

ResNet50

Description

- ResNet50 - 5 upper layers are trainable
- Flatten the extracted feature
- Dense-512 (prediction)
- Activation function - *softmax*
- Loss function - *Categorical Cross Entropy*
- Optimizer - *SGD (Stochastic Gradient Descent)*
- Learning rate - 0.00005

```
1
2 # base model
3 restnet = ResNet50(include_top=False, weights='imagenet', input_shape=(IMG_HEIGHT,IMG_WIDTH,3))
4
5 # all 170 layers among 175 are non-trainable
6 # top 5 layers will be trainable
7 for layer in restnet.layers[:170]:
8     layer.trainable = False
9
10 base_model = restnet
11 x = base_model.output
12
13
14 x = Flatten()(x)
15
16 # a dense layer for prediction
17 predictions = Dense(NUM_CLASSES, activation='softmax')(x)
18
19 # compile the model
20 # loss = 'categorical_crossentropy'
21 # optimizer = SGD
22 # learning rate = 0.00005
23 # metrics = 'accuracy'
24 model_fin tuned = Model(inputs=base_model.input, outputs=predictions)
25 model_fin tuned.compile(loss='categorical_crossentropy',
26                         optimizer=optimizers.SGD(lr=0.00005),
27                         metrics=['accuracy'])
```

Fig 01- Model description. Classifier on top of ResNet50

Model Performance

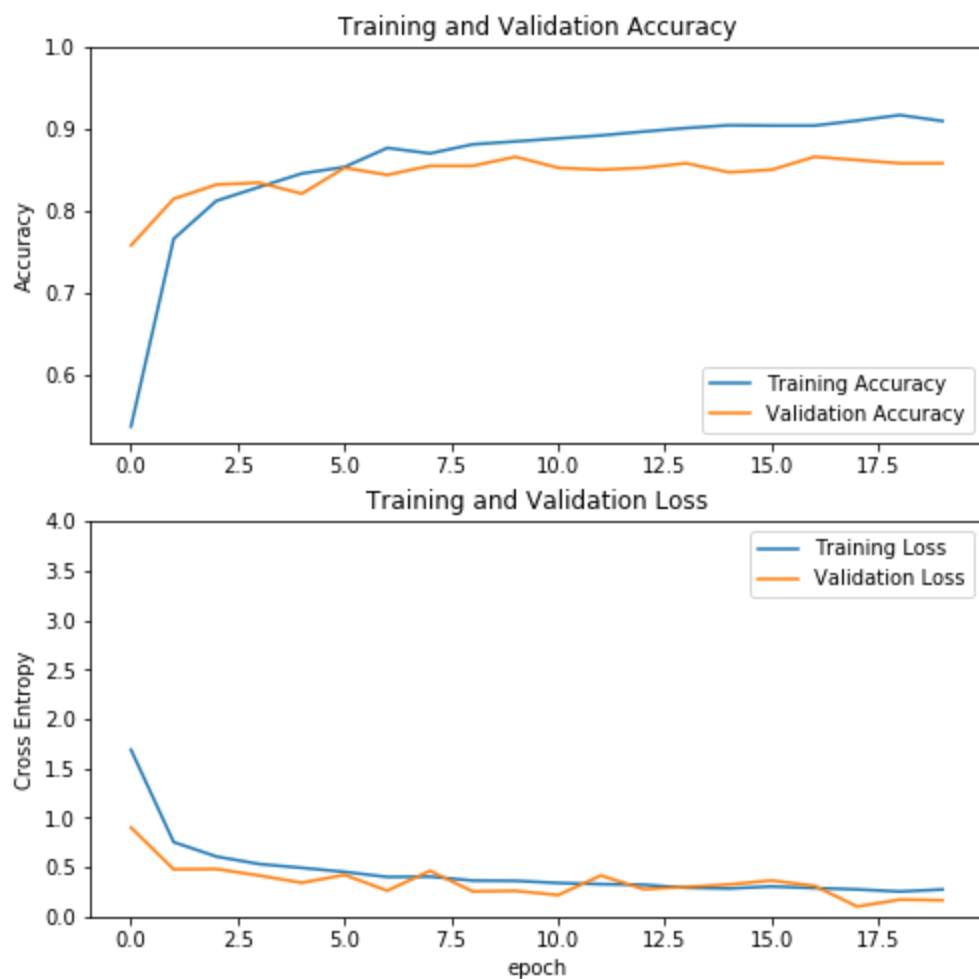


Fig 02- Model training and validation accuracy and losses

Train accuracy - 90%

Train loss - 0.27

Validation accuracy -85%

Validation loss - 0.16

Test accuracy - 86.46% (1367 / 1581)

