Transfer Learning Assignment

Download all the data in this rar_file , it contains all the data required for the assignment. When you unrar the file you'll get the files in the following format: **path/to/the/image.tif,category**

```
where the categories are numbered 0 to 15, in the following order:

    0 letter
    1 form
    2 email
    3 handwritten
    4 advertisement
    5 scientific report
    6 scientific publication
    7 specification
    8 file folder
    9 news article
    10 budget
    11 invoice
    12 presentation
    13 questionnaire
    14 resume
    15 memo
```

There is a file named as 'labels_final.csv' , it consists of two columns. First column is path which is the required path to the images and second is the class label.

The dataset that you are dealing with is quite large 3.7 GB and hence there are two methods to import the data to Colab

Method 1 - You can use gdown module to get the data directly from Google drive to Colab

The syntax is as follows,

```
! gdown --id file_id
```

for ex - running the below cell will

```
import the rvl-cdip.rar dataset
! gdown --id 1Z4TyI7FcFVEx8qdl4jO9qxvxaqLSqoEu
```

Method 2 - You can also import the data using wget function

https://www.youtube.com/watch?v=BPUfVq7RaY8

Unzip `rar` file using,

```
#unrar the file
get_ipython().system_raw("unrar x rvl-cdip.rar")
```

2. On this image data, you have to train 3 types of models as given below You have to split the data into Train and Validation data.

In [1]:

```
import os
import numpy as np
import pandas as pd

from datetime import datetime

import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')

import tensorflow
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras import Input

from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import MaxPool2D
from tensorflow.keras.layers import Activation
from tensorflow.keras.callbacks import Callback
```

```
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import ReduceLROnPlateau

from tensorflow.keras.utils import plot_model
from tensorflow.keras.applications import VGG16
from tensorflow.keras.preprocessing.image import ImageDataGenerator
%load_ext tensorboard
```

In [2]:

```
df = pd.read_csv('labels_final.csv',dtype = str)
```

In [3]:

```
print(df.shape)
df.head()
```

```
(48000, 2)
```

Out[3]:

	path	label
0	imagesv/v/o/h/voh71d00/509132755+-2755.tif	3
1	imagesl/l/x/t/lxt19d00/502213303.tif	3
2	imagesx/x/e/d/xed05a00/2075325674.tif	2
3	imageso/o/j/b/ojb60d00/517511301+-1301.tif	3
4	imagesq/q/z/k/qzk17e00/2031320195.tif	7

1. Try not to load all the images into memory, use the gernarators that we have given the reference notebooks to load the batch of images only during the train data. or you can use this method also https://medium.com/@vijayabhaskar96/tutorial-on-keras-imagedatagenerator-with-flow-from-dataframe-8bd5776e45c1

https://medium.com/@vijayabhaskar96/tutorial-on-keras-flow-from-dataframe-1fd4493d237c

Note- In the reference notebook you were dealing with jpg images, in the given dataset you are dealing with tiff images. Imagedatagenrator works with both type of images. If you want to use custom data pipeline then you have to convert your tiff images to jpg images.

1. You are free to choose Learning rate, optimizer, loss function, image augmentation, any hyperparameters. but you have to use the same architechture what we are asking below.
2. Use tensorboard for every model and analyse your gradients. (you need to upload the screenshots for each model for evaluation)

1. You can check about Transfer Learning in this link - https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html

https://www.appliedaicourse.com/lecture/11/applied-machine-learning-online-course/3426/code-example-cats-vs-dogs/8/module-8-neural-networks-computer-vision-and-deep-learning </pre>

1. Do print model.summary() and draw model_plots for each of the model.

Threshold Accuracies

Model	Accuracy
Model 1	60 %
Model 2	60 %
Model 3	6 %

Model-1

```
1. Use VGG-16 pretrained network without Fully Connected layers and initilize all the weights
with Imagenet trained weights.
2. After VGG-16 network without FC layers, add a new Conv block ( 1 Conv layer and 1 Maxpooling
), 2 FC layers and an output layer to classify 16 classes. You are free to choose any
```

hyperparameters/parameters of conv block, FC layers, output layer.
3. Final architecture will be **INPUT --> VGG-16 without Top layers(FC) --> Conv Layer --> Maxpool Layer --> 2 FC layers --> Output Layer**
4.Print model.summary() and plot the architecture of the model.
Reference for plotting model
5. Train only new Conv block, FC layers, output layer. Don't train the VGG-16 network.

In [4]:

```
# https://stackoverflow.com/a/35765856

# !watch -n1 nvidia-smi
!nvidia-smi
```

```
Thu Jul 14 14:58:15 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 440.33.01    Driver Version: 440.33.01    CUDA Version: 11.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla T4            On   | 00000000:00:1E.0 Off |                    0 |
| N/A   33C    P8     8W /  70W |      0MiB / 15109MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

In [5]:

```
os.mkdir('Model_Weights')
os.mkdir('Model_Plots')
```

In [6]:

```
tensorflow.random.set_seed(42)
```

In [7]:

```
# https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image/ImageDataGenerator

datagen = ImageDataGenerator(rescale =  1./255, shear_range = 0.2, zoom_range = 0.2,
                             validation_split = 0.25)
```

In [8]:

```
# https://medium.datadriveninvestor.com/keras-imagedatagenerator-methods-an-easy-guide-550ecd3c0a92

BATCH_SIZE = 32
DATA_DIR = 'data_final'

train_gen = datagen.flow_from_dataframe(dataframe = df, directory = DATA_DIR,
                        x_col = 'path', y_col = 'label', target_size = (256,256),
                        class_mode = 'categorical', batch_size = BATCH_SIZE,
                        subset = 'training', seed = 7, shuffle = True, color_mode = 'rgb')

test_gen = datagen.flow_from_dataframe(dataframe = df, directory = DATA_DIR,
                        x_col = 'path', y_col = 'label', target_size = (256,256),
                        class_mode = 'categorical', batch_size = BATCH_SIZE,
                        subset = 'validation', seed = 7, shuffle = True, color_mode = 'rgb')
```

```
Found 36000 validated image filenames belonging to 16 classes.
Found 12000 validated image filenames belonging to 16 classes.
```

In [9]:

```
base_model = VGG16(weights = 'imagenet', input_shape = (256, 256, 3), include_top = False)
base_model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ord
ering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 0s 0us/step
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 256, 256, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 256, 256, 64)      36928
_________________________________________________________________
```

```
block1_pool (MaxPooling2D)   (None, 128, 128, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 128, 128, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 128, 128, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 64, 64, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 64, 64, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 64, 64, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 64, 64, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 32, 32, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 32, 32, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 32, 32, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 32, 32, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 16, 16, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 8, 8, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

INPUT --> VGG-16 without Top layers(FC) --> Conv Layer --> Maxpool Layer --> 2 FC layers --> Output Layer

In [10]:

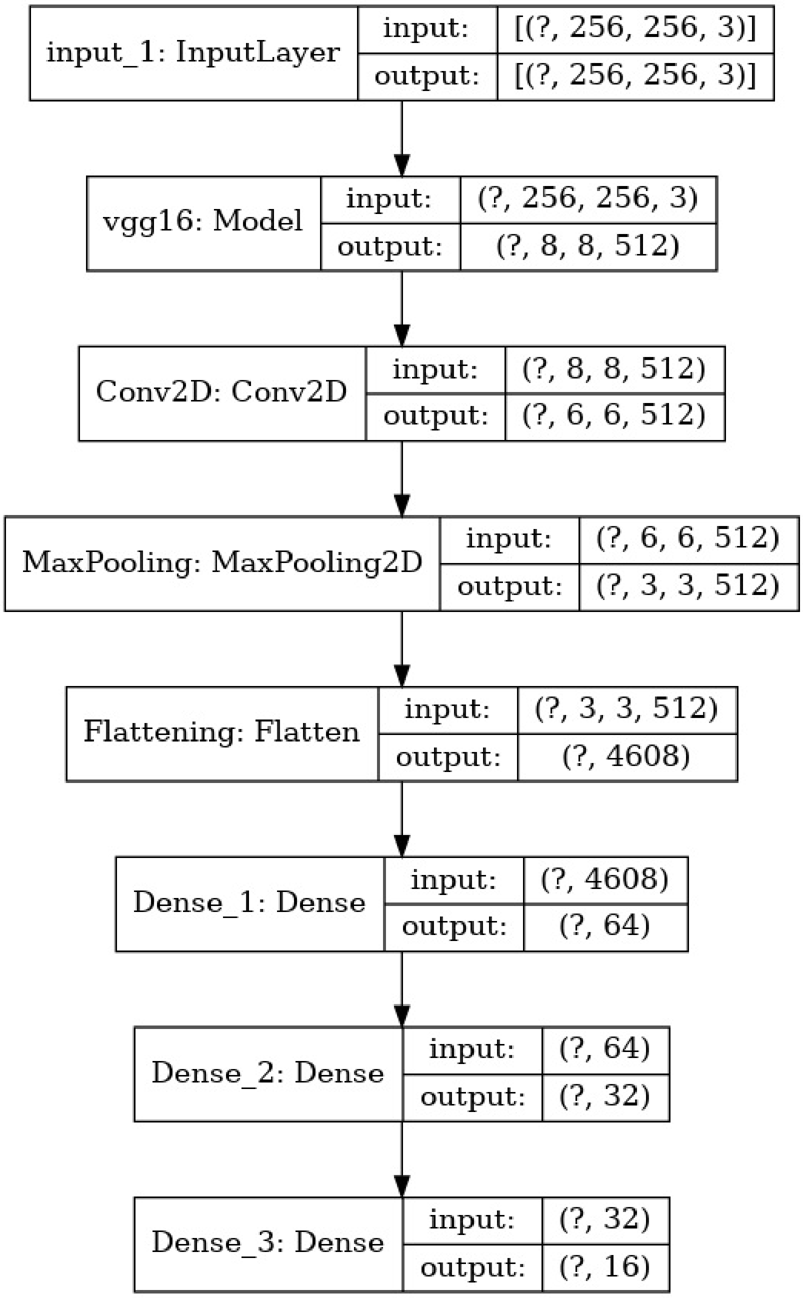
```
tensorflow.keras.backend.clear_session()

# https://keras.io/guides/transfer_learning/
# https://catalog.ngc.nvidia.com/orgs/nvidia/containers/dli-dl-fundamentals

base_model.trainable = False
inputs = Input(shape = (256, 256, 3))

x = base_model(inputs, training = False)
x = Conv2D(filters = 512, kernel_size = (3, 3), activation = 'relu', name = 'Conv2D')(x)
x = MaxPool2D(name = 'MaxPooling')(x)
x = Flatten(name = 'Flattening')(x)
x = Dense(64, activation = 'relu', name = 'Dense_1')(x)
x = Dense(32, activation = 'relu', name = 'Dense_2')(x)
output_ = Dense(16, activation = 'softmax', name = 'Dense_3')(x)

final_model_1 = Model(inputs = inputs, outputs = output_, name = 'Model_1')
final_model_1.summary()
```

```
Model: "Model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
vgg16 (Model)                (None, 8, 8, 512)         14714688
_________________________________________________________________
Conv2D (Conv2D)              (None, 6, 6, 512)         2359808
_________________________________________________________________
MaxPooling (MaxPooling2D)    (None, 3, 3, 512)         0
_________________________________________________________________
Flattening (Flatten)         (None, 4608)              0
_________________________________________________________________
Dense_1 (Dense)              (None, 64)                294976
_________________________________________________________________
Dense_2 (Dense)              (None, 32)                2080
_________________________________________________________________
Dense_3 (Dense)              (None, 16)                528
=================================================================
Total params: 17,372,080
Trainable params: 2,657,392
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [11]:

```
plot_model(final_model_1, to_file = 'Model_Plots/Model_1.png', show_shapes = True)
```

Out[11]:



In [12]:

```
final_model_1.compile(optimizer = 'adam', loss = 'categorical_crossentropy',
                      metrics = ['accuracy'])
```

In [13]:

```
logdir = 'logs/model_1/' + datetime.now().strftime('%Y%m%d_%H%M%S')
tensorBoard = TensorBoard(log_dir = logdir, histogram_freq = 1)

filepath = 'modelCheck/model_1/epo_{epoch:02d}-accu_{val_accuracy:.4f}.hdf5'
modelCheck = ModelCheckpoint(filepath, monitor = 'val_accuracy', verbose = 1)

earlyStopping = EarlyStopping(monitor = 'accuracy', patience = 2, verbose = 1)
reduceLr = ReduceLROnPlateau(monitor = 'accuracy', factor = 0.9, patience = 2, verbose = 1)

callBack_List = [tensorBoard, modelCheck, earlyStopping, reduceLr]
```

In [14]:

```
step_train = train_gen.n // train_gen.batch_size
step_test = test_gen.n // test_gen.batch_size
```

In [15]:

```
EPOCHS_1 = 6
model_1 = final_model_1.fit(train_gen, steps_per_epoch = step_train, epochs = EPOCHS_1,
              validation_data = test_gen, validation_steps = step_test, callbacks = callBack_List)
```

```
Epoch 1/6
1125/1125 [==============================] - ETA: 0s - loss: 1.6810 - accuracy: 0.4734
Epoch 00001: saving model to modelCheck/model_1/epo_01-accu_0.5727.hdf5
1125/1125 [==============================] - 713s 634ms/step - loss: 1.6810 - accuracy: 0.4734 - val_loss: 1.3635
```

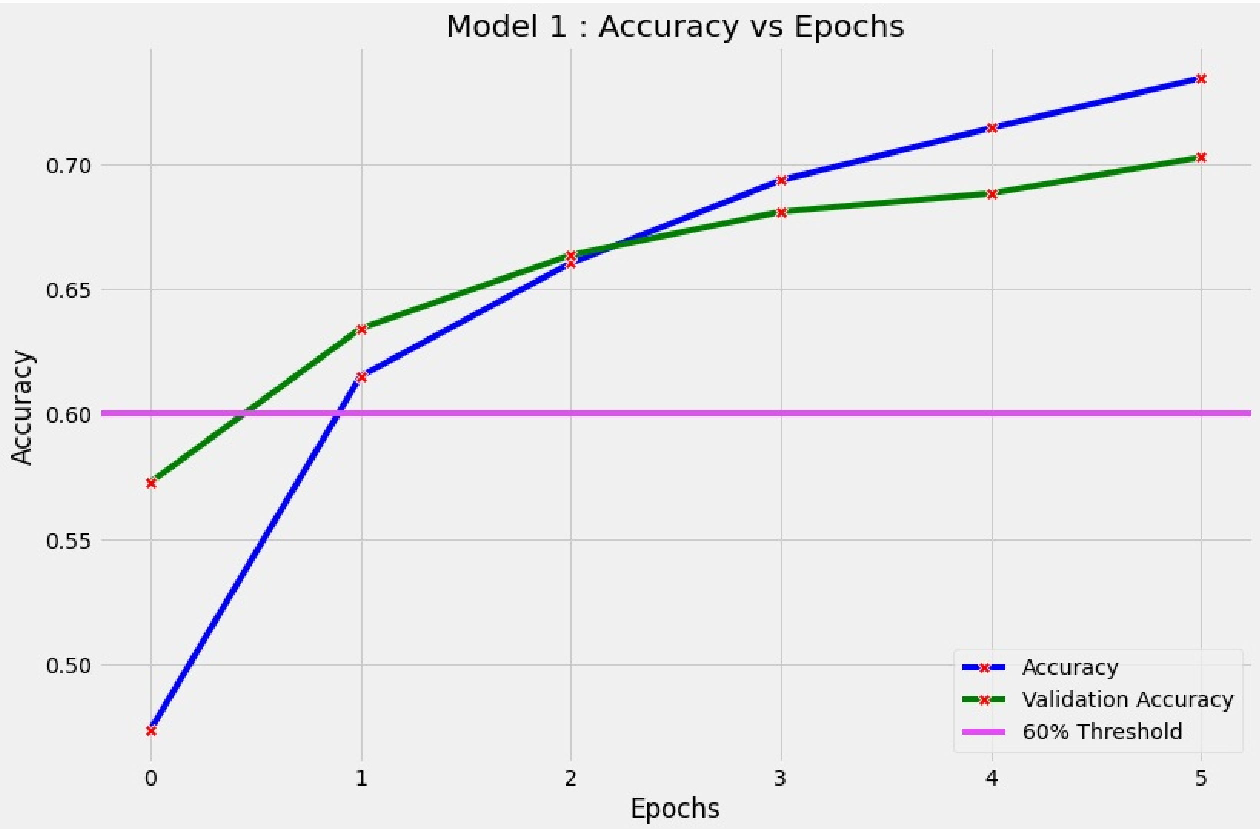
```
- val_accuracy: 0.5727 - lr: 0.0010
Epoch 2/6
1125/1125 [==============================] - ETA: 0s - loss: 1.2388 - accuracy: 0.6151
Epoch 00002: saving model to modelCheck/model_1/epo_02-accu_0.6342.hdf5
1125/1125 [==============================] - 671s 596ms/step - loss: 1.2388 - accuracy: 0.6151 - val_loss: 1.2049
- val_accuracy: 0.6342 - lr: 0.0010
Epoch 3/6
1125/1125 [==============================] - ETA: 0s - loss: 1.0989 - accuracy: 0.6604
Epoch 00003: saving model to modelCheck/model_1/epo_03-accu_0.6637.hdf5
1125/1125 [==============================] - 673s 598ms/step - loss: 1.0989 - accuracy: 0.6604 - val_loss: 1.1289
- val_accuracy: 0.6637 - lr: 0.0010
Epoch 4/6
1125/1125 [==============================] - ETA: 0s - loss: 1.0028 - accuracy: 0.6936
Epoch 00004: saving model to modelCheck/model_1/epo_04-accu_0.6810.hdf5
1125/1125 [==============================] - 673s 598ms/step - loss: 1.0028 - accuracy: 0.6936 - val_loss: 1.0616
- val_accuracy: 0.6810 - lr: 0.0010
Epoch 5/6
1125/1125 [==============================] - ETA: 0s - loss: 0.9284 - accuracy: 0.7145
Epoch 00005: saving model to modelCheck/model_1/epo_05-accu_0.6883.hdf5
1125/1125 [==============================] - 676s 601ms/step - loss: 0.9284 - accuracy: 0.7145 - val_loss: 1.0538
- val_accuracy: 0.6883 - lr: 0.0010
Epoch 6/6
1125/1125 [==============================] - ETA: 0s - loss: 0.8707 - accuracy: 0.7345
Epoch 00006: saving model to modelCheck/model_1/epo_06-accu_0.7028.hdf5
1125/1125 [==============================] - 675s 600ms/step - loss: 0.8707 - accuracy: 0.7345 - val_loss: 0.9977
- val_accuracy: 0.7028 - lr: 0.0010
```

In [16]:

