```
In [ ]: !unzip "/content/drive/My Drive/ADM/dataset3.zip" -d "/content/sample d
        ata/dataset"
        Archive: /content/drive/My Drive/ADM/dataset3.zip
        replace /content/sample data/dataset/dataset3/test images from train/
        00fb450622785388.jpg? [y]es, [n]o, [A]ll, [N]one, [r]ename:
In []: | # Make sure we are pointing to the directory that has all the files nec
        essary
        import numpy as np
        import pandas as pd
        import sys, requests, shutil, os
        import numpy as np
        from shutil import copyfile
        import urllib
        from tensorflow.keras.preprocessing.image import ImageDataGenerator, im
        g to array, load img
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dropout, Flatten, Dense, GlobalAver
        agePooling2D
        from tensorflow.keras import applications
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras import optimizers
        #from tensorflow.keras.utils.np utils import to categorical
        from tensorflow.keras.utils import to categorical
        from tensorflow.keras.callbacks import ModelCheckpoint
        from tensorflow.keras.models import Model
        import csv
        import os
        import cv2
        from tensorflow.keras.models import load model
        import matplotlib.pyplot as plt
        import math
        from tensorflow.keras.optimizers import Adam
        from sklearn.model selection import train test split
        from tensorflow.keras.preprocessing.image import img to array
        from tensorflow.keras.utils import to categorical
        import matplotlib.pyplot as plt
        import numpy as np
        import argparse
        import random
        import tensorflow as tf
        import tensorflow.keras
        from keras.optimizers import SGD, Adam
In [ ]: | cd "/content/sample data/dataset/dataset3"
```

/content/sample data/dataset/dataset3

```
In [ ]: # This is where we fine tune the pretrained model according to our data
        img width, img height = 96, 96
        save model weights = "VGG16 weights.h5"
        train data dir = 'train images model'
        validation data dir = 'validation images model'
        batch size = 200
        epochs = 100
        def train VGG16():
            base model = applications.VGG16(weights='imagenet', include top= Fal
        se, input shape=(96, 96, 3))
            top model = Sequential()
            top model.add(Flatten(input shape=base model.output shape[1:]))
            top model.add(Dense(256, activation='relu'))
            top model.add(Dense(256, activation='relu'))
            n class = 6000
            top model.add(Dense(n class, activation='softmax'))
            model = Model(base model.input, top model(base model.output))
            # set the first 16 layers to non-trainable (weights will not be upd
        ated)
            # 1 conv layer and three dense layers will be trained
            for layer in model.layers[:16]:
                layer.trainable = False
            #model.load weights("/content/sample data/dataset/dataset3/VGG16 we
        ights.h5")
            model.compile(loss='categorical crossentropy',
                           optimizer=optimizers.Adam(lr=0.001, beta 1=0.9,beta 2
        =0.999,epsilon=1e-8, decay=0.0),
                          metrics=['accuracy'])
            print ('Compilation done.')
            train datagen = ImageDataGenerator(rescale=1. / 255,
                                                rotation range=90,
                                                 width shift range=0.2,
                                                 height shift range=0.2,
                                                 zoom range = 0.5)
            valid datagen = ImageDataGenerator(rescale=1. / 255)
            train generator = train datagen.flow from directory(
                train data dir,
                target size=(img height, img width),
                batch size=batch size,
                class mode='categorical')
            #np.save('class indices.npy', train generator.class indices)
            validation generator = valid datagen.flow from directory(
                validation data dir,
                target size=(img height, img width),
                batch size=batch size,
```

```
class mode='categorical')
    print ('Model fit begins...')
    history1=model.fit generator(
       train_generator,
        steps per epoch=150,
        epochs=epochs,
        validation data=validation generator,
        validation steps=75,
        callbacks=[ModelCheckpoint(filepath="vgg16 weights tf dim order
ing tf kernels-notop.h5",
                                   save best only=True, save weights on
ly=True)]
    model.save weights(save model weights)
    # final weights are saved in bottleneck fc model.h5 file
    return history1
history1=train_VGG16()
```

Compilation done.

Found 246794 images belonging to 6000 classes.

Found 54916 images belonging to 6000 classes.

Model fit begins...

/usr/local/lib/python3.6/dist-packages/PIL/Image.py:932: UserWarning: Palette images with Transparency expressed in bytes should be converted to RGBA images

"Palette images with Transparency expressed in bytes should be "

```
Epoch 1/100
4300 - accuracy: 0.0090 - val loss: 7.1718 - val accuracy: 0.0139
9714 - accuracy: 0.0192 - val loss: 6.9208 - val accuracy: 0.0205
6725 - accuracy: 0.0275 - val loss: 6.6716 - val accuracy: 0.0251
Epoch 4/100
5231 - accuracy: 0.0335 - val loss: 6.4537 - val accuracy: 0.0350
Epoch 5/100
4007 - accuracy: 0.0410 - val loss: 6.3077 - val accuracy: 0.0434
Epoch 6/100
2400 - accuracy: 0.0529 - val loss: 6.3571 - val accuracy: 0.0443
Epoch 7/100
1298 - accuracy: 0.0607 - val loss: 6.1201 - val accuracy: 0.0615
Epoch 8/100
9918 - accuracy: 0.0681 - val loss: 6.0070 - val accuracy: 0.0675
Epoch 9/100
8889 - accuracy: 0.0771 - val loss: 5.9660 - val accuracy: 0.0698
Epoch 10/100
7831 - accuracy: 0.0857 - val loss: 5.6975 - val accuracy: 0.0823
Epoch 11/100
7154 - accuracy: 0.0882 - val loss: 5.6943 - val accuracy: 0.0902
Epoch 12/100
6435 - accuracy: 0.0931 - val loss: 5.5814 - val accuracy: 0.0971
Epoch 13/100
5917 - accuracy: 0.0958 - val loss: 5.5662 - val accuracy: 0.1003
Epoch 14/100
5090 - accuracy: 0.0989 - val loss: 5.4818 - val accuracy: 0.1073
Epoch 15/100
4479 - accuracy: 0.1081 - val loss: 5.4121 - val accuracy: 0.1115
Epoch 16/100
4146 - accuracy: 0.1098 - val loss: 5.3636 - val accuracy: 0.1151
Epoch 17/100
3553 - accuracy: 0.1113 - val_loss: 5.3788 - val accuracy: 0.1195
Epoch 18/100
3490 - accuracy: 0.1151 - val loss: 5.4474 - val accuracy: 0.1133
```

```
2971 - accuracy: 0.1209 - val loss: 5.3283 - val accuracy: 0.1272
Epoch 20/100
2446 - accuracy: 0.1248 - val loss: 5.2383 - val accuracy: 0.1331
Epoch 21/100
2162 - accuracy: 0.1228 - val loss: 5.1954 - val accuracy: 0.1388
Epoch 22/100
2105 - accuracy: 0.1253 - val loss: 5.1831 - val accuracy: 0.1293
Epoch 23/100
1667 - accuracy: 0.1315 - val loss: 5.1527 - val accuracy: 0.1325
Epoch 24/100
1345 - accuracy: 0.1336 - val loss: 5.2340 - val accuracy: 0.1307
1241 - accuracy: 0.1340 - val loss: 5.2166 - val accuracy: 0.1418
Epoch 26/100
1025 - accuracy: 0.1361 - val loss: 5.0651 - val accuracy: 0.1508
Epoch 27/100
0498 - accuracy: 0.1392 - val loss: 5.1113 - val accuracy: 0.1483
Epoch 28/100
0443 - accuracy: 0.1408 - val loss: 5.1296 - val accuracy: 0.1529
Epoch 29/100
0499 - accuracy: 0.1398 - val loss: 5.0342 - val accuracy: 0.1507
Epoch 30/100
150/150 [============== ] - 108s 721ms/step - loss: 4.
9938 - accuracy: 0.1462 - val loss: 5.0420 - val accuracy: 0.1569
Epoch 31/100
9983 - accuracy: 0.1471 - val loss: 5.0137 - val accuracy: 0.1583
Epoch 32/100
150/150 [=============== ] - 109s 724ms/step - loss: 4.
9832 - accuracy: 0.1482 - val loss: 5.0043 - val accuracy: 0.1606
Epoch 33/100
150/150 [=============== ] - 110s 730ms/step - loss: 4.
9514 - accuracy: 0.1527 - val loss: 4.9065 - val accuracy: 0.1719
Epoch 34/100
150/150 [============== ] - 109s 725ms/step - loss: 4.
9365 - accuracy: 0.1472 - val loss: 4.9690 - val accuracy: 0.1697
Epoch 35/100
150/150 [============== ] - 110s 732ms/step - loss: 4.
9152 - accuracy: 0.1490 - val loss: 4.8987 - val accuracy: 0.1738
Epoch 36/100
150/150 [============== ] - 110s 731ms/step - loss: 4.
8905 - accuracy: 0.1535 - val loss: 4.8897 - val accuracy: 0.1688
Epoch 37/100
8836 - accuracy: 0.1577 - val loss: 5.0219 - val accuracy: 0.1615
Epoch 38/100
```

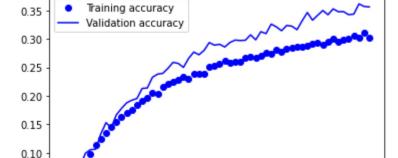
```
150/150 [=============== ] - 109s 728ms/step - loss: 4.
8446 - accuracy: 0.1567 - val loss: 4.9855 - val accuracy: 0.1672
Epoch 39/100
150/150 [============== ] - 109s 724ms/step - loss: 4.
8623 - accuracy: 0.1564 - val loss: 4.9100 - val accuracy: 0.1745
Epoch 40/100
8319 - accuracy: 0.1631 - val loss: 4.9599 - val accuracy: 0.1672
Epoch 41/100
150/150 [============== ] - 108s 723ms/step - loss: 4.
8018 - accuracy: 0.1641 - val loss: 4.8263 - val accuracy: 0.1813
8038 - accuracy: 0.1625 - val loss: 4.8219 - val accuracy: 0.1865
Epoch 43/100
8120 - accuracy: 0.1608 - val loss: 4.8227 - val accuracy: 0.1813
Epoch 44/100
150/150 [=============== ] - 109s 724ms/step - loss: 4.
8053 - accuracy: 0.1621 - val loss: 4.7299 - val accuracy: 0.1912
Epoch 45/100
7757 - accuracy: 0.1666 - val loss: 4.9076 - val accuracy: 0.1785
Epoch 46/100
7433 - accuracy: 0.1683 - val loss: 4.8026 - val accuracy: 0.1888
Epoch 47/100
7614 - accuracy: 0.1668 - val loss: 4.7838 - val accuracy: 0.1893
Epoch 48/100
7155 - accuracy: 0.1739 - val loss: 4.8190 - val accuracy: 0.1835
Epoch 49/100
150/150 [============== ] - 109s 728ms/step - loss: 4.
7411 - accuracy: 0.1712 - val loss: 4.7230 - val accuracy: 0.1908
Epoch 50/100
7027 - accuracy: 0.1734 - val loss: 4.7255 - val accuracy: 0.1964
Epoch 51/100
7041 - accuracy: 0.1739 - val loss: 4.7440 - val accuracy: 0.1863
Epoch 52/100
6709 - accuracy: 0.1782 - val loss: 4.9017 - val accuracy: 0.1861
Epoch 53/100
150/150 [============== ] - 110s 734ms/step - loss: 4.
6747 - accuracy: 0.1765 - val loss: 4.6901 - val accuracy: 0.2022
Epoch 54/100
6791 - accuracy: 0.1747 - val loss: 4.6284 - val accuracy: 0.2114
Epoch 55/100
6236 - accuracy: 0.1842 - val loss: 4.8191 - val accuracy: 0.1897
Epoch 56/100
6483 - accuracy: 0.1785 - val loss: 4.8465 - val accuracy: 0.1816
```

```
Epoch 57/100
6349 - accuracy: 0.1788 - val loss: 4.6319 - val accuracy: 0.1984
Epoch 58/100
150/150 [============== ] - 111s 740ms/step - loss: 4.
6469 - accuracy: 0.1795 - val loss: 4.8030 - val accuracy: 0.1935
150/150 [============== ] - 111s 738ms/step - loss: 4.
6271 - accuracy: 0.1807 - val loss: 4.6667 - val accuracy: 0.2045
Epoch 60/100
5969 - accuracy: 0.1824 - val loss: 4.7158 - val accuracy: 0.1982
Epoch 61/100
150/150 [=============== ] - 111s 739ms/step - loss: 4.
6065 - accuracy: 0.1827 - val loss: 4.7126 - val accuracy: 0.2009
Epoch 62/100
5993 - accuracy: 0.1829 - val loss: 4.8235 - val accuracy: 0.1881
Epoch 63/100
150/150 [=============== ] - 111s 739ms/step - loss: 4.
5754 - accuracy: 0.1884 - val loss: 4.6701 - val accuracy: 0.2016
Epoch 64/100
150/150 [=============== ] - 111s 739ms/step - loss: 4.
6165 - accuracy: 0.1832 - val loss: 4.6406 - val accuracy: 0.2095
Epoch 65/100
150/150 [=============== ] - 110s 734ms/step - loss: 4.
5615 - accuracy: 0.1873 - val loss: 4.6796 - val accuracy: 0.2053
Epoch 66/100
5861 - accuracy: 0.1844 - val loss: 4.7908 - val accuracy: 0.2001
Epoch 67/100
150/150 [=============== ] - 110s 734ms/step - loss: 4.
5303 - accuracy: 0.1902 - val loss: 4.6051 - val accuracy: 0.2157
Epoch 68/100
150/150 [=============== ] - 110s 734ms/step - loss: 4.
5441 - accuracy: 0.1920 - val loss: 4.6863 - val accuracy: 0.2141
Epoch 69/100
150/150 [=============== ] - 110s 734ms/step - loss: 4.
5555 - accuracy: 0.1838 - val loss: 4.6632 - val accuracy: 0.2169
Epoch 70/100
5475 - accuracy: 0.1881 - val loss: 4.6371 - val_accuracy: 0.2157
Epoch 71/100
150/150 [============== ] - 109s 730ms/step - loss: 4.
5341 - accuracy: 0.1900 - val loss: 4.6168 - val accuracy: 0.2135
Epoch 72/100
5506 - accuracy: 0.1891 - val loss: 4.6198 - val accuracy: 0.2141
Epoch 73/100
150/150 [============== ] - 109s 729ms/step - loss: 4.
4899 - accuracy: 0.1952 - val loss: 4.6055 - val accuracy: 0.2180
Epoch 74/100
150/150 [============== ] - 109s 730ms/step - loss: 4.
5188 - accuracy: 0.1936 - val loss: 4.7596 - val accuracy: 0.2003
Epoch 75/100
150/150 [============== ] - 110s 730ms/step - loss: 4.
```

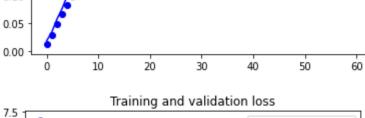
```
5118 - accuracy: 0.1942 - val loss: 4.7052 - val accuracy: 0.2155
      Epoch 76/100
      150/150 [=============== ] - 108s 720ms/step - loss: 4.
      5407 - accuracy: 0.1928 - val loss: 4.4593 - val accuracy: 0.2325
      Epoch 77/100
      5090 - accuracy: 0.1949 - val loss: 4.7124 - val accuracy: 0.2168
      Epoch 78/100
      150/150 [============== ] - 108s 718ms/step - loss: 4.
      4910 - accuracy: 0.1924 - val loss: 4.6655 - val accuracy: 0.2123
      Epoch 79/100
      150/150 [=============== ] - 108s 721ms/step - loss: 4.
      4860 - accuracy: 0.1936 - val loss: 4.5779 - val accuracy: 0.2245
      Epoch 80/100
      150/150 [============== ] - 110s 731ms/step - loss: 4.
      4877 - accuracy: 0.1953 - val loss: 4.5497 - val accuracy: 0.2271
      Epoch 81/100
      150/150 [=============== ] - 109s 726ms/step - loss: 4.
      4845 - accuracy: 0.1953 - val loss: 4.7317 - val accuracy: 0.2072
      Epoch 82/100
      4688 - accuracy: 0.1976 - val loss: 4.5545 - val accuracy: 0.2273
      Epoch 83/100
      150/150 [============== ] - 111s 743ms/step - loss: 4.
      4392 - accuracy: 0.1977 - val loss: 4.5983 - val accuracy: 0.2251
      Epoch 84/100
      150/150 [============== ] - 110s 731ms/step - loss: 4.
      4504 - accuracy: 0.1988 - val loss: 4.6340 - val accuracy: 0.2145
In [ ]: history1
```

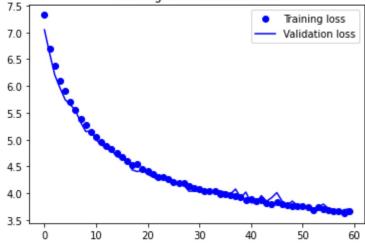
Out[]: <tensorflow.python.keras.callbacks.History at 0x7f04acdab198>

```
acc = history1.history['accuracy']
In [ ]:
        val acc = history1.history['val accuracy']
        loss = history1.history['loss']
        val loss = history1.history['val loss']
        epochs = range(60)
        plt.figure()
        plt.plot(epochs, acc, 'bo', label='Training accuracy')
        plt.plot(epochs, val acc, 'b', label='Validation accuracy')
        plt.title('Training and validation accuracy')
        plt.legend()
        plt.show()
        epochs = range(60)
        plt.figure()
        plt.plot(epochs, loss, 'bo', label='Training loss')
        plt.plot(epochs, val loss, 'b', label='Validation loss')
        plt.title('Training and validation loss')
        plt.legend()
        plt.show()
```



Training and validation accuracy





```
In [ ]:
```