Result Analysis

→ Total number of classes - 15

→ Train Images per-classes

◆ Bags = 339	◆ Fragrance = 339	◆ Shoes = 336
◆ Belts = 337	◆ Innerwear = 334	◆ Socks = 344
◆ Bottomwear = 336	◆ Jewellery = 318	◆ Topwear = 356
◆ Eyewear = 357	◆ Lips = 342	◆ Wallets = 341
◆ Flip Flops = 327	◆ Sandal = 323	◆ Watches = 330

→ Validation Images per-classes

◆ Bags = 92	◆ Fragrance = 87	◆ Shoes = 87
◆ Belts = 87	◆ Innerwear = 90	◆ Socks = 76
◆ Bottomwear = 85	◆ Jewellery = 85	◆ Topwear = 76
◆ Eyewear = 73	◆ Lips = 83	◆ Wallets = 74
◆ Flip Flops = 84	◆ Sandal = 87	◆ Watches = 99

→ Test Images per-classes

◆ Bags = 96	◆ Fragrance = 101	◆ Shoes = 104
◆ Belts = 103	◆ Innerwear = 103	◆ Socks = 107
◆ Bottomwear = 106	◆ Jewellery = 124	◆ Topwear = 95
◆ Eyewear = 97	◆ Lips = 102	◆ Wallets = 112
◆ Flip Flops = 116	◆ Sandal = 117	◆ Watches = 98

→ Wrong prediction per-classes

◆ Bags = 18	◆ Fragrance = 15	◆ Shoes = 35
◆ Belts = 2	◆ Innerwear = 14	◆ Socks = 10
◆ Bottomwear = 13	◆ Jewellery = 14	◆ Topwear = 5
◆ Eyewear = 0	◆ Lips = 10	◆ Wallets = 10
◆ Flip Flops = 11	◆ Sandal = 50	◆ Watches = 7

→ Accuracy per-classes (%)

◆ Bags = 81.25	◆ Fragrance = 85.14	◆ Shoes = 66.34
◆ Belts = 98.05	◆ Innerwear = 86.40	◆ Socks = 90.65
◆ Bottomwear = 87.7	◆ Jewellery = 88.70	◆ Topwear = 94.73
◆ Eyewear = 100	◆ Lips = 90.19	◆ Wallets = 91.07
◆ Flip Flops = 90.51	◆ Sandal = 57.26	◆ Watches = 92.85

Model Accuracy Metric

For calculating accuracy, we used the accuracy algorithm that was built in in the model. For accuracy the metric is:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

- True Positive, or TP, are cases with positive labels which have been correctly classified as positive.
- True Negative, or TN, are cases with negative labels which have been correctly classified as negative.
- False Positive, or FP, are cases with negative labels which have been incorrectly classified as positive.
- False Negative, or FN, are cases with positive labels which have been incorrectly classified as negative.

In our case,

- If a T-shirt is correctly classified as a T-shirt, then it is true positive or TP.
- If a Pant is classified as T-shirt, then for T-shirt it is false positive or FP.
- If a Pant is classified as anything other than a T-shirt, then for a T-shirt it is true negative or TN.
- If a T-shirt is classified as anything other than a T-shirt, then for T-shirt it is false negative or FN.

So basically the accuracy we calculated is, the percentage of correctly predicted classes. Mathematically,

Accuracy = correct prediction / total samples.

		True/Actual		
		Cat (🐱)	Fish (🐟)	Hen (🐔)
Predicted	Cat (🐱)	TP 4	6 FP 3	
	Fish (🐟)	1 FN	2 TN	0
	Hen (🐔)	1	2	6 TN