```python
final_model_1.save_weights('Model_Weights/best_model_1.h5')
```

In [17]:

```python
# https://wellsr.com/python/seaborn-line-plot-data-visualization/
# https://seaborn.pydata.org/generated/seaborn.lineplot.html

epochs_ = list(range(len(model_1.history['accuracy'])))
plt.figure(figsize = (12, 8))

sns.lineplot(y = 'accuracy', data = model_1.history , x = epochs_, label = 'Accuracy',
             color = 'b', marker = 'X', mfc = 'red', ms = 8)
sns.lineplot(y = 'val_accuracy', data = model_1.history , x = epochs_,
             label = 'Validation Accuracy', color = 'g', marker = 'X', mfc = 'red', ms = 8)

plt.axhline(0.6, color = '#E44CF6', label = '60% Threshold')
plt.title('Model 1 : Accuracy vs Epochs') ; plt.legend(loc = 4)
plt.xticks(epochs_) ; plt.xlabel('Epochs') ; plt.ylabel('Accuracy') ; plt.show()
```



Observation

- Only around 15% of parameters are trainable in total parameters.

- With 6 epochs we got ~73.45% accuracy and the loss got reduced from 1.6810 to 0.8707.
- The loss and accuracy shows that with higher epoch we can reduce loss and increase the accuracy of the model.

Model-2

```
1. Use VGG-16 pretrained network without Fully Connected layers and initilize all the weights
with Imagenet trained weights.
2. After VGG-16 network without FC layers, don't use FC layers, use conv layers only as Fully
connected layer.Any FC
layer can be converted to a CONV layer. This conversion will reduce the No of Trainable
parameters in FC layers.
For example, an FC layer with K=4096 that is looking at some input volume of size 7×7×512 can be
equivalently expressed as a CONV layer with F=7,P=0,S=1,K=4096.
In other words, we are setting the filter size to be exactly the size of the input volume, and
hence the output will
simply be 1×1×4096 since only a single depth column “fits” across the input volume, giving
identical result as the
initial FC layer. You can refer this link to better understanding of using Conv layer in place of
fully connected layers.
3. Final architecture will be VGG-16 without FC layers(without top), 2 Conv layers identical to
FC layers, 1 output layer for 16 class classification. INPUT --> VGG-16 without Top layers(FC) --
> 2 Conv Layers identical to FC -->Output Layer
4. 4.Print model.summary() and plot the architecture of the model.
Reference for plotting model
5. Train only last 2 Conv layers identical to FC layers, 1 output layer. Don't train the VGG-16
network.
```

INPUT --> VGG-16 without Top layers(FC) --> 2 Conv Layers identical to FC -->Output Layer

- $$W_{out} = \frac{W - F + 2P}{S} + 1$$
- $$H_{out} = \frac{H - F + 2P}{S} + 1$$

In [18]:

```
tensorflow.keras.backend.clear_session()
```

In [19]:

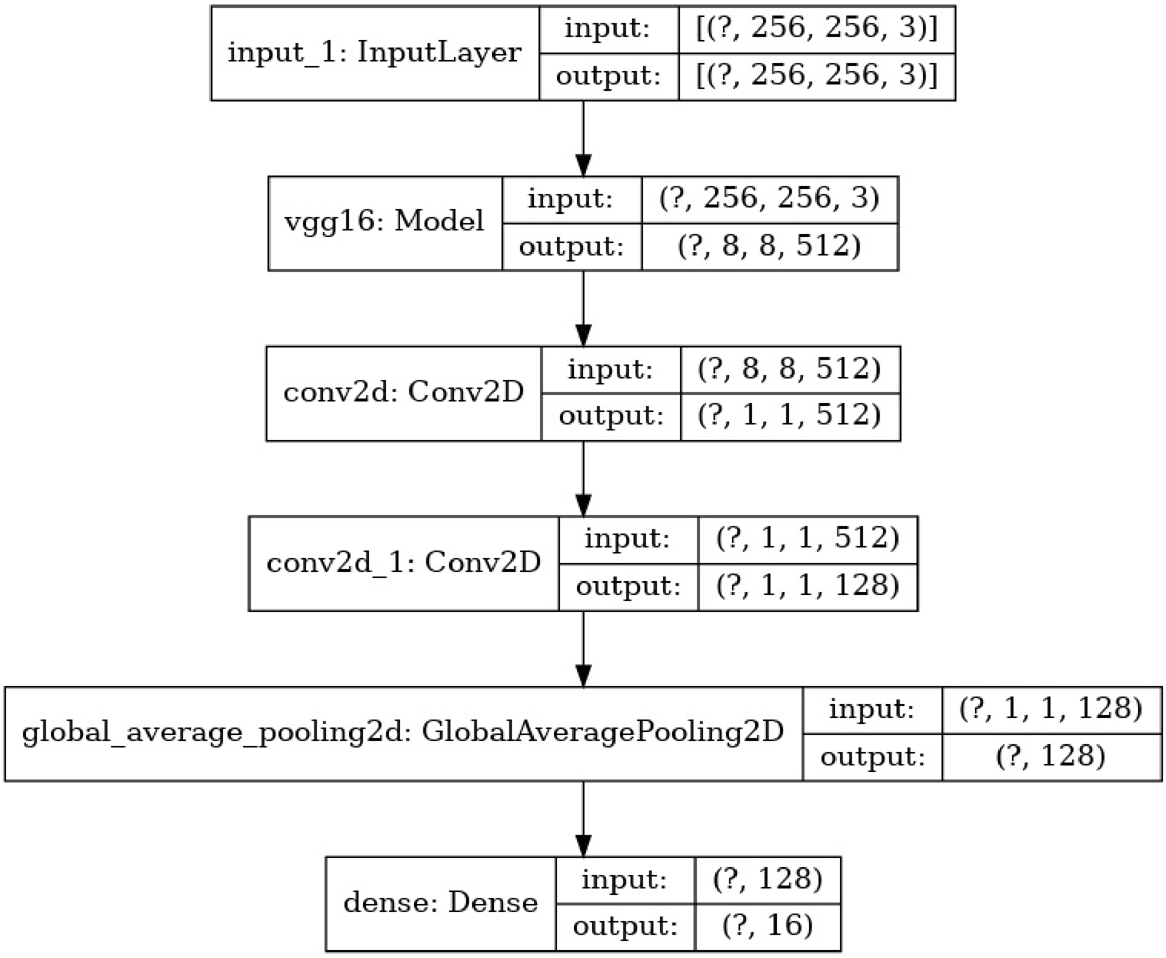
```
# https://keras.io/guides/transfer_learning/
# https://catalog.ngc.nvidia.com/orgs/nvidia/containers/dli-dl-fundamentals
# https://mein2work.medium.com/converting-fc-layers-to-conv-layers-8a43880a44ed

base_model.trainable = False
inputs = Input(shape = (256, 256, 3))

x = base_model(inputs, training = False)
x = Conv2D(filters = 512, kernel_size = (8, 8), activation = 'relu')(x)
x = Conv2D(filters = 128, kernel_size = (1, 1), activation = 'relu')(x)
# x = Conv2D(filters = 16, kernel_size = (1, 1), activation = 'relu')(x)
x = tf.keras.layers.GlobalAveragePooling2D()(x)
output_ = Dense(16, activation='softmax')(x)


final_model_2 = Model(inputs = inputs, outputs = output_, name = 'Model_2')
final_model_2.summary()
```

```
Model: "Model_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0         
_________________________________________________________________
vgg16 (Model)                (None, 8, 8, 512)         14714688  
_________________________________________________________________
conv2d (Conv2D)              (None, 1, 1, 512)         16777728  
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 1, 1, 128)         65664     
_________________________________________________________________
global_average_pooling2d (Gl (None, 128)               0         
_________________________________________________________________
dense (Dense)                (None, 16)                2064      
=================================================================
Total params: 31,560,144
Trainable params: 16,845,456
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [20]:

```python
plot_model(final_model_2, to_file = 'Model_Plots/Model_2.png', show_shapes = True)
```

Out[20]:



In [21]:

```python
logdir = 'logs/model_2/' + datetime.now().strftime('%Y%m%d_%H%M%S')
tensorBoard = TensorBoard(log_dir = logdir, histogram_freq = 1)

filepath = 'modelCheck/model_2/epo_{epoch:02d}-accu_{val_accuracy:.4f}.hdf5'
modelCheck = ModelCheckpoint(filepath, monitor = 'val_accuracy', verbose = 1)

callBack_List = [tensorBoard, modelCheck, earlyStopping, reduceLr]
```

In [22]:

```python
final_model_2.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
```

In [23]:

```python
EPOCHS_2 = 6
model_2 = final_model_2.fit(train_gen, steps_per_epoch = step_train, epochs = EPOCHS_2,
                validation_data = test_gen, validation_steps = step_test, callbacks = callBack_List)
```

```
Epoch 1/6
1125/1125 [==============================] - ETA: 0s - loss: 1.4232 - accuracy: 0.5759
Epoch 00001: saving model to modelCheck/model_2/epo_01-accu_0.6572.hdf5
1125/1125 [==============================] - 677s 602ms/step - loss: 1.4232 - accuracy: 0.5759 - val_loss: 1.1485
- val_accuracy: 0.6572 - lr: 0.0010
Epoch 2/6
1125/1125 [==============================] - ETA: 0s - loss: 1.0631 - accuracy: 0.6741
Epoch 00002: saving model to modelCheck/model_2/epo_02-accu_0.6690.hdf5
1125/1125 [==============================] - 675s 600ms/step - loss: 1.0631 - accuracy: 0.6741 - val_loss: 1.1056
- val_accuracy: 0.6690 - lr: 0.0010
Epoch 3/6
1125/1125 [==============================] - ETA: 0s - loss: 0.9474 - accuracy: 0.7098
Epoch 00003: saving model to modelCheck/model_2/epo_03-accu_0.6873.hdf5
1125/1125 [==============================] - 672s 598ms/step - loss: 0.9474 - accuracy: 0.7098 - val_loss: 1.0582
- val_accuracy: 0.6873 - lr: 0.0010
Epoch 4/6
1125/1125 [==============================] - ETA: 0s - loss: 0.8784 - accuracy: 0.7284
Epoch 00004: saving model to modelCheck/model_2/epo_04-accu_0.7083.hdf5
1125/1125 [==============================] - 673s 598ms/step - loss: 0.8784 - accuracy: 0.7284 - val_loss: 0.9910
- val_accuracy: 0.7083 - lr: 0.0010
Epoch 5/6
1125/1125 [==============================] - ETA: 0s - loss: 0.8250 - accuracy: 0.7454
Epoch 00005: saving model to modelCheck/model_2/epo_05-accu_0.7057.hdf5
1125/1125 [==============================] - 675s 600ms/step - loss: 0.8250 - accuracy: 0.7454 - val_loss: 0.9834
```

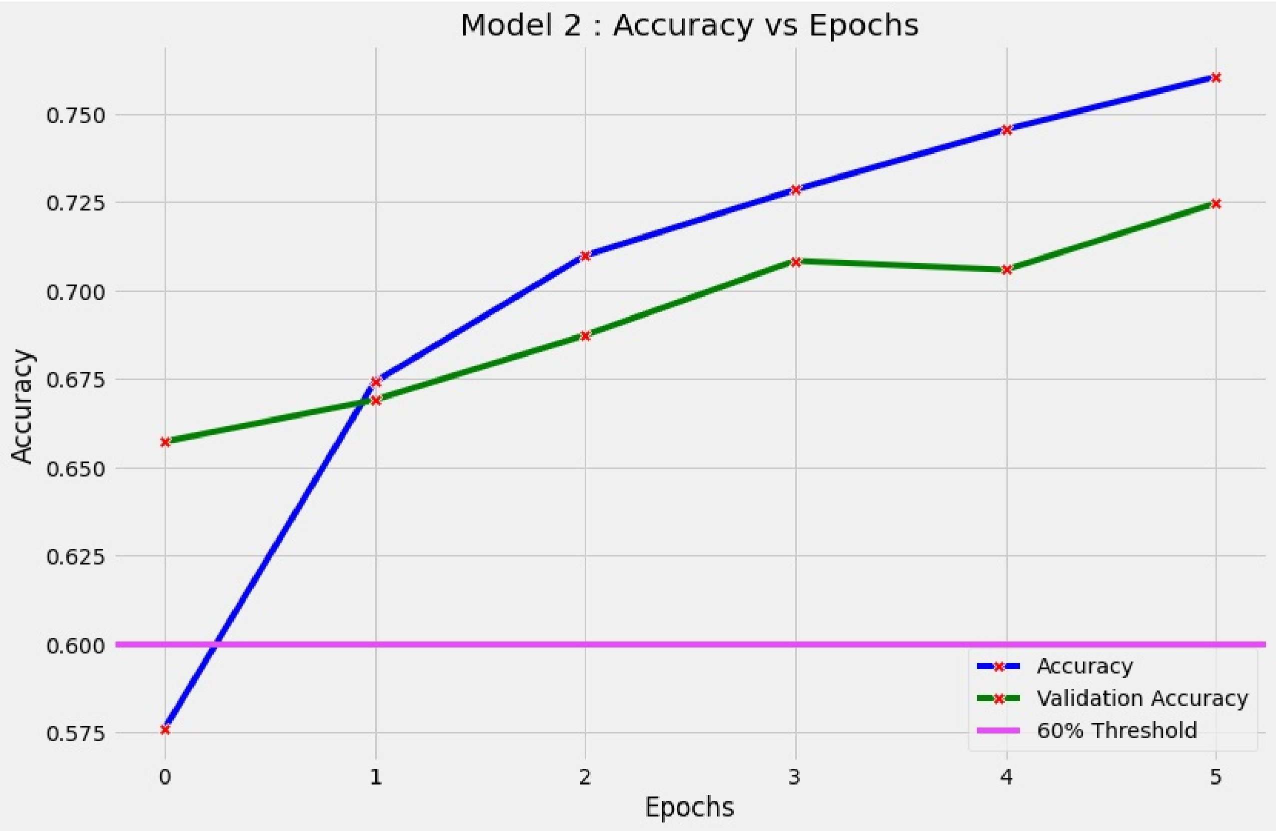
```
- val_accuracy: 0.7057 - lr: 0.0010
Epoch 6/6
1125/1125 [==============================] - ETA: 0s - loss: 0.7710 - accuracy: 0.7603
Epoch 00006: saving model to modelCheck/model_2/epo_06-accu_0.7246.hdf5
1125/1125 [==============================] - 674s 599ms/step - loss: 0.7710 - accuracy: 0.7603 - val_loss: 0.9490
- val_accuracy: 0.7246 - lr: 0.0010
```

In [24]:

```
final_model_2.save_weights('Model_Weights/best_model_2.h5')
```

In [25]:

```
# https://wellsr.com/python/seaborn-line-plot-data-visualization/
# https://seaborn.pydata.org/generated/seaborn.lineplot.html

epochs_ = list(range(len(model_2.history['accuracy'])))
plt.figure(figsize = (12, 8))

sns.lineplot(y = 'accuracy', data = model_2.history , x = epochs_, label = 'Accuracy',
             color = 'b', marker = 'X', mfc = 'red', ms = 8)
sns.lineplot(y = 'val_accuracy', data = model_2.history , x = epochs_,
             label = 'Validation Accuracy', color = 'g', marker = 'X', mfc = 'red', ms = 8)

plt.axhline(0.6, color = '#E44CF6', label = '60% Threshold')
plt.title('Model 2 : Accuracy vs Epochs') ; plt.legend(loc = 4)
plt.xticks(epochs_) ; plt.xlabel('Epochs') ; plt.ylabel('Accuracy') ; plt.show()
```



Observation

- Around 53% of parameters are trainable here.
- The loss was 0.7710 and accuracy was 76.03% in this model.
- This shows comparing to pervious model this model is giving much more better result in same 6 epochs.
- The curve also indicates that probably with more epoch we can increase the accuracy and reduce the loss.

Model-3

1. Use same network as Model-2 '**INPUT --> VGG-16 without Top layers(FC) --> 2 Conv Layers identical to FC --> Output Layer**' and train only Last 6 Layers of VGG-16 network, 2 Conv layers identical to FC layers, 1 output layer.

In [26]:

```
tensorflow.keras.backend.clear_session()
tensorflow.random.set_seed(42)
```

In [27]:

```python
# https://www.w3resource.com/python/python-format.php

base_model = VGG16(weights = 'imagenet', input_shape = (256, 256, 3), include_top = False)

le_ = len(base_model.layers)

for layer in range(le_-6):
    base_model.layers[layer].trainable = False

count_true = 0
for layer in base_model.layers:
    if layer.trainable:
        count_true += 1
    print(f'{layer.name:15} {layer.trainable}')
print(f'\nNumber of Trainable Layers from base_model : {count_true}')
```

```
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    True
block4_pool     True
block5_conv1    True
block5_conv2    True
block5_conv3    True
block5_pool     True

Number of Trainable Layers from base_model : 6
```

In [28]:

```python
base_model.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 256, 256, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 256, 256, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 128, 128, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 128, 128, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 128, 128, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 64, 64, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 64, 64, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 64, 64, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 64, 64, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 32, 32, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 32, 32, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 32, 32, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 32, 32, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 16, 16, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 8, 8, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 9,439,232
Non-trainable params: 5,275,456
```

In [29]:

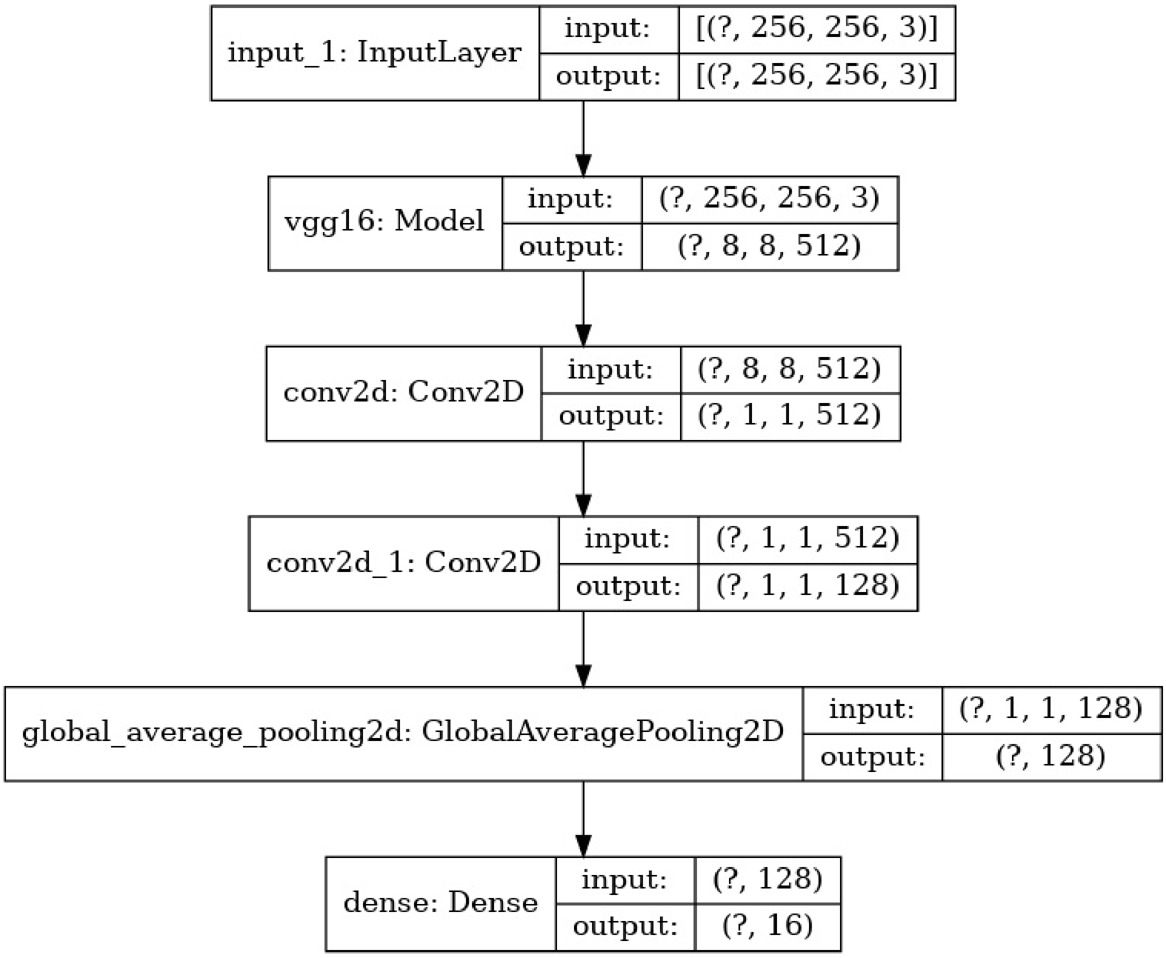
```
tensorflow.keras.backend.clear_session()

# https://keras.io/guides/transfer_learning/
# https://catalog.ngc.nvidia.com/orgs/nvidia/containers/dli-dl-fundamentals
# https://mein2work.medium.com/converting-fc-layers-to-conv-layers-8a43880a44ed

inputs = Input(shape = (256, 256, 3))

x = base_model(inputs, training = False)
x = Conv2D(filters = 512, kernel_size = (8, 8), activation = 'relu')(x)
x = Conv2D(filters = 128, kernel_size = (1, 1), activation = 'relu')(x)
x = tf.keras.layers.GlobalAveragePooling2D()(x)
output_ =Dense(16, activation='softmax')(x)

final_model_3 = Model(inputs = inputs, outputs = output_, name = 'Model_3')

final_model_3.summary()
```

```
Model: "Model_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0         
_________________________________________________________________
vgg16 (Model)                (None, 8, 8, 512)         14714688  
_________________________________________________________________
conv2d (Conv2D)              (None, 1, 1, 512)         16777728  
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 1, 1, 128)         65664     
_________________________________________________________________
global_average_pooling2d (Gl (None, 128)               0         
_________________________________________________________________
dense (Dense)                (None, 16)                2064      
=================================================================
Total params: 31,560,144
Trainable params: 26,284,688
Non-trainable params: 5,275,456
_________________________________________________________________
```

In [30]:

```
plot_model(final_model_3, to_file = 'Model_Plots/Model_3.png', show_shapes = True)
```

Out[30]:



In [31]:
```
final_model_3.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
```

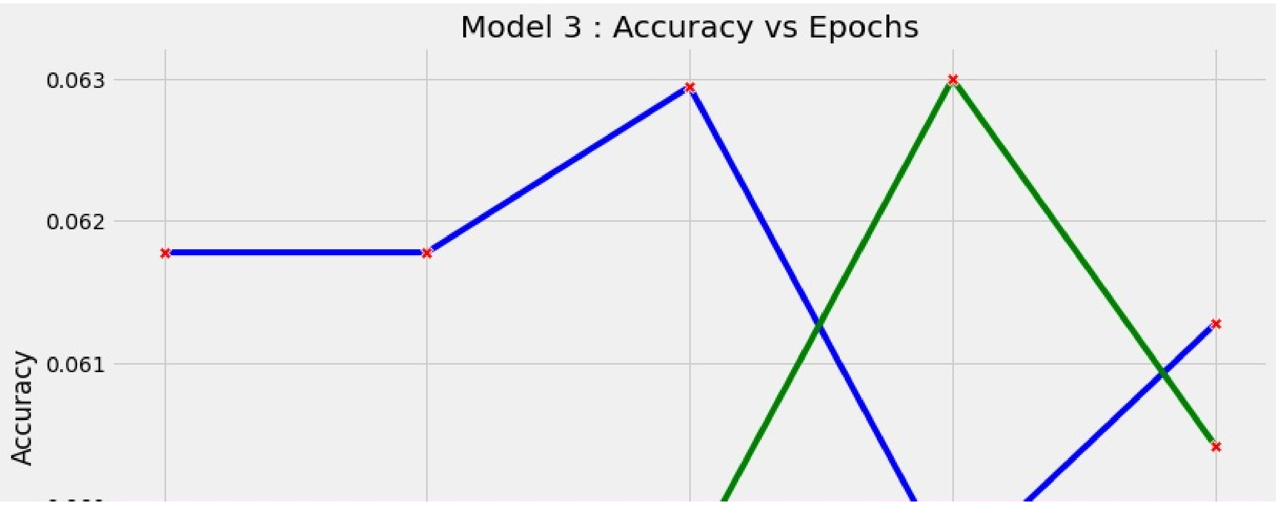
In [32]:
```
logdir = 'logs/model_3/' + datetime.now().strftime('%Y%m%d_%H%M%S')
tensorBoard = TensorBoard(log_dir = logdir, histogram_freq = 1)

filepath = 'modelCheck/model_3/epo_{epoch:02d}-accu_{val_accuracy:.4f}.hdf5'
modelCheck = ModelCheckpoint(filepath, monitor = 'val_accuracy', verbose = 1)

callBack_List = [tensorBoard, modelCheck, earlyStopping, reduceLr]
```

