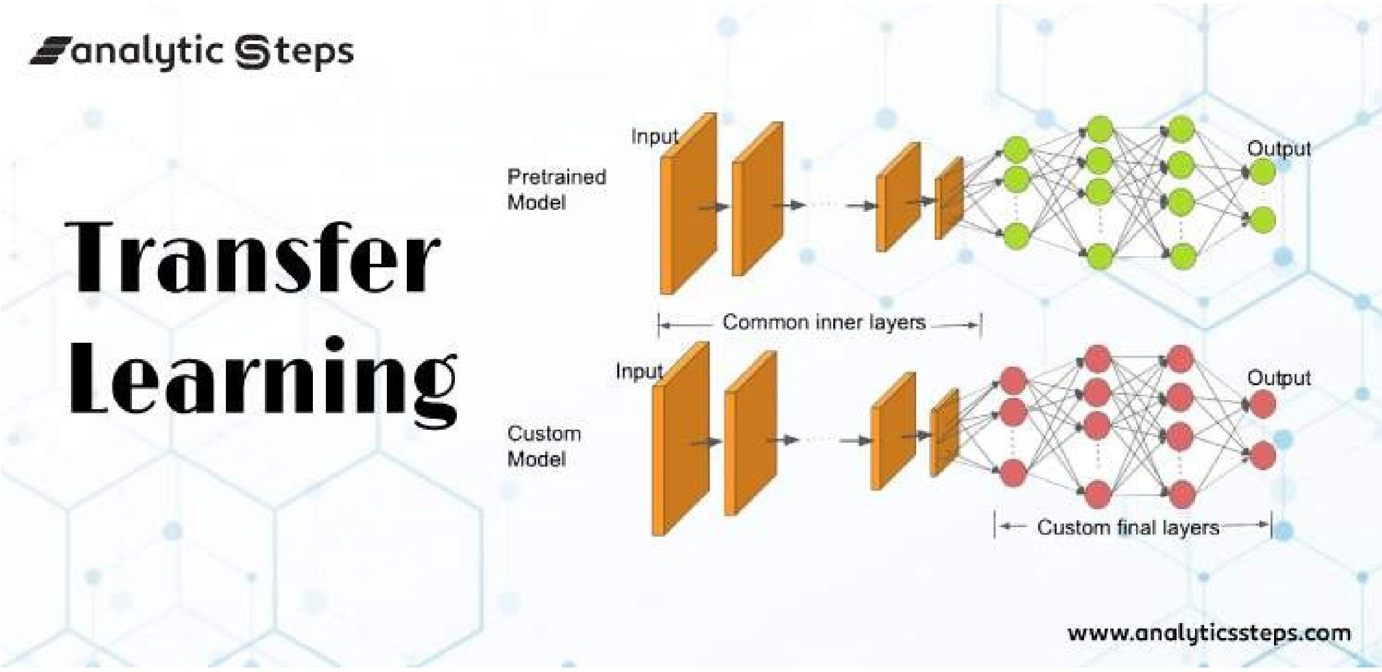
Transfer Learning using Fine Tuning Method -- Without Data Augmentation

Transfer learning is a machine learning `technique that allows a model trained on one task to be reused or adapted for a different task`**. There are two main types of transfer learning:**

- `Feature Extraction:` **In feature extraction, a pre-trained model is used as a fixed feature extractor. The pre-trained model is typically trained on a large dataset, such as ImageNet, and the final layer(s) that output the class predictions are removed. The remaining layers are then used as a feature extractor for a new dataset. These extracted features can be used as input to train a new model on the new dataset.**
- `Fine-tuning:` **In fine-tuning, a pre-trained model is used as an initialization for a new model. The pre-trained model is typically trained on a large dataset, such as ImageNet, and the final layer(s) that output the class predictions are replaced with new ones for the new task. The new model is then trained on the new dataset while keeping the weights of the pre-trained layers fixed or with a small learning rate.**



In [ ]:

```
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
```

Downloading & Loading the dataset

In [ ]:

```
!kaggle datasets download -d salader/dogs-vs-cats
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggle.json'
Downloading dogs-vs-cats.zip to /content
100% 1.06G/1.06G [00:05<00:00, 196MB/s]
100% 1.06G/1.06G [00:05<00:00, 197MB/s]
```

In [ ]:

```
import zipfile
zip_ref = zipfile.ZipFile('/content/dogs-vs-cats.zip', 'r')
zip_ref.extractall('/content')
zip_ref.close()
```

Import Necessary Libraries

In [ ]:

```
import tensorflow
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense,Flatten
from keras.applications.vgg16 import VGG16
```

