
```

Train - Validation Loss and Accuracy Grapgh

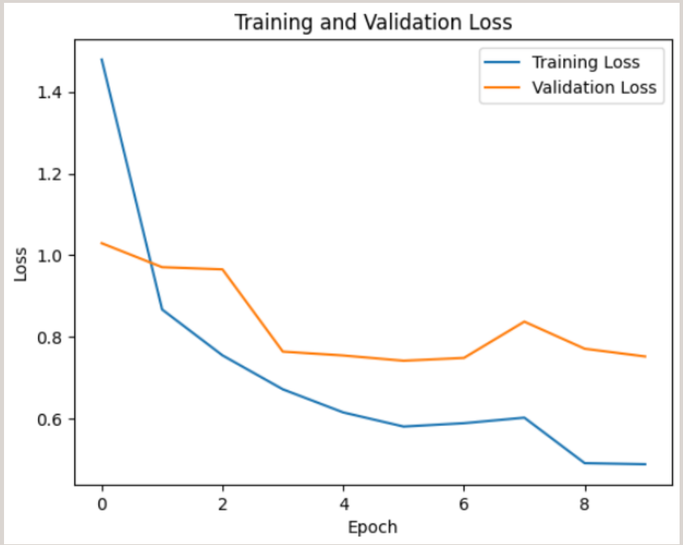
VGG16

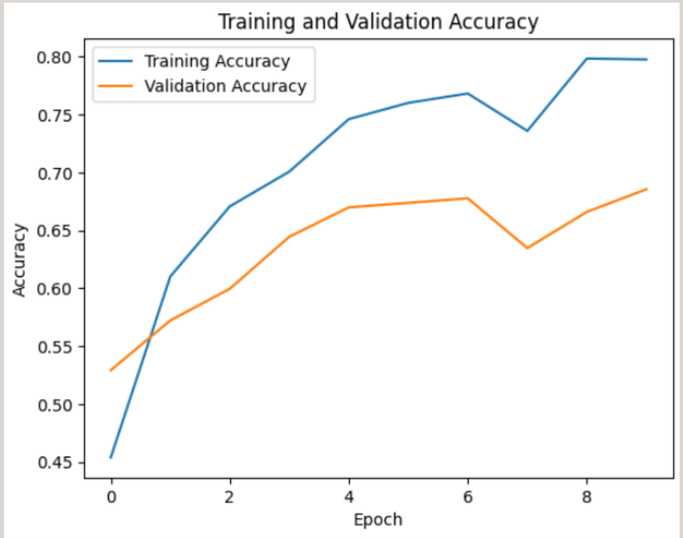
Oversampling





Weighted Classes





2.MobileNet

MobileNet consists of 86 layers.

Block 1

```
Model: "mobilenet_1.00_224"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 224, 224, 3)]     0

 conv1 (Conv2D)              (None, 112, 112, 32)      864

 conv1_bn (BatchNormalizati  (None, 112, 112, 32)      128
 on)

 conv1_relu (ReLU)           (None, 112, 112, 32)      0

 conv_dw_1 (DepthwiseConv2D  (None, 112, 112, 32)      288
 )

 conv_dw_1_bn (BatchNormali  (None, 112, 112, 32)      128
 zation)

 conv_dw_1_relu (ReLU)       (None, 112, 112, 32)      0

 conv_pw_1 (Conv2D)          (None, 112, 112, 64)      2048

 conv_pw_1_bn (BatchNormali  (None, 112, 112, 64)      256
 zation)

 conv_pw_1_relu (ReLU)       (None, 112, 112, 64)      0
```

Block 2

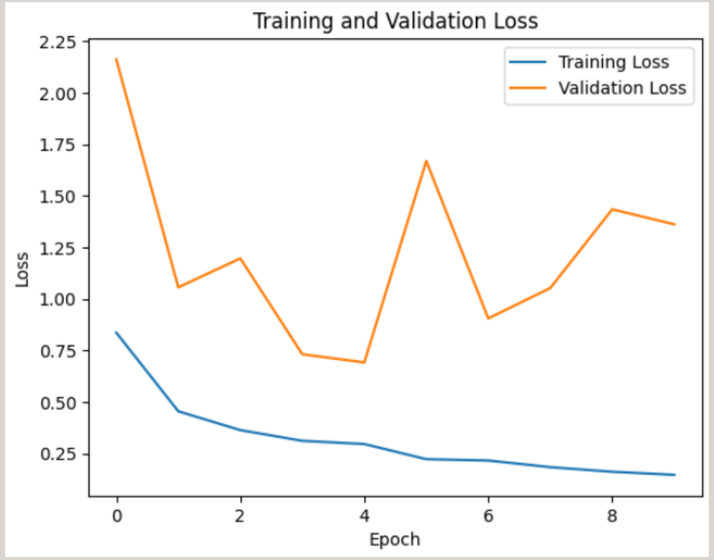
```
conv_pad_2 (ZeroPadding2D)  (None, 113, 113, 64)      0

conv_dw_2 (DepthwiseConv2D  (None, 56, 56, 64)        576
)

conv_dw_2_bn (BatchNormali  (None, 56, 56, 64)        256
zation)

conv_dw_2_relu (ReLU)       (None, 56, 56, 64)        0

conv_pw_2 (Conv2D)          (None, 56, 56, 128)       8192

conv_pw_2_bn (BatchNormali  (None, 56, 56, 128)       512
zation)

conv_pw_2_relu (ReLU)       (None, 56, 56, 128)       0
```

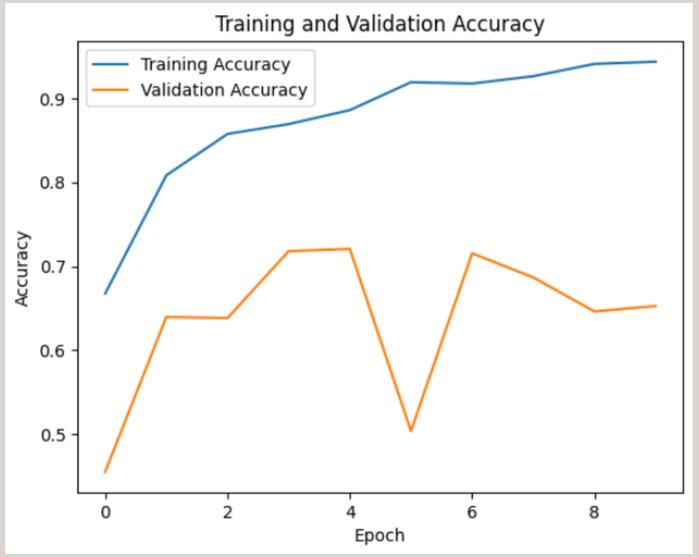
These blocks repeat for 13 times.

Train - Validation Loss and Accuracy Graph

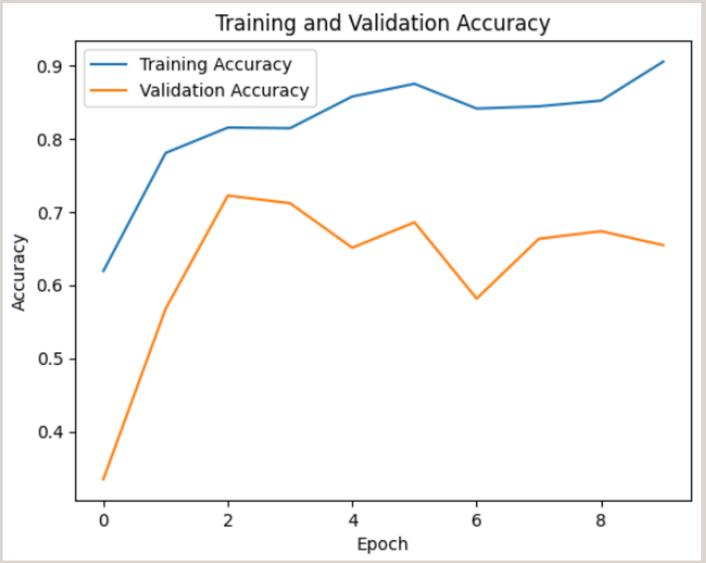
MobileNet

Oversampling



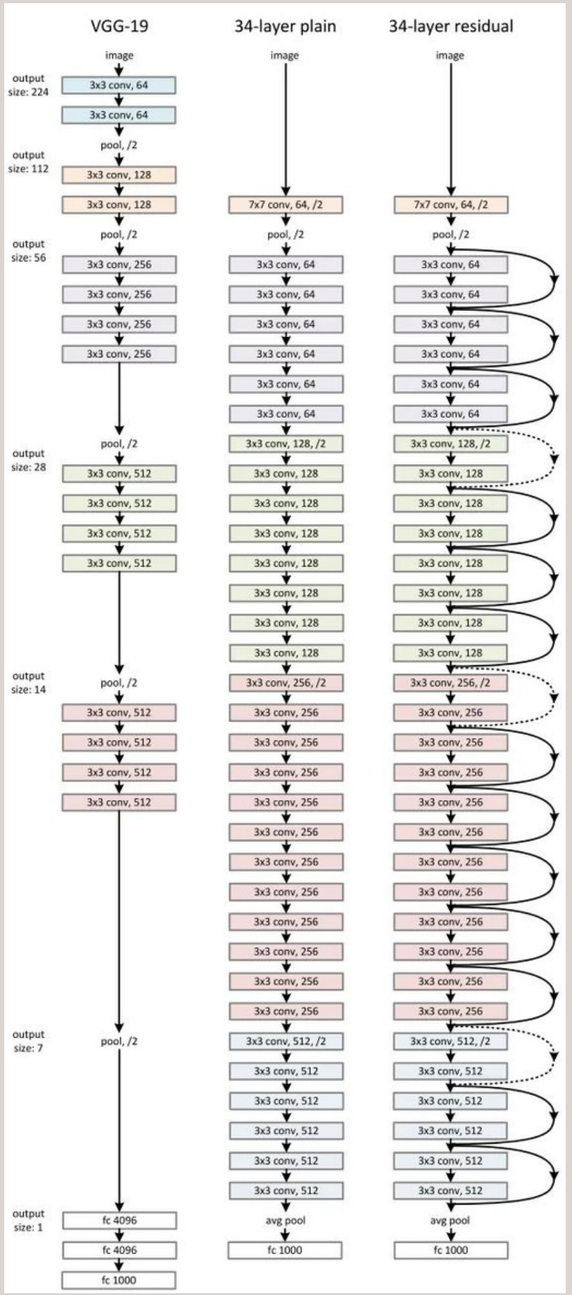


Weighted Classes



3. ResNet50

- 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.

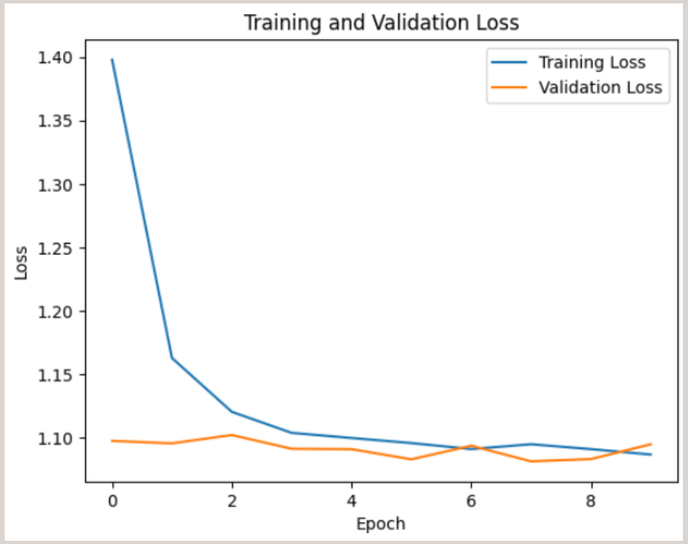


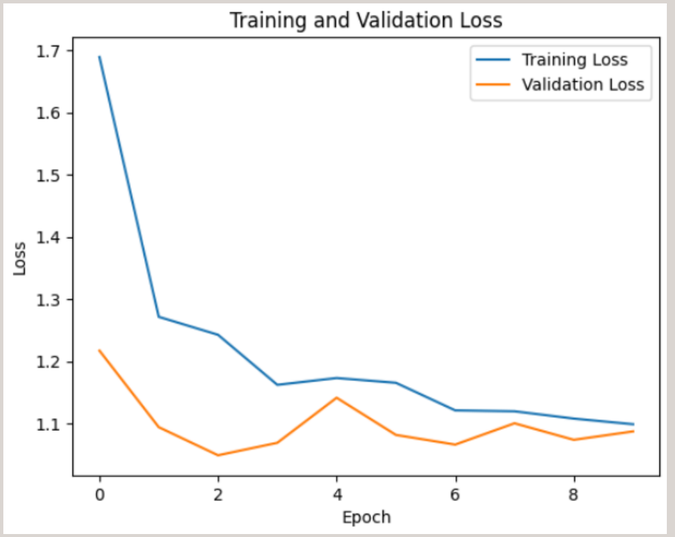
Train - Validation Loss and Accuracy Grapgh

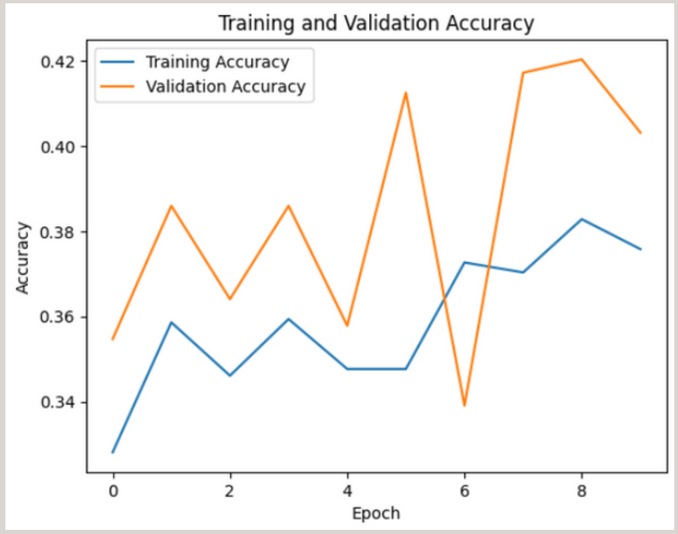
Oversampling

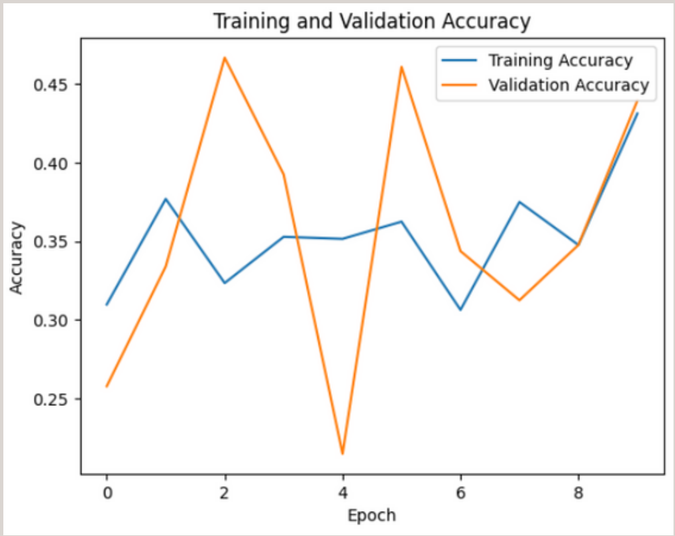
Weighted Classes

ResNet50





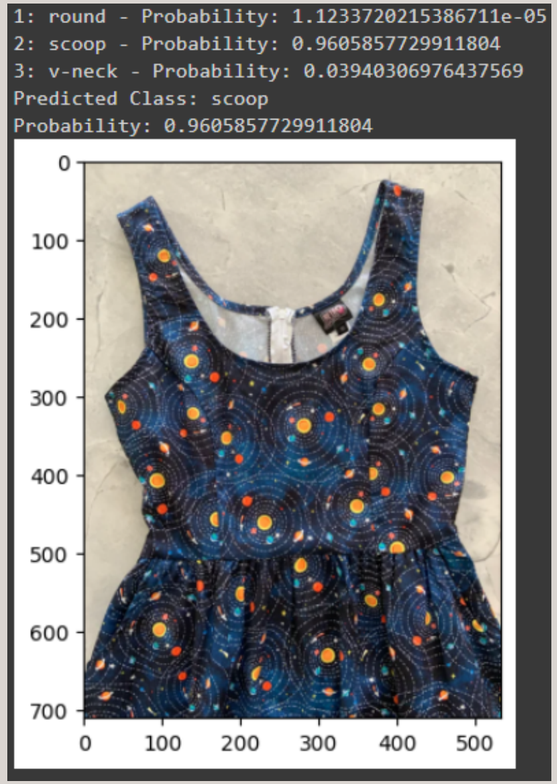




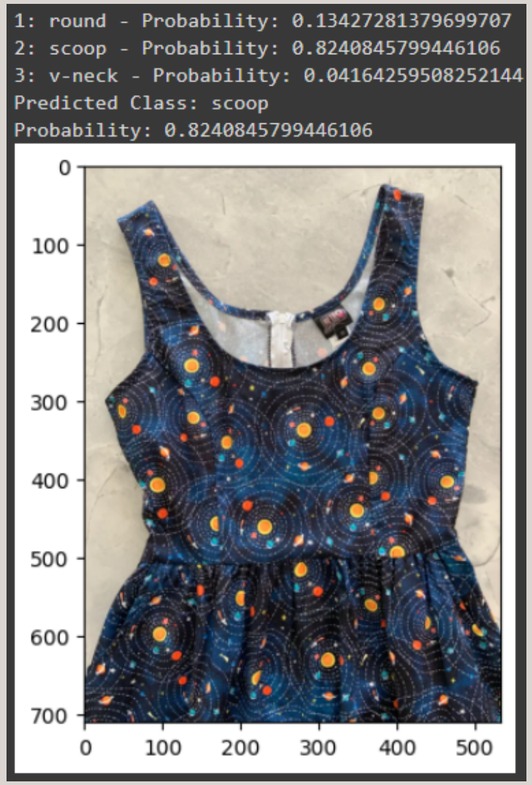
Oversampling

VGG16

MobileNet



ResNet50



Probability of Classes	**Oversampling**			**Weighted Classes**		
	VGG16	*MobileNet*	*ResNet50*	*VGG16*	*MobileNet*	*ResNet50*
Round	0.0	0.0000001	0.13	0.0	0.12	0.14
Scoop	1.0	0.96	0.82	1.0	0.12	0.65
V-Neck	0.0	0.03	0.04	0.0	0.75	0.2
Predicted Class	Scoop	Scoop	Scoop	Scoop	V-Neck	Scoop

Weighted Classes

VGG16

MobileNet

ResNet50

Probability of Classes	Oversampling			Weighted Classes		
	VGG16	*MobileNet*	*ResNet50*	*VGG16*	*MobileNet*	*ResNet50*
Round	0.0	0.0000001	0.13	0.0	0.12	0.14
Scoop	1.0	0.96	0.82	1.0	0.12	0.65
V-Neck	0.0	0.03	0.04	0.0	0.75	0.2
Predicted Class	Scoop	Scoop	Scoop	Scoop	V-Neck	Scoop