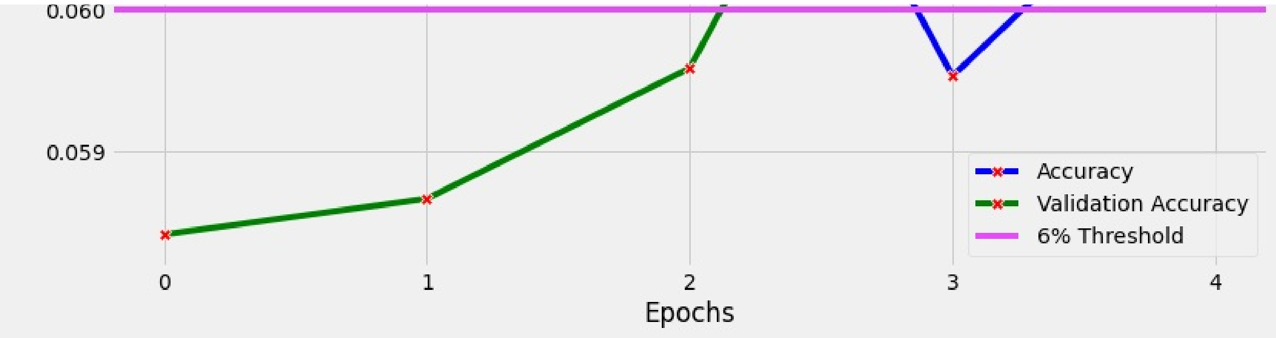
In [33]:
```
EPOCHS_3 = 5
model_3 = final_model_3.fit(train_gen, steps_per_epoch = step_train, epochs = EPOCHS_3,
                validation_data = test_gen, validation_steps = step_test, callbacks = callBack_List)
```

```
Epoch 1/5
1125/1125 [==============================] - ETA: 0s - loss: 2.7965 - accuracy: 0.0618
Epoch 00001: saving model to modelCheck/model_3/epo_01-accu_0.0584.hdf5
1125/1125 [==============================] - 683s 607ms/step - loss: 2.7965 - accuracy: 0.0618 - val_loss: 2.7728
- val_accuracy: 0.0584 - lr: 0.0010
Epoch 2/5
1125/1125 [==============================] - ETA: 0s - loss: 2.7728 - accuracy: 0.0618
Epoch 00002: saving model to modelCheck/model_3/epo_02-accu_0.0587.hdf5
1125/1125 [==============================] - 684s 608ms/step - loss: 2.7728 - accuracy: 0.0618 - val_loss: 2.7728
- val_accuracy: 0.0587 - lr: 0.0010
Epoch 3/5
1125/1125 [==============================] - ETA: 0s - loss: 2.7728 - accuracy: 0.0629
Epoch 00003: saving model to modelCheck/model_3/epo_03-accu_0.0596.hdf5
1125/1125 [==============================] - 686s 609ms/step - loss: 2.7728 - accuracy: 0.0629 - val_loss: 2.7730
- val_accuracy: 0.0596 - lr: 0.0010
Epoch 4/5
1125/1125 [==============================] - ETA: 0s - loss: 2.7728 - accuracy: 0.0595
Epoch 00004: saving model to modelCheck/model_3/epo_04-accu_0.0630.hdf5
1125/1125 [==============================] - 678s 603ms/step - loss: 2.7728 - accuracy: 0.0595 - val_loss: 2.7730
- val_accuracy: 0.0630 - lr: 0.0010
Epoch 5/5
1125/1125 [==============================] - ETA: 0s - loss: 2.7728 - accuracy: 0.0613
Epoch 00005: saving model to modelCheck/model_3/epo_05-accu_0.0604.hdf5

Epoch 00005: ReduceLROnPlateau reducing learning rate to 0.0009000000427477062.
1125/1125 [==============================] - 682s 606ms/step - loss: 2.7728 - accuracy: 0.0613 - val_loss: 2.7728
- val_accuracy: 0.0604 - lr: 0.0010
Epoch 00005: early stopping
```

In [34]:
```
final_model_3.save_weights('Model_Weights/best_model_3.h5')
```

In [35]:
```
# https://wellsr.com/python/seaborn-line-plot-data-visualization/
# https://seaborn.pydata.org/generated/seaborn.lineplot.html

epochs_ = list(range(len(model_3.history['accuracy'])))
plt.figure(figsize = (12, 8))
sns.lineplot(y = 'accuracy', data = model_3.history , x = epochs_, label = 'Accuracy',
             color = 'b', marker = 'X', mfc = 'red', ms = 8)
sns.lineplot(y = 'val_accuracy', data = model_3.history , x = epochs_,
             label = 'Validation Accuracy', color = 'g', marker = 'X', mfc = 'red', ms = 8)
plt.axhline(0.06, color = '#E44CF6', label = '6% Threshold')
plt.title('Model 3 : Accuracy vs Epochs') ; plt.legend(loc = 4)
plt.xticks(epochs_) ; plt.xlabel('Epochs') ; plt.ylabel('Accuracy') ; plt.show()
```





Observation

- The accuracy for this model is only less than 10%.
- Morethan 83% of parameters are trainable from total parameters.
- The loss was more than 2.5. This both indicates the model performance was pritty bad.
- This indicates that training VGG16 layaers won't give better accuracy always.
- Since from the grapgh indications, it is clear that may be with more epoch values may be we will get much more better results.
- Higher trainable parameters will give better result at higher epochs.

Models Summary

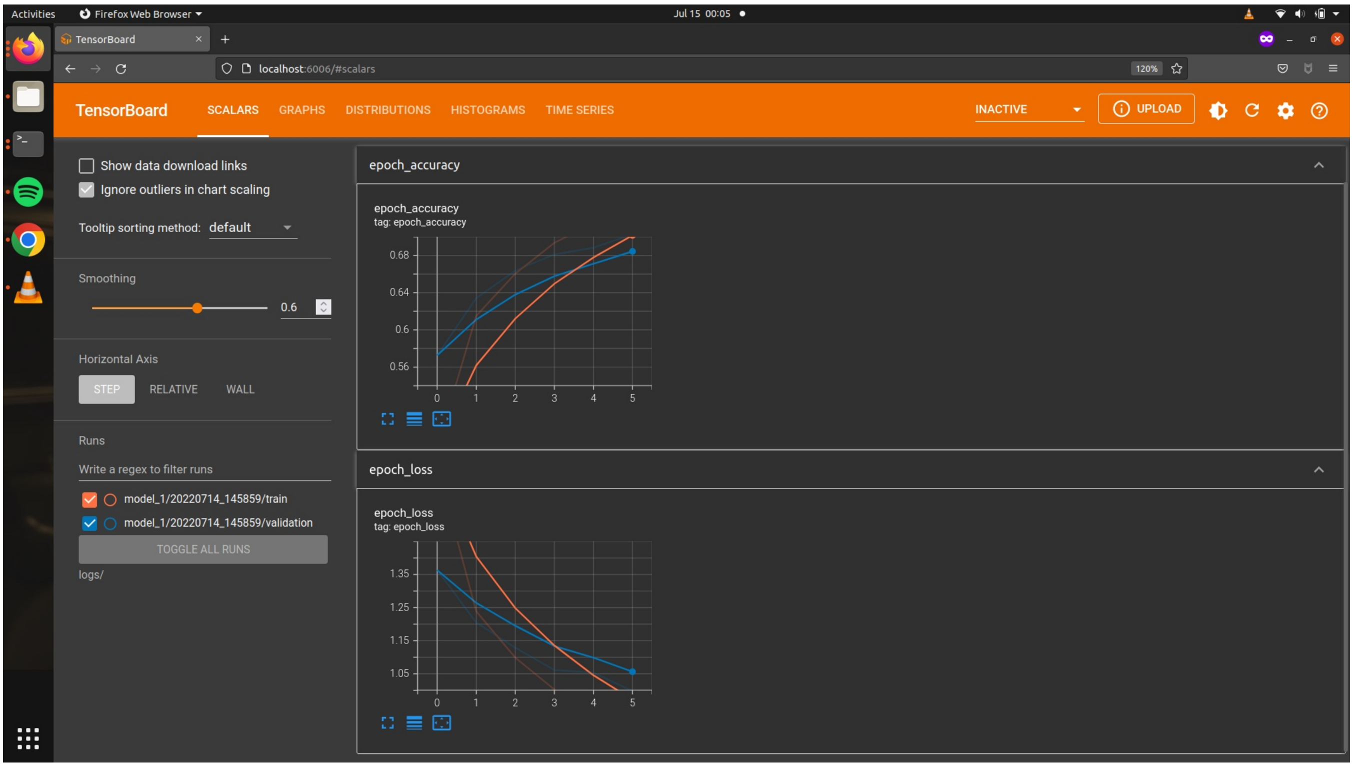
In [36]:

```
# https://pypi.org/project/prettytable/

from prettytable import PrettyTable

table = PrettyTable()

table.field_names = ['Model', 'Number of epochs', 'Accuracy',
                     'Validation Accuracy']

table.add_row(['Model_1', EPOCHS_1, round(model_1.history['accuracy'][-1], 4),
               round(model_1.history['val_accuracy'][-1], 4)])

table.add_row(['Model_2', EPOCHS_2, round(model_2.history['accuracy'][-1], 4),
               round(model_2.history['val_accuracy'][-1], 4)])

table.add_row(['Model_3', EPOCHS_3, round(model_3.history['accuracy'][-1], 4),
               round(model_3.history['val_accuracy'][-1], 4)])

print(table)
```

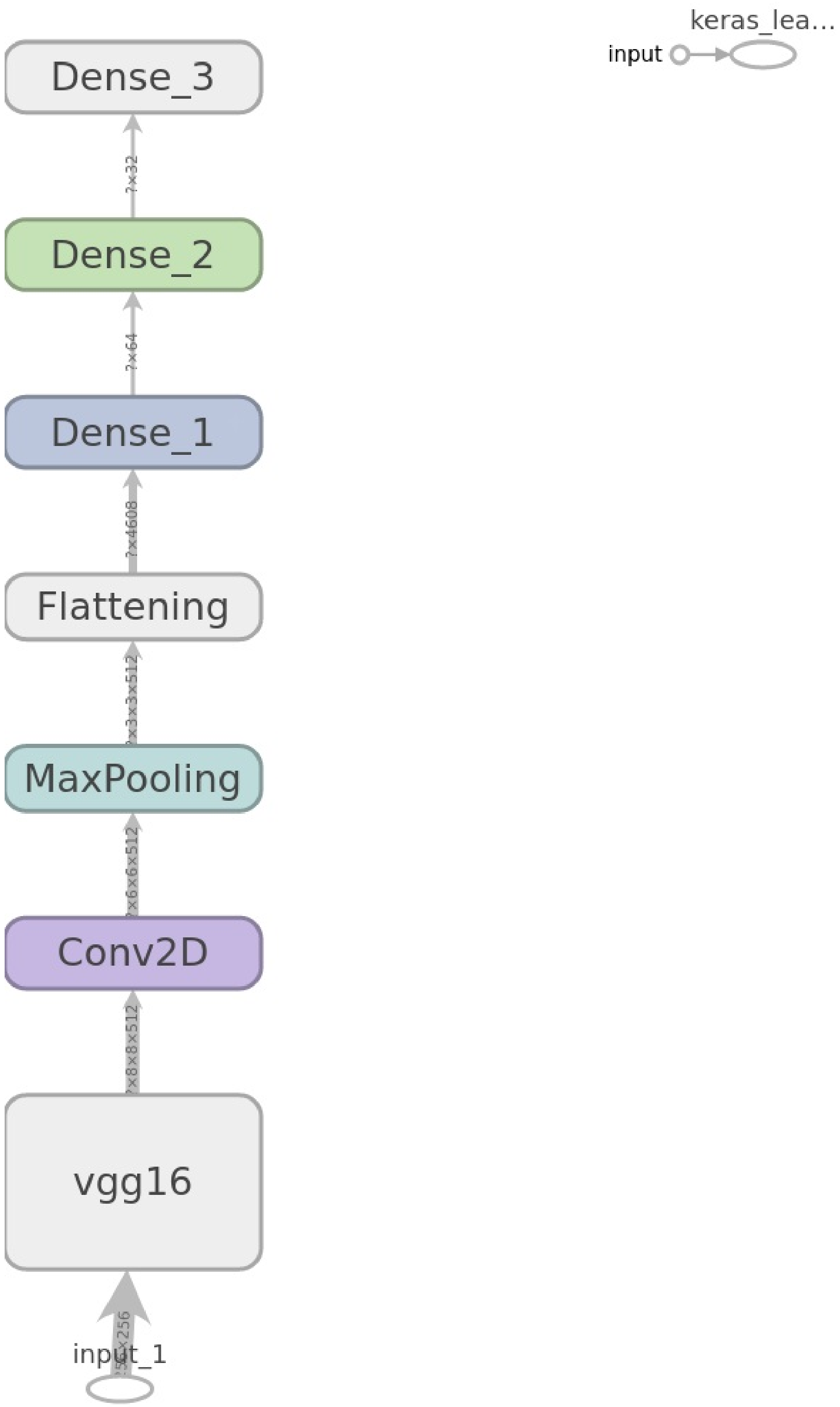
```
+---------+------------------+----------+---------------------+
|  Model  | Number of epochs | Accuracy | Validation Accuracy |
+---------+------------------+----------+---------------------+
| Model_1 |        6         |  0.7345  |        0.7028       |
| Model_2 |        6         |  0.7603  |        0.7246       |
| Model_3 |        5         |  0.0613  |        0.0604       |
+---------+------------------+----------+---------------------+
```

TensorBoard Outputs

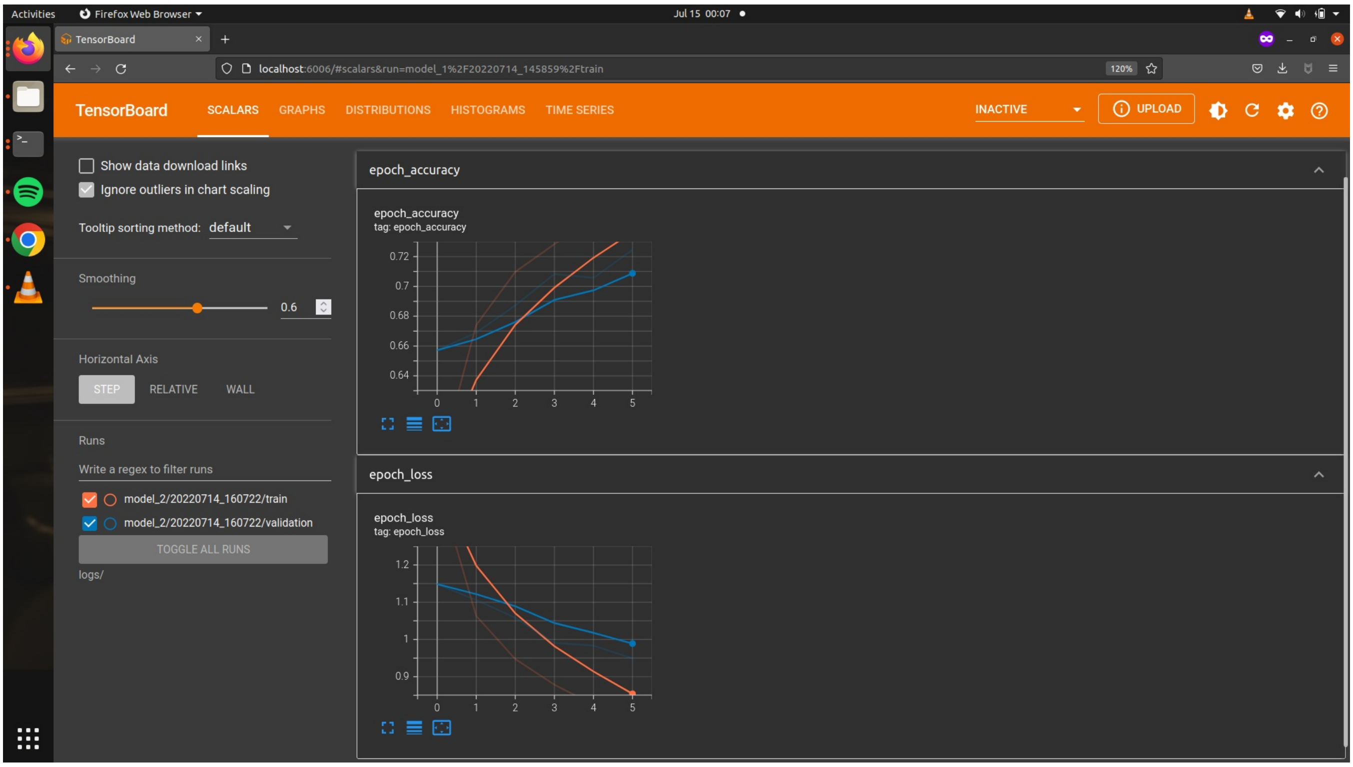
Model - 1

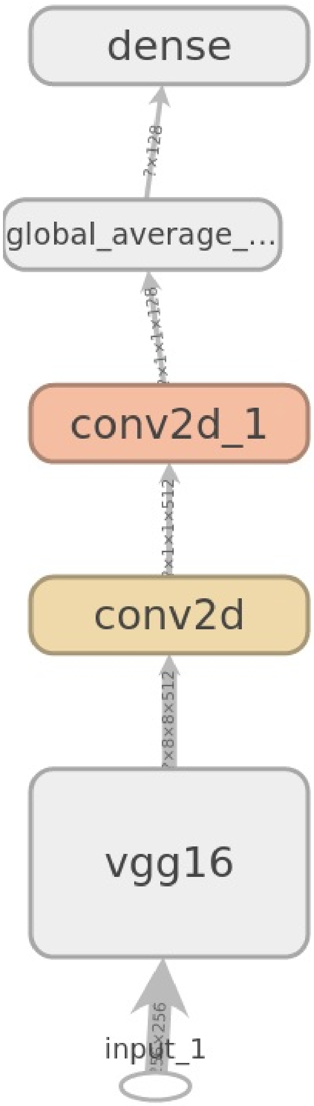


Activities
Firefox Web Browser
Jul 15 00:05
TensorBoard
localhost:6006/#scalars
120%
TensorBoard
SCALARS
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
TIME SERIES
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
model_1/20220714_145859/train
model_1/20220714_145859/validation
TOGGLE ALL RUNS
logs/
epoch_accuracy
epoch_accuracy
tag: epoch_accuracy
0.68
0.64
0.6
0.56
0
1
2
3
4
5
epoch_loss
epoch_loss
tag: epoch_loss
1.35
1.25
1.15
1.05
0
1
2
3
4
5


keras_lea...
input
Dense_3
?×32
Dense_2
?×64
Dense_1
?×4608
Flattening
MaxPooling
?×6×6×512
Conv2D
?×8×8×512
vgg16
input_1

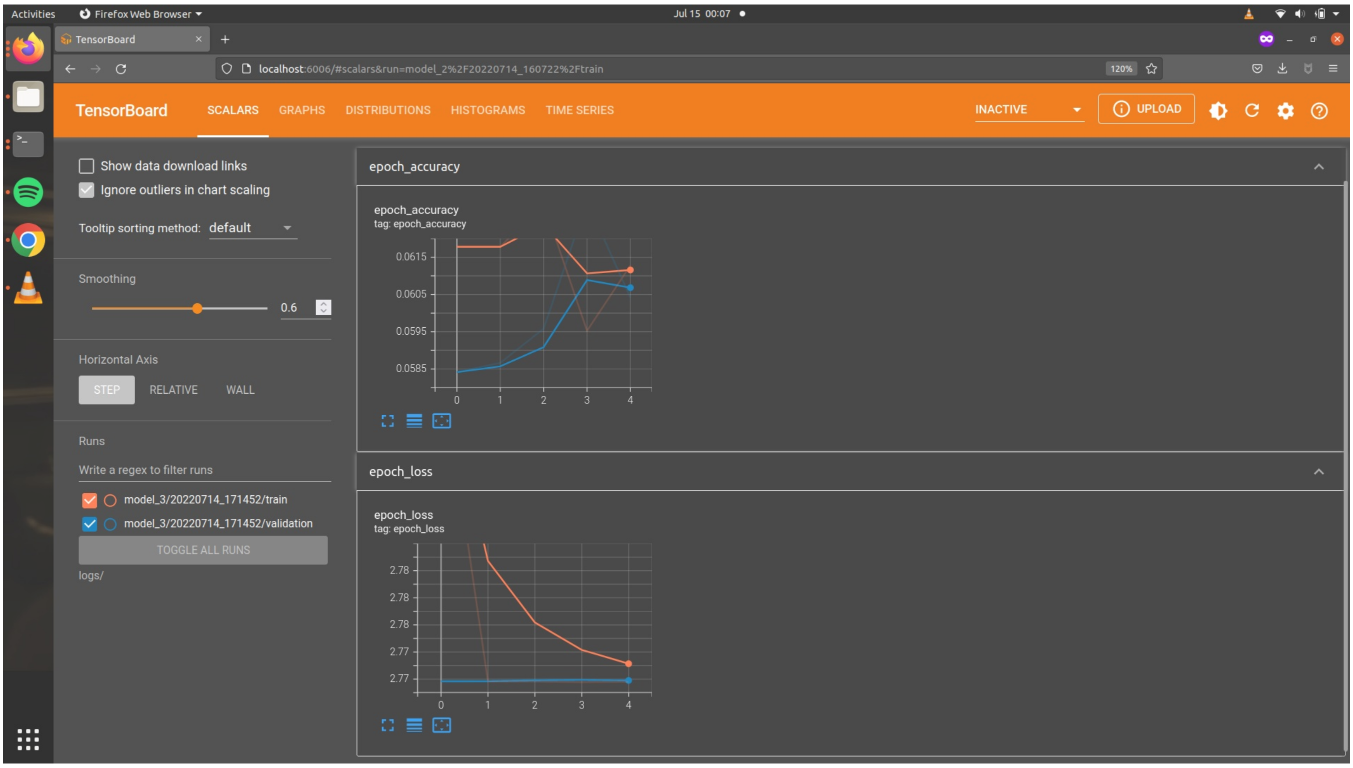
Model - 2

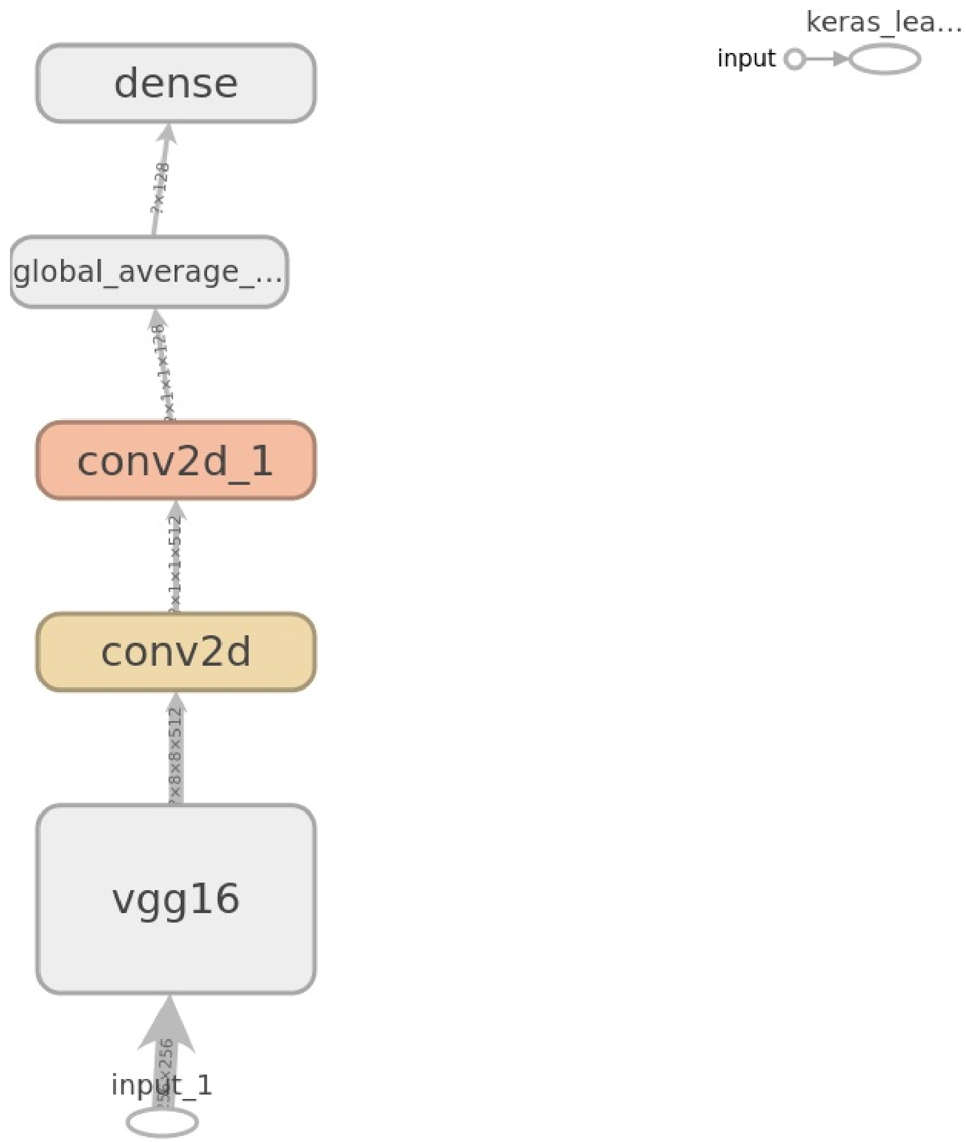

Activities
Firefox Web Browser
Jul 15 00:07
TensorBoard
localhost:6006/#scalars&run=model_1%2F20220714_145859%2Ftrain
120%
TensorBoard
SCALARS
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
TIME SERIES
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
model_2/20220714_160722/train
model_2/20220714_160722/validation
TOGGLE ALL RUNS
logs/
epoch_accuracy
epoch_accuracy
tag: epoch_accuracy
0.72
0.7
0.68
0.66
0.64
0
1
2
3
4
5
epoch_loss
epoch_loss
tag: epoch_loss
1.2
1.1
1
0.9
0
1
2
3
4
5


dense
?×128
global_average_...
?×1×1×128
conv2d_1
?×1×1×512
conv2d
?×8×8×512
vgg16
input_1


keras_lea...
input

Model - 3


TensorBoard
SCALARS
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
TIME SERIES
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
model_3/20220714_171452/train
model_3/20220714_171452/validation
TOGGLE ALL RUNS
logs/
epoch_accuracy
epoch_accuracy
tag: epoch_accuracy
epoch_loss
epoch_loss
tag: epoch_loss


keras_lea...
input
dense
?×128
global_average_...
conv2d_1
conv2d
vgg16
input_1