Defining the Convolutional Base & Freezing it & discarding the top layer (Dense Layer to train again)

In [ ]:

```
conv_base = VGG16(
    weights='imagenet',
    include_top = False,
    input_shape=(150,150,3)
)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/
vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 0s 0us/step
58900480/58889256 [==============================] - 0s 0us/step
```

In [ ]:

```
conv_base.trainable = True

set_trainable = False

for layer in conv_base.layers:
  if layer.name == 'block5_conv1':
    set_trainable = True
  if set_trainable:
    layer.trainable = True
  else:
    layer.trainable = False

for layer in conv_base.layers:
  print(layer.name,layer.trainable)
```

```
input_1 False
block1_conv1 False
block1_conv2 False
block1_pool False
block2_conv1 False
block2_conv2 False
block2_pool False
block3_conv1 False
block3_conv2 False
block3_conv3 False
block3_pool False
block4_conv1 False
block4_conv2 False
block4_conv3 False
block4_pool False
block5_conv1 True
block5_conv2 True
block5_conv3 True
block5_pool True
```

From the model.summary(), it can be easilty insighted that we're freezing the convolutional_layer upto block4 & training block5.

The above image shows the actual difference between feature extraction & fine-tuning methods of Transfer Learning.

In [ ]:

```
conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 150, 150, 3)]     0

 block1_conv1 (Conv2D)       (None, 150, 150, 64)      1792

 block1_conv2 (Conv2D)       (None, 150, 150, 64)      36928

 block1_pool (MaxPooling2D)  (None, 75, 75, 64)        0

 block2_conv1 (Conv2D)       (None, 75, 75, 128)       73856

 block2_conv2 (Conv2D)       (None, 75, 75, 128)       147584

 block2_pool (MaxPooling2D)  (None, 37, 37, 128)       0

 block3_conv1 (Conv2D)       (None, 37, 37, 256)       295168

 block3_conv2 (Conv2D)       (None, 37, 37, 256)       590080

 block3_conv3 (Conv2D)       (None, 37, 37, 256)       590080

 block3_pool (MaxPooling2D)  (None, 18, 18, 256)       0

 block4_conv1 (Conv2D)       (None, 18, 18, 512)       1180160

 block4_conv2 (Conv2D)       (None, 18, 18, 512)       2359808

 block4_conv3 (Conv2D)       (None, 18, 18, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 9, 9, 512)         0

 block5_conv1 (Conv2D)       (None, 9, 9, 512)         2359808
```

```
 block5_conv2 (Conv2D)       (None, 9, 9, 512)         2359808

 block5_conv3 (Conv2D)       (None, 9, 9, 512)         2359808

 block5_pool (MaxPooling2D)  (None, 4, 4, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 7,079,424
Non-trainable params: 7,635,264
_________________________________________________________________
```

Here it can be noticed that the Trainable Parameters have been reduced to `7,079,424` from `14,714,688` (Taking the conv_base 5 layer block).(After adding the `dense layer (2,097,665) to the conv_base (14,714,688)`).

Defining the sequential model & adding the conv_base

In [ ]:

```
model = Sequential()

model.add(conv_base)
model.add(Flatten())
model.add(Dense(256,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
```

Defining Training & Validation set for model training

In [ ]:

```
# generators
train_ds = keras.utils.image_dataset_from_directory(
    directory = '/content/train',
    labels='inferred',
    label_mode = 'int',
    batch_size=32,
    image_size=(150,150)
)

validation_ds = keras.utils.image_dataset_from_directory(
    directory = '/content/test',
    labels='inferred',
    label_mode = 'int',
    batch_size=32,
    image_size=(150,150)
)
```

```
Found 20000 files belonging to 2 classes.
Found 5000 files belonging to 2 classes.
```

Normalizing the dataset for smooth training

In [ ]:

```
# Normalize
def process(image,label):
    image = tensorflow.cast(image/255. ,tensorflow.float32)
    return image,label

train_ds = train_ds.map(process)
validation_ds = validation_ds.map(process)
```

Model Training

In [ ]:

```
model.compile(
    optimizer=keras.optimizers.RMSprop(lr=1e-5),
    loss='binary_crossentropy',
    metrics=['accuracy']
  )
```

```
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/rmsprop.py:130: UserWarning: Th
e `lr` argument is deprecated, use `learning_rate` instead.
  super(RMSprop, self).__init__(name, **kwargs)
```

In [ ]:

```
history = model.fit(train_ds,epochs=10,validation_data=validation_ds)
```

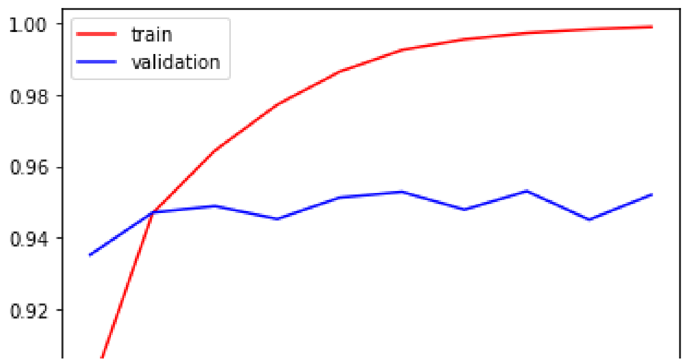
```
Epoch 1/10
625/625 [==============================] - 87s 119ms/step - loss: 0.2385 - accuracy: 0.89
68 - val_loss: 0.1606 - val_accuracy: 0.9352
Epoch 2/10
625/625 [==============================] - 76s 120ms/step - loss: 0.1311 - accuracy: 0.94
68 - val_loss: 0.1308 - val_accuracy: 0.9470
Epoch 3/10
625/625 [==============================] - 75s 120ms/step - loss: 0.0921 - accuracy: 0.96
43 - val_loss: 0.1247 - val_accuracy: 0.9488
Epoch 4/10
625/625 [==============================] - 83s 132ms/step - loss: 0.0650 - accuracy: 0.97
72 - val_loss: 0.1391 - val_accuracy: 0.9452
Epoch 5/10
625/625 [==============================] - 75s 120ms/step - loss: 0.0430 - accuracy: 0.98
64 - val_loss: 0.1278 - val_accuracy: 0.9512
Epoch 6/10
625/625 [==============================] - 76s 121ms/step - loss: 0.0280 - accuracy: 0.99
24 - val_loss: 0.1371 - val_accuracy: 0.9528
Epoch 7/10
625/625 [==============================] - 75s 120ms/step - loss: 0.0169 - accuracy: 0.99
55 - val_loss: 0.1633 - val_accuracy: 0.9478
Epoch 8/10
625/625 [==============================] - 76s 120ms/step - loss: 0.0111 - accuracy: 0.99
72 - val_loss: 0.1592 - val_accuracy: 0.9530
Epoch 9/10
625/625 [==============================] - 75s 120ms/step - loss: 0.0077 - accuracy: 0.99
83 - val_loss: 0.2120 - val_accuracy: 0.9450
Epoch 10/10
625/625 [==============================] - 75s 120ms/step - loss: 0.0052 - accuracy: 0.99
89 - val_loss: 0.1859 - val_accuracy: 0.9520
```

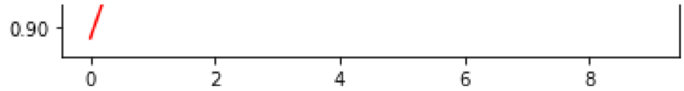
Loss curve for Accuracy

In [ ]:

```
import matplotlib.pyplot as plt

plt.plot(history.history['accuracy'],color='red',label='train')
plt.plot(history.history['val_accuracy'],color='blue',label='validation')
plt.legend()
plt.show()
```

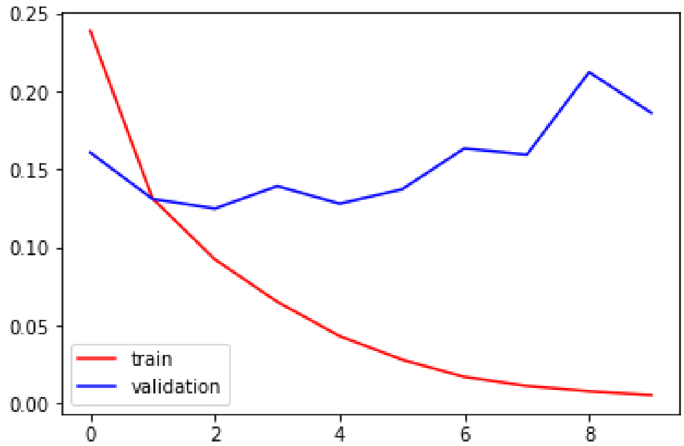




Loss curve for training loss

In [ ]:

```
plt.plot(history.history['loss'],color='red',label='train')
plt.plot(history.history['val_loss'],color='blue',label='validation')
plt.legend()
plt.show()
```



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In [ ]: