# Problem Statement: ¶

From an Image dataset we need to find N similar images on a given query image

# Importing Data:

**Loading Data using Curl-WGet:**

In [ ]:
```
!wget --header="Host: doc-10-1c-docs.googleusercontent.com" --header="User-Agent: Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/84.0.
```

**Unzipping the folder:**

In [ ]:
```
!unzip dataset.zip
```

- Using CurlWget method takes couple of seconds to load the data.

**Note1:** When the PC gets turned off all the data you loaded through it will get lost. So you need to load the data again when you run the below code snippets.

**Note2:** CurlWget gives a .zip file. So we need to unzip the folders before using it.

**Mounting Google Drive:**

To access/create files in google drive

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

**Loading Dependencies:**

In [ ]:
```
# For commands
import os
os.chdir('/content/')
import time
from tqdm.notebook import tqdm
import warnings
warnings.filterwarnings('ignore')
# For array manipulation
import numpy as np
import pandas as pd
import pandas.util.testing as tm
# For visualization
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import seaborn as sns
import cv2
import imageio as io
from pylab import *
from sklearn.manifold import TSNE
#For model performance
from sklearn.metrics import pairwise_distances
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.externals import joblib
#For model training
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
import tensorflow as tf
from sklearn.neighbors import KNeighborsClassifier
from tensorflow.keras.models import Sequential
from keras.applications.vgg16 import preprocess_input
from tensorflow.keras.layers import Conv2D, Activation, MaxPooling2D, UpSampling2D
from tensorflow.keras.optimizers import Adam, Adagrad, RMSprop
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from keras import backend as K
from keras.models import load_model
from keras.preprocessing import image
```

- I am using tensorflow.keras (2.0 version) throughout this assignment.
- I am doing this case study in google colab. So all the paths will be specified according to colab directories.

In [ ]:
```
file_path = os.listdir('dataset')
print(len(file_path))
```

```
4738
```

- Their are of total 4738 images.
- Since the dataset is small we need to take of model training so that it won't get overfit or underfit.
- Interestingly all the images are in same resolution. (512x512)

**Splitting the data into Train & Test sets:**

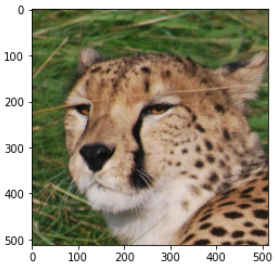
In [ ]:
```
train_files, test_files = train_test_split(file_path, test_size = 0.15)
print(len(train_files))
print(len(test_files))

train_files = pd.DataFrame(train_files,columns=['filepath'])
test_files = pd.DataFrame(test_files,columns=['filepath'])
#converting into .csv file for future reference.
train_files.to_csv('/content/drive/My Drive/train_file.csv')
test_files.to_csv('/content/drive/My Drive/test_file.csv')
```

In [ ]:
```
#loading csv files.
train_files = list(pd.read_csv('/content/drive/My Drive/image_similarity/train_file.csv')['filepath'])
test_files = list(pd.read_csv('/content/drive/My Drive/image_similarity/test_file.csv')['filepath'])
```

- Taking the file path of all the images and splitting that list into train and test. So that their will be no need of splitting the data again in future and we can access those sets directly by storing it in drive.
- Storing the end result into .csv format so that their will be no data leakage problems in future.

In [ ]:
```
img = cv2.imread('/content/dataset/'+train_files[0])
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plt.imshow(img)
```

Out[3]: <matplotlib.image.AxesImage at 0x7f32798a6748>




**Reading Images:**

In [ ]:
```
def image2array(file_array):

    """
    Reading and Converting images into numpy array by taking path of images.
    Arguments:
    file_array - (list) - list of file(path) names
    Returns:
    A numpy array of images. (np.ndarray)
    """

    image_array = []
    for path in tqdm(file_array):
        img = cv2.imread('/content/dataset/'+path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        img = cv2.resize(img, (224,224))
        image_array.append(np.array(img))
    image_array = np.array(image_array)
    image_array = image_array.reshape(image_array.shape[0], 224, 224, 3)
    image_array = image_array.astype('float32')
    image_array /= 255
    return np.array(image_array)
```

In [ ]:
```
train_data = image2array(train_files)
print("Length of training dataset:",train_data.shape)
test_data = image2array(test_files)
print("Length of test dataset:",test_data.shape)
```

```
HBox(children=(FloatProgress(value=0.0, max=4027.0), HTML(value='')))


Length of training dataset: (4027, 224, 224, 3)

HBox(children=(FloatProgress(value=0.0, max=711.0), HTML(value='')))


Length of test dataset: (711, 224, 224, 3)
```

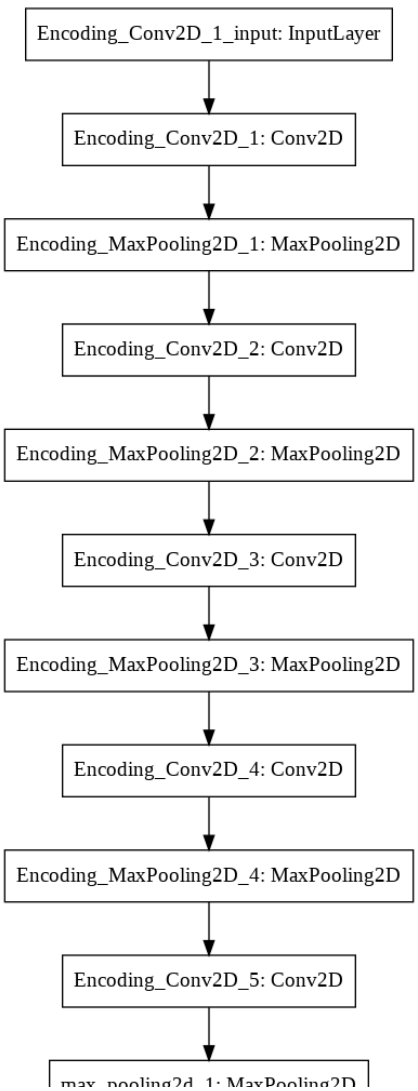
## Model Architecture & Model Training:

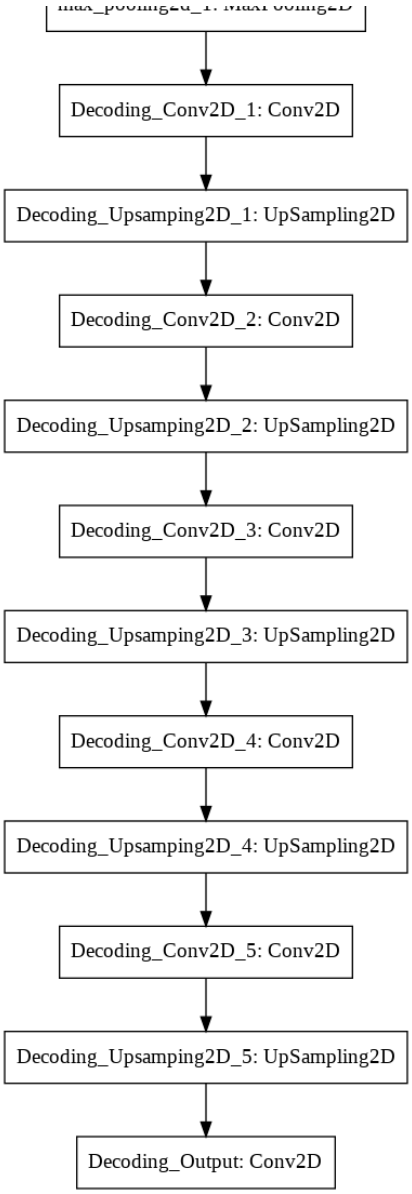
In [ ]:
```
def encoder_decoder_model():

    """
    Used to build Convolutional Autoencoder model architecture to get compressed image data which is easier to process.
    Returns:
    Auto encoder model
    """
    #Encoder
    model = Sequential(name='Convolutional_AutoEncoder_Model')
    model.add(Conv2D(64, kernel_size=(3, 3),activation='relu',input_shape=(224, 224, 3),padding='same', name='Encoding_Conv2D_1'))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=2, padding='same', name='Encoding_MaxPooling2D_1'))
    model.add(Conv2D(128, kernel_size=(3, 3),strides=1,kernel_regularizer = tf.keras.regularizers.L2(0.001),activation='relu',padding='same', name='Encoding_Conv2D_2'))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=2, padding='same', name='Encoding_MaxPooling2D_2'))
    model.add(Conv2D(256, kernel_size=(3, 3), activation='relu',kernel_regularizer= tf.keras.regularizers.L2(0.001), padding='same', name='Encoding_Conv2D_3'))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=2, padding='same', name='Encoding_MaxPooling2D_3'))
    model.add(Conv2D(512, kernel_size=(3, 3), activation='relu',kernel_regularizer= tf.keras.regularizers.L2(0.001), padding='same', name='Encoding_Conv2D_4'))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=2,padding='valid', name='Encoding_MaxPooling2D_4'))
    model.add(Conv2D(512, kernel_size=(3, 3), activation='relu', padding='same', name='Encoding_Conv2D_5'))
    model.add(MaxPooling2D(pool_size=(2,2), strides=2, padding='valid'))

    #Decoder
    model.add(Conv2D(512, kernel_size=(3, 3), kernel_regularizer = tf.keras.regularizers.L2(0.001),activation='relu', padding='same', name='Decoding_Conv2D_1'))
    model.add(UpSampling2D((2, 2), name='Decoding_Upsamping2D_1'))
    model.add(Conv2D(512, kernel_size=(3, 3), kernel_regularizer = tf.keras.regularizers.L2(0.001), activation='relu', padding='same', name='Decoding_Conv2D_2'))
    model.add(UpSampling2D((2, 2), name='Decoding_Upsamping2D_2'))
    model.add(Conv2D(256, kernel_size=(3, 3), kernel_regularizer = tf.keras.regularizers.L2(0.001), activation='relu', padding='same',name='Decoding_Conv2D_3'))
    model.add(UpSampling2D((2, 2),name='Decoding_Upsamping2D_3'))
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu', kernel_regularizer = tf.keras.regularizers.L2(0.001), padding='same',name='Decoding_Conv2D_4'))
    model.add(UpSampling2D((2, 2),name='Decoding_Upsamping2D_4'))
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', kernel_regularizer = tf.keras.regularizers.L2(0.001), padding='same',name='Decoding_Conv2D_5'))
    model.add(UpSampling2D((2, 2),name='Decoding_Upsamping2D_5'))
    model.add(Conv2D(3, kernel_size=(3, 3), padding='same',activation='sigmoid',name='Decoding_Output'))
    return model
```

In [ ]:
```
model = encoder_decoder_model()
model.summary()
print("\n")
tf.keras.utils.plot_model(model, to_file='/content/drive/My Drive/model.png')
```

```
Model: "Convolutional_AutoEncoder_Model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Encoding_Conv2D_1 (Conv2D)   (None, 224, 224, 64)      1792
_________________________________________________________________
Encoding_MaxPooling2D_1 (Max (None, 112, 112, 64)      0
_________________________________________________________________
Encoding_Conv2D_2 (Conv2D)   (None, 112, 112, 128)     73856
_________________________________________________________________
Encoding_MaxPooling2D_2 (Max (None, 56, 56, 128)       0
_________________________________________________________________
Encoding_Conv2D_3 (Conv2D)   (None, 56, 56, 256)       295168
_________________________________________________________________
Encoding_MaxPooling2D_3 (Max (None, 28, 28, 256)       0
_________________________________________________________________
Encoding_Conv2D_4 (Conv2D)   (None, 28, 28, 512)       1180160
_________________________________________________________________
Encoding_MaxPooling2D_4 (Max (None, 14, 14, 512)       0
_________________________________________________________________
Encoding_Conv2D_5 (Conv2D)   (None, 14, 14, 512)       2359808
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 7, 7, 512)         0
_________________________________________________________________
Decoding_Conv2D_1 (Conv2D)   (None, 7, 7, 512)         2359808
_________________________________________________________________
Decoding_Upsamping2D_1 (UpSa (None, 14, 14, 512)       0
_________________________________________________________________
Decoding_Conv2D_2 (Conv2D)   (None, 14, 14, 512)       2359808
_________________________________________________________________
Decoding_Upsamping2D_2 (UpSa (None, 28, 28, 512)       0
_________________________________________________________________
Decoding_Conv2D_3 (Conv2D)   (None, 28, 28, 256)       1179904
_________________________________________________________________
Decoding_Upsamping2D_3 (UpSa (None, 56, 56, 256)       0
_________________________________________________________________
Decoding_Conv2D_4 (Conv2D)   (None, 56, 56, 128)       295040
_________________________________________________________________
Decoding_Upsamping2D_4 (UpSa (None, 112, 112, 128)     0
_________________________________________________________________
Decoding_Conv2D_5 (Conv2D)   (None, 112, 112, 64)      73792
_________________________________________________________________
Decoding_Upsamping2D_5 (UpSa (None, 224, 224, 64)      0
_________________________________________________________________
Decoding_Output (Conv2D)     (None, 224, 224, 3)       1731
=================================================================
Total params: 10,180,867
Trainable params: 10,180,867
Non-trainable params: 0
_________________________________________________________________
```

Out[8]:






**Hyper parameter Tuning:**

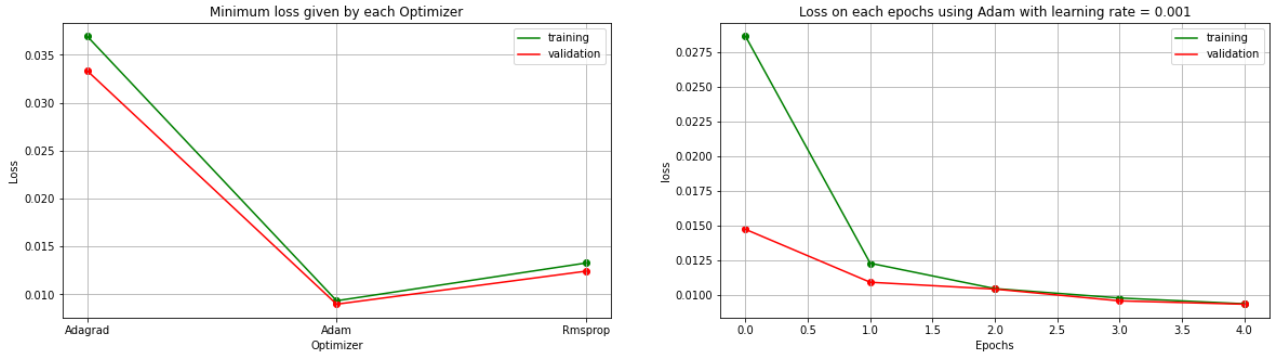
In [ ]:
```
parameters = {'Adagrad':[0.01,0.001,0.0001,0.00001],'Adam':[0.01,0.001,0.0001,0.00001],'Rmsprop':[0.01,0.001,0.0001,0.00001]}
result = []
for i in parameters.keys():
    print("{} as an optimizer:".format(i))
    values = parameters[i]
    result_ = []
    for learning_rate in values:
        print("\t\tUsing learning_rate: "+str(learning_rate))
        model = encoder_decoder_model()
        if i=='Adam':
            optimizer = Adam(learning_rate=learning_rate)
        elif i=='Adagrad':
            optimizer = Adagrad(learning_rate=learning_rate)
        else:
            optimizer = RMSprop(learning_rate=learning_rate)
        model.compile(optimizer=optimizer, loss='mse')            # compiling
        model.fit(train_data, train_data, epochs=5, batch_size=32,validation_data=(test_data,test_data))  # fitting data
        result_.append(model.history.history)          # taking result to judge the best parameters.
    print()
    result.append(result_)
```

```
Adagrad as an optimizer:
                Using learning_rate: 0.01
Epoch 1/5
126/126 [==============================] - 20s 158ms/step - loss: 0.0533 - val_loss: 0.0512
Epoch 2/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0504 - val_loss: 0.0487
Epoch 3/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0475 - val_loss: 0.0453
Epoch 4/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0431 - val_loss: 0.0401
Epoch 5/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0369 - val_loss: 0.0333
                Using learning_rate: 0.001
Epoch 1/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0562 - val_loss: 0.0555
Epoch 2/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0558 - val_loss: 0.0552
Epoch 3/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0555 - val_loss: 0.0549
Epoch 4/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0552 - val_loss: 0.0546
Epoch 5/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0549 - val_loss: 0.0544
                Using learning_rate: 0.0001
Epoch 1/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0568 - val_loss: 0.0563
Epoch 2/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0567 - val_loss: 0.0562
Epoch 3/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0567 - val_loss: 0.0562
Epoch 4/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0567 - val_loss: 0.0562
Epoch 5/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0566 - val_loss: 0.0561
                Using learning_rate: 1e-05
Epoch 1/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0562 - val_loss: 0.0557
Epoch 2/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0562 - val_loss: 0.0557
Epoch 3/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0562 - val_loss: 0.0557
Epoch 4/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0562 - val_loss: 0.0557
Epoch 5/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0562 - val_loss: 0.0557

Adam as an optimizer:
                Using learning_rate: 0.01
Epoch 1/5
126/126 [==============================] - 18s 146ms/step - loss: 0.0225 - val_loss: 0.0145
Epoch 2/5
126/126 [==============================] - 18s 144ms/step - loss: 0.0131 - val_loss: 0.0147
Epoch 3/5
126/126 [==============================] - 18s 144ms/step - loss: 0.0120 - val_loss: 0.0112
Epoch 4/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0117 - val_loss: 0.0114
Epoch 5/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0098 - val_loss: 0.0090
                Using learning_rate: 0.001
Epoch 1/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0287 - val_loss: 0.0147
Epoch 2/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0123 - val_loss: 0.0109
Epoch 3/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0104 - val_loss: 0.0104
Epoch 4/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0098 - val_loss: 0.0095
Epoch 5/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0093 - val_loss: 0.0093
                Using learning_rate: 0.0001
Epoch 1/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0485 - val_loss: 0.0306
Epoch 2/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0221 - val_loss: 0.0179
Epoch 3/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0155 - val_loss: 0.0140
Epoch 4/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0130 - val_loss: 0.0125
Epoch 5/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0120 - val_loss: 0.0117
                Using learning_rate: 1e-05
Epoch 1/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0559 - val_loss: 0.0548
Epoch 2/5
126/126 [==============================] - 18s 147ms/step - loss: 0.0546 - val_loss: 0.0534
Epoch 3/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0534 - val_loss: 0.0525
Epoch 4/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0526 - val_loss: 0.0517
Epoch 5/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0517 - val_loss: 0.0506

Rmsprop as an optimizer:
                Using learning_rate: 0.01
Epoch 1/5
126/126 [==============================] - 19s 147ms/step - loss: 0.0536 - val_loss: 0.0511
```

```
Epoch 2/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0515 - val_loss: 0.0511
Epoch 3/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0515 - val_loss: 0.0511
Epoch 4/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0515 - val_loss: 0.0511
Epoch 5/5
126/126 [==============================] - 18s 145ms/step - loss: 0.0514 - val_loss: 0.0511
                Using learning_rate: 0.001
Epoch 1/5
126/126 [==============================] - 19s 150ms/step - loss: 0.0279 - val_loss: 0.0184
Epoch 2/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0179 - val_loss: 0.0160
Epoch 3/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0157 - val_loss: 0.0124
Epoch 4/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0143 - val_loss: 0.0129
Epoch 5/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0133 - val_loss: 0.0129
                Using learning_rate: 0.0001
Epoch 1/5
126/126 [==============================] - 19s 150ms/step - loss: 0.0446 - val_loss: 0.0281
Epoch 2/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0229 - val_loss: 0.0202
Epoch 3/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0190 - val_loss: 0.0188
Epoch 4/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0175 - val_loss: 0.0174
Epoch 5/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0165 - val_loss: 0.0157
                Using learning_rate: 1e-05
Epoch 1/5
126/126 [==============================] - 19s 150ms/step - loss: 0.0552 - val_loss: 0.0541
Epoch 2/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0540 - val_loss: 0.0531
Epoch 3/5
126/126 [==============================] - 19s 148ms/step - loss: 0.0533 - val_loss: 0.0525
Epoch 4/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0527 - val_loss: 0.0519
Epoch 5/5
126/126 [==============================] - 19s 149ms/step - loss: 0.0520 - val_loss: 0.0511
```

In [ ]:
```python
def plot_(x,y1,y2,row,col,ind,title,xlabel,ylabel,label,isimage=False,color='r'):

    """
    This function is used for plotting images and graphs (Visualization of end results of model training)
    Arguments:
    x - (np.ndarray or list) - an image array
    y1 - (list) - for plotting graph on left side.
    y2 - (list) - for plotting graph on right side.
    row - (int) - row number of subplot
    col - (int) - column number of subplot
    ind - (int) - index number of subplot
    title - (string) - title of the plot
    xlabel - (list) - labels of x axis
    ylabel - (list) - labels of y axis
    label - (string) - for adding legend in the plot
    isimage - (boolean) - True in case of image else False
    color - (char) - color of the plot (prefered green for training and red for testing).
    """

    plt.subplot(row,col,ind)
    if isimage:
        plt.imshow(x)
        plt.title(title)
        plt.axis('off')
    else:
        plt.plot(y1,label=label,color='g'); plt.scatter(x,y1,color='g')
        if y2!='': plt.plot(y2,color=color,label='validation'); plt.scatter(x,y2,color=color)
        plt.grid()
        plt.legend()
        plt.title(title); plt.xlabel(xlabel); plt.ylabel(ylabel)
```

In [ ]:
```python
min_train = []; min_val = []
rates = list(parameters.keys())
epochs = [0,1,2,3,4]
for i in result:
    train = []; val = []
    for j in i:
        train.append(min(j['loss'])); val.append(min(j['val_loss']))  # taking minimum loss of each optimizer over all learning rates.
    min_train.append(min(train)); min_val.append(min(val))
plt.figure(figsize=(20,5))
plot_(rates,min_train,min_val,1,2,1,'Minimum loss given by each Optimizer','Optimizer','Loss','training',False,'r')
# plotting the result of adam with learning rate = 0.001 .
plot_(epochs, result[1][1]['loss'],result[1][1]['val_loss'],1,2,2,'Loss on each epochs using Adam with learning rate = 0.001','Epochs','loss','training',False,'r')
plt.show()
```




- After training the model with different optimizers(Adagrad, Adam, Rmsprop), adam giving the least local minimum loss on training with learning rate = 0.001.
- Both training loss and validation loss are almost equal and we can see our model training is not prone to overfitting and underfitting.
- Achieved 0.0093 on five epochs using Adam(0.001)(optimal value).

**Training the model with Best Optimizer with Best Learning Rate:**

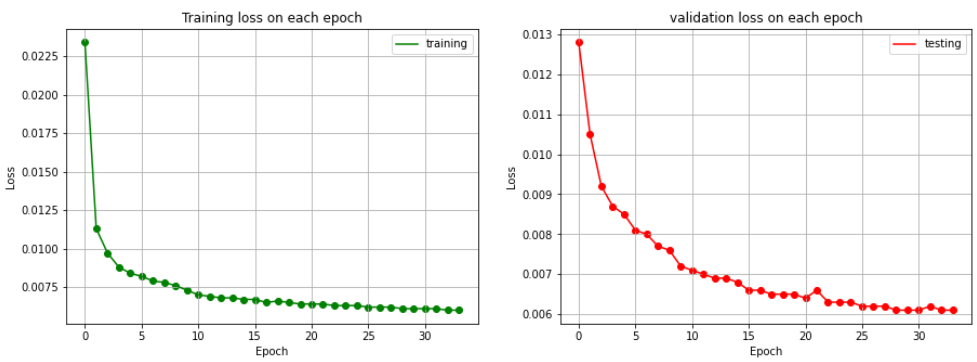
In [ ]:
```
optimizer = Adam(learning_rate=0.001)
model = encoder_decoder_model()
model.compile(optimizer=optimizer, loss='mse')
early_stopping = EarlyStopping(monitor='val_loss', mode='min',verbose=1,patience=6,min_delta=0.0001)
checkpoint = ModelCheckpoint('/content/drive/My Drive/encoder_model.h5', monitor='val_loss', mode='min', save_best_only=True)
model.fit(train_data, train_data, epochs=35, batch_size=32,validation_data=(test_data,test_data),callbacks=[early_stopping,checkpoint])
```

```
Epoch 1/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0234 - val_loss: 0.0128
Epoch 2/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0113 - val_loss: 0.0105
Epoch 3/35
126/126 [==============================] - 20s 157ms/step - loss: 0.0097 - val_loss: 0.0092
Epoch 4/35
126/126 [==============================] - 20s 158ms/step - loss: 0.0088 - val_loss: 0.0087
Epoch 5/35
126/126 [==============================] - 20s 157ms/step - loss: 0.0084 - val_loss: 0.0085
Epoch 6/35
126/126 [==============================] - 20s 157ms/step - loss: 0.0082 - val_loss: 0.0081
Epoch 7/35
126/126 [==============================] - 20s 157ms/step - loss: 0.0079 - val_loss: 0.0080
Epoch 8/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0078 - val_loss: 0.0077
Epoch 9/35
126/126 [==============================] - 20s 157ms/step - loss: 0.0076 - val_loss: 0.0076
Epoch 10/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0073 - val_loss: 0.0072
Epoch 11/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0072 - val_loss: 0.0071
Epoch 12/35
126/126 [==============================] - 19s 154ms/step - loss: 0.0070 - val_loss: 0.0070
Epoch 13/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0069 - val_loss: 0.0069
Epoch 14/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0068 - val_loss: 0.0069
Epoch 15/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0068 - val_loss: 0.0068
Epoch 16/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0067 - val_loss: 0.0067
Epoch 17/35
126/126 [==============================] - 19s 155ms/step - loss: 0.0067 - val_loss: 0.0066
Epoch 18/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0065 - val_loss: 0.0066
Epoch 19/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0066 - val_loss: 0.0065
Epoch 20/35
126/126 [==============================] - 19s 154ms/step - loss: 0.0065 - val_loss: 0.0065
Epoch 21/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0064 - val_loss: 0.0065
Epoch 22/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0064 - val_loss: 0.0064
Epoch 23/35
126/126 [==============================] - 19s 147ms/step - loss: 0.0064 - val_loss: 0.0066
Epoch 24/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0063 - val_loss: 0.0063
Epoch 25/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0063 - val_loss: 0.0063
Epoch 26/35
126/126 [==============================] - 19s 147ms/step - loss: 0.0063 - val_loss: 0.0063
Epoch 27/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0062 - val_loss: 0.0062
Epoch 28/35
126/126 [==============================] - 20s 158ms/step - loss: 0.0062 - val_loss: 0.0062
Epoch 29/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0062 - val_loss: 0.0062
Epoch 30/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0061 - val_loss: 0.0061
Epoch 31/35
126/126 [==============================] - 20s 155ms/step - loss: 0.0061 - val_loss: 0.0061
Epoch 32/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0061 - val_loss: 0.0061
Epoch 33/35
126/126 [==============================] - 18s 147ms/step - loss: 0.0061 - val_loss: 0.0062
Epoch 34/35
126/126 [==============================] - 20s 156ms/step - loss: 0.0060 - val_loss: 0.0061
Epoch 35/35
126/126 [==============================] - 19s 154ms/step - loss: 0.0060 - val_loss: 0.0061
```

Out[20]:
```
<tensorflow.python.keras.callbacks.History at 0x7f2b0cf774a8>
```

**Plotting loss on each epoch:**

In [ ]:
```
#model.history.history
plt.figure(figsize=(15,5))
epochs = [i for i in range(34)]
plot_(epochs,loss,'',1,2,1,'Training loss on each epoch','Epoch','Loss','training',False,'g')
plot_(epochs,val_loss,'',1,2,2,'validation loss on each epoch','Epoch','Loss','testing',False,'r')
```



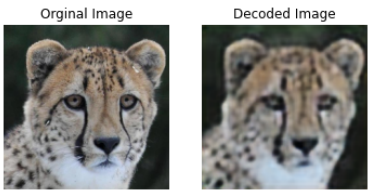

- Their is a strict decrement in the loss for both training and validation.
- After 30 epochs achieved 0.0061 loss

**Loading the trained model:**

In [ ]:
```
model = load_model("/content/drive/My Drive/encoder_model.h5")
model.compile(optimizer=optimizer, loss='mse')
```

**Model Testing:**

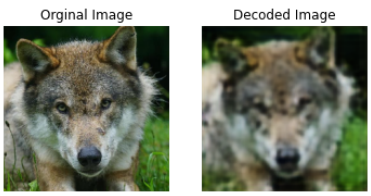
In [ ]:
```
sample_image = train_data[7]
sample_image = np.expand_dims(sample_image,axis=0)
image = model.predict(sample_image)
plot_(sample_image[0,:,:,:],'','',1,2,1,"Orginal Image","","","",True)
plot_(image[0,:,:],'','',1,2,2,"Decoded Image","","","",True)
plt.show()
```




In [ ]:
```
sample_image = train_data[2396]
sample_image = np.expand_dims(sample_image,axis=0)
image = model.predict(sample_image)
plot_(sample_image[0,:,:,:],'','',1,2,1,"Orginal Image","","","",True)
plot_(image[0,:,:],'','',1,2,2,"Decoded Image","","","",True)
plt.show()
```


**Restoring the Best Model using Model Checkpoint:**

In [ ]:
```
model = load_model('/content/drive/My Drive/encoder_model.h5')
sample_image = train_data[15]
sample_image = np.expand_dims(sample_image,axis=0)
image = model.predict(sample_image)
plot_(train_data[15],'','',1,2,1,"Orginal Image","","","",True)
plot_(image[0,:,:],'','',1,2,2,"Decoded Image","","","",True)
plt.show()
```

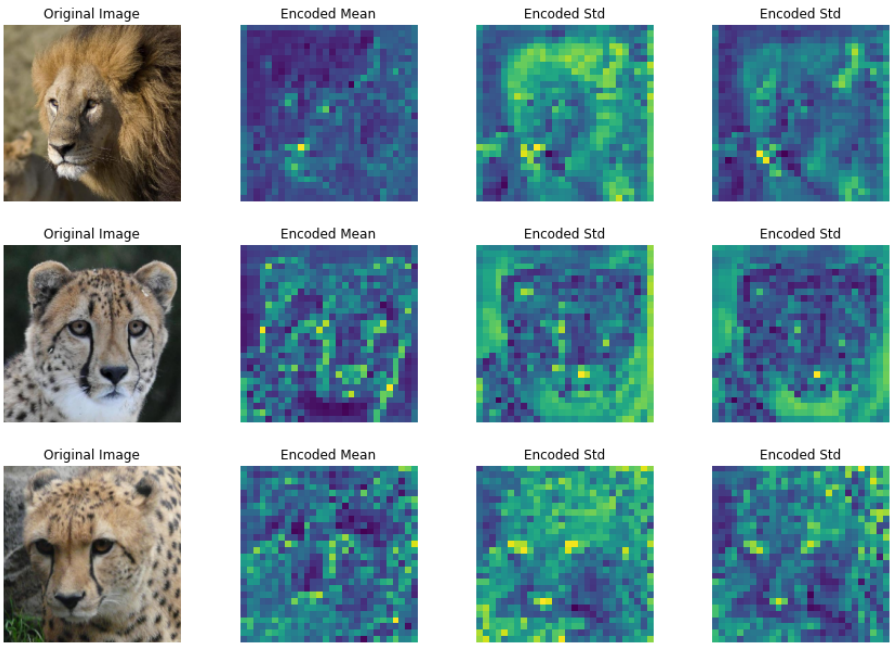



- Restorations seems really satisfactory. Images on the left side are original images whereas images on the right side are restored from compressed representation.
- Decoded image is much flexible and efficient to work rather than working with original image since the compressed representation takes 8 times less space to original image.

# Feature Extraction:

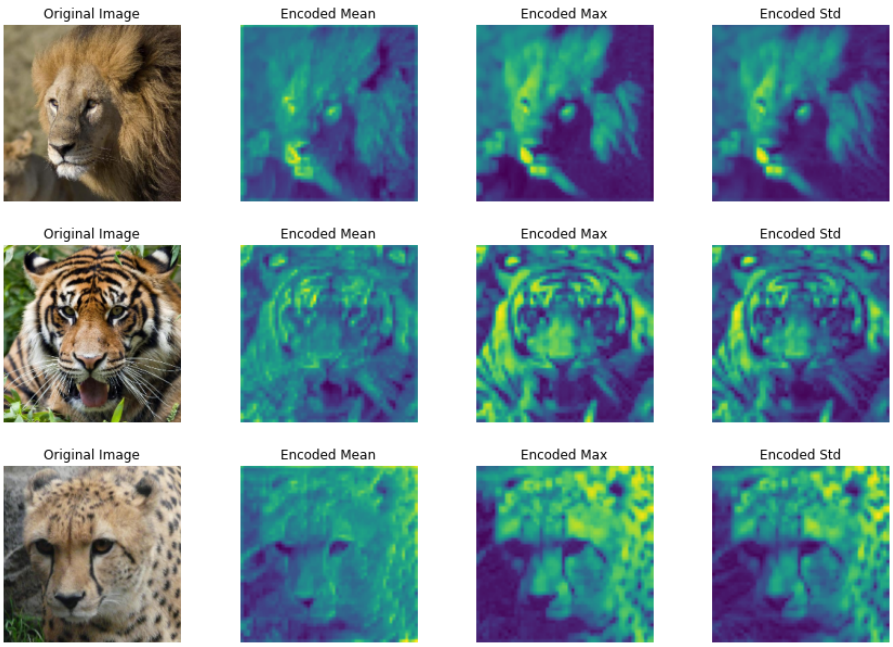
In [ ]:
```
from keras import backend as K
def feature_extraction(model, data, layer = 4):

    """
    Creating a function to run the initial layers of the encoder model. (to get feature extraction from any layer of the model)
    Arguments:
    model - (Auto encoder model) - Trained model
    data - (np.ndarray) - list of images to get feature extraction from trained model
    layer - (int) - from which layer to take the features(by default = 4)
    Returns:
    pooled_array - (np.ndarray) - array of extracted features of given images
    """

    encoded = K.function([model.layers[0].input],[model.layers[layer].output])
    encoded_array = encoded([data])[0]
    pooled_array = encoded_array.max(axis=-1)
    return encoded_array
encoded = feature_extraction(model,train_data[:10],12)
```

In [ ]:
```
for index in [2,7,9]:   # 3 random images
    plt.figure(figsize=(15,3))
    plot_(train_data[index],'','',1,4,1,"Original Image","","",'',True)
    plot_(encoded[index].mean(axis=-1),'','',1,4,2,"Encoded Mean","","",'',True)
    plot_(encoded[index].max(axis=-1),'','',1,4,3,"Encoded Std","","",'',True)
    plot_(encoded[index].std(axis=-1),'','',1,4,4,"Encoded Std","","",'',True)
    plt.show()
```




- Extracting features from the 12th layer.
- Dark pixels(yellow) indicates the high activation which helps in differentiating with other images.

In [ ]:
```
encoded = feature_extraction(model,train_data[:10],9)
for index in [2,6,9]:   # 3 random images
    plt.figure(figsize=(15,3))
    plot_(train_data[index],'','',1,4,1,"Original Image","","",'',True)
    plot_(encoded[index].mean(axis=-1),'','',1,4,2,"Encoded Mean","","",'',True)
    plot_(encoded[index].max(axis=-1),'','',1,4,3,"Encoded Max","","",'',True)
    plot_(encoded[index].std(axis=-1),'','',1,4,4,"Encoded Std","","",'',True)
    plt.show()
```




Extracting features from the 9th layer. Dark pixels(yellow) indicates the high activation which helps in differentiating with other images.

1. High activation on mane of lion.
2. Nose and lines on tigers.
3. Dots and lines on the nose for cheetah.
4. Nose on foxes. These activation helps in label classification.

In [ ]:
```
def get_batches(data, batch_size=1000):

    """
    Taking batch of images for extraction of images.
    Arguments:
    data - (np.ndarray or list) - list of image array to get extracted features.
    batch_size - (int) - Number of images per each batch
    Returns:
    list - extracted features of each images
    """

    if len(data) < batch_size:
        return [data]
    n_batches = len(data) // batch_size

    # If batches fit exactly into the size of df.
    if len(data) % batch_size == 0:
        return [data[i*batch_size:(i+1)*batch_size] for i in range(n_batches)]

    # If there is a remainder.
    else:
        return [data[i*batch_size:min((i+1)*batch_size, len(data))] for i in range(n_batches+1)]
```

In [ ]:
```
d = np.concatenate([train_data,test_data],axis=0)
d.shape
```

Out[25]:
```
(4738, 224, 224, 3)
```

In [ ]:
```
X_encoded = []
i=0
# Iterate through the full training set.
for batch in get_batches(d, batch_size=300):
    i+=1
    # This line runs our pooling function on the model for each batch.
    X_encoded.append(feature_extraction(model, batch),12)

X_encoded = np.concatenate(X_encoded)
```

In [ ]:
```
X_encoded.shape
```

Out[27]:
```
(4738, 7, 7, 512)
```

In [ ]:
```
X_encoded_reshape = X_encoded.reshape(X_encoded.shape[0], X_encoded.shape[1]*X_encoded.shape[2]*X_encoded.shape[3])
print('Encoded shape:', X_encoded_reshape.shape)
np.save('/content/drive/My Drive/X_encoded_compressed.npy',X_encoded_reshape)
```

```
Encoded shape: (4738, 25088)
```

In [ ]:
```
X_encoded = np.load('/content/drive/My Drive/X_encoded_compressed.npy')
X_encoded.shape
```

Out[84]:
```
(4738, 25088)
```

In [ ]:
```
lisp=train_files
lisp.extend(test_files)
print(len(lisp))
```

```
4738
```

**Dimensionality Reduction through T-SNE:**

In [ ]:
```
transform = TSNE
trans = transform(n_components=2)
values = trans.fit_transform(X_encoded_reshape)
```

In [ ]:
```
def plot_(x,y1,y2,row,col,ind,title,xlabel,ylabel,label,isimage=False,color='b'):

    """
    This function is used for plotting images and graphs (Visualization of end results of model training)
    Arguments:
    x - (np.ndarray or list) - an image array
    y1 - (list) - for plotting graph on left side.
    y2 - (list) - for plotting graph on right side.
    row - (int) - row number of subplot
    col - (int) - column number of subplot
    ind - (int) - index number of subplot
    title - (string) - title of the plot
    xlabel - (list) - labels of x axis
    ylabel - (list) - labels of y axis
    label - (string) - for adding legend in the plot
    isimage - (boolean) - True in case of image else False
    color - (char) - color of the plot (prefered green for training and red for testing).
    """

    plt.subplot(row,col,ind)
    if isimage:
        plt.imshow(x)
        plt.title(title)
        plt.axis('off')
    else:
        plt.plot(y1,label=label,color='g'); plt.scatter(x,y1,color='g')
        if y2!='': plt.plot(y2,color=color,label='validation'); plt.scatter(x,y2,color=color)
        plt.grid()
        plt.legend()
        plt.title(title); plt.xlabel(xlabel); plt.ylabel(ylabel)
```

In [ ]:
```
lisp=train_files
lisp.extend(test_files)
print(len(lisp))
```

```
4738
```

# Clustering Image Data:(K-Means)

**Plotting few images of each cluster:**

In [ ]:
```
K = [4,5,6,7]
for k in K:
    print("if Number of clusters: "+str(k))
    kmeans = KMeans(n_clusters = k, random_state=0).fit(X_encoded_reshape)
    labels=kmeans.labels_
    centroids = kmeans.cluster_centers_
    plt.figure(figsize=(10,5))
    plt.subplot(1,1,1)
    plt.scatter(values[:,0], values[:,1], c= kmeans.labels_.astype(float), s=50, alpha=0.5)
    plt.scatter(centroids[:, 0], centroids[:, 1], c=None, s=50)
    plt.show()
    for row in range(k):
        iter=0
        plt.figure(figsize=(13,3))
        for i,iterator in enumerate(labels):
            if iterator == row:
                img = cv2.imread("/content/dataset/"+lisp[i])
                img = cv2.cvtColor(img,cv2.COLOR_BGR2RGB)
                plot_(img,"","",1,6,iter+1,"cluster="+str(row),"","","",True)
                iter+=1
            if iter>=5: break
        plt.show()
    print()
```

Output hidden; open in https://colab.research.google.com (https://colab.research.google.com) to view.

with cluster = 4

1. lions into first cluster.
2. cheetahs into second cluster.
3. foxes into third cluster.
4. Tigers into fourth cluster.

with cluster = 5

1. foxes into first cluster.
2. cheetahs into second cluster.
3. lions into third cluster.
4. Tigers into fourth cluster.
5. Tiger images with different lighthing conditions and white tigers into fifth cluster.

with cluster = 6

1. cheetahs into first cluster.
2. lions into second cluster.
3. snow dogs into third, tigers into fourth cluster.
4. leopards into fifth cluster.
5. foxes into sixth cluster. (**optimal parameter**)

with cluster = 7

1. Taking white tigers,cheetahs into separate cluster.

In [ ]:
```
#Training the model with optimial K value (6 in our case)
kmeans = KMeans(n_clusters = 6, random_state=0).fit(X_encoded_reshape)
labels=kmeans.labels_
centroids = kmeans.cluster_centers_
```

**Storing the model for future reference:**

In [ ]:
```
kmeans_file = '/content/drive/My Drive/kmeans_model.pkl'
joblib.dump(kmeans,kmeans_file)
```

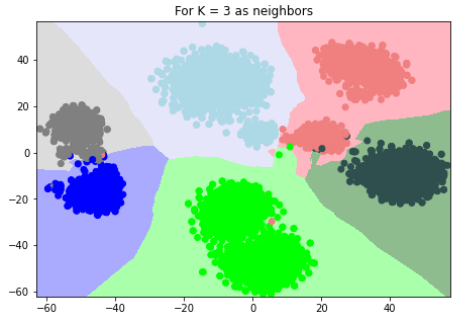
In [ ]:
```
clusters_features = []
cluster_files=[]
for i in [0,1,2,3,4,5]:
    i_cluster = []
    i_labels=[]
    for iter,j in enumerate(kmeans.labels_):
        if j==i:
            i_cluster.append(X_encoded_reshape[iter])
            i_labels.append(lisp[iter])
    i_cluster = np.array(i_cluster)
    clusters_features.append(i_cluster)
    cluster_files.append(i_labels)
```

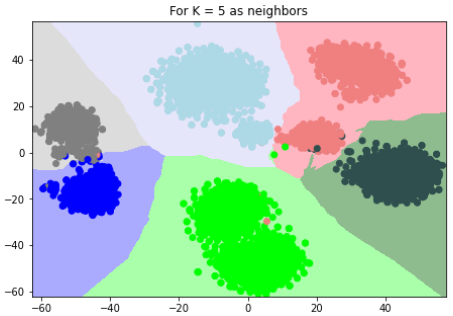
In [ ]:
```
labels=[]
data=[]
files=[]
for iter,i in enumerate(clusters_features):
    data.extend(i)
    labels.extend([iter for i in range(i.shape[0])])
    files.extend(cluster_files[iter])
print(np.array(labels).shape)
print(np.array(data).shape)
print(np.array(files).shape)
```

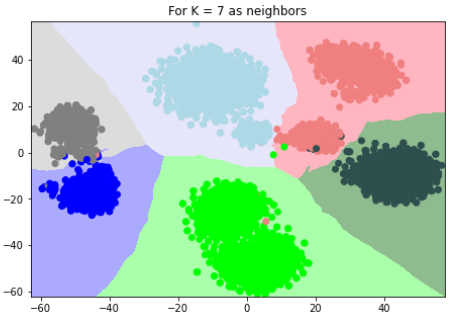
```
(4738,)
(4738, 25088)
(4738,)
```

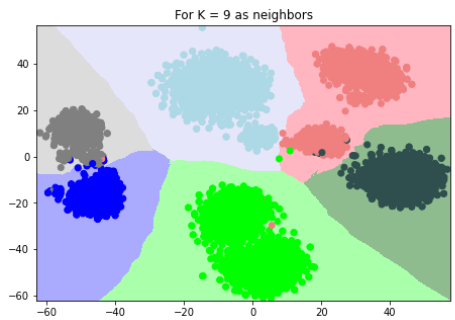
## Finding Nearest Neighbors(K-NN):

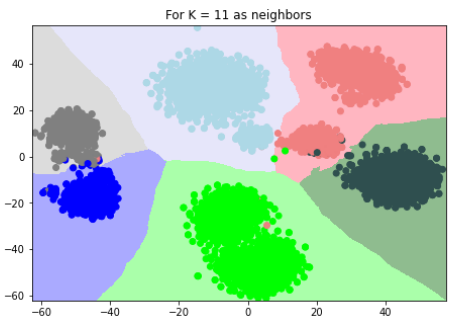
In [ ]:
```
for i in [[3,5,7],[9,11,13]]:
    plt.figure(figsize=(25,5))
    for iter,j in enumerate(i):
        n_neighbors = j
        X = values
        y = labels
        h = .09  # step size in the mesh
        cmap_light = ListedColormap(['#FFB6C1', '#AAFFAA', '#AAAAFF','#E6E6FA','#8FBC8F','#DCDCDC'])
        cmap_bold = ListedColormap(['#F08080', '#00FF00', '#0000FF','#ADD8E6','#2F4F4F','#808080'])
        clf = KNeighborsClassifier(n_neighbors)
        clf.fit(X, y)

        x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
        y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
        xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
        Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

        plt.subplot(1,3,iter+1)
        Z = Z.reshape(xx.shape)
        plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

        # Plot also the training points
        plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cmap_bold)
        plt.xlim(xx.min(), xx.max())
        plt.ylim(yy.min(), yy.max())
        plt.title("For K = {} as neighbors".format(j))
    plt.show()
```

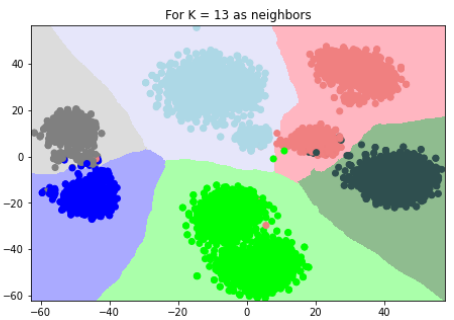



**Training the model with optimal hyperparameter:**

In [ ]:
```
knn = KNeighborsClassifier(n_neighbors=9,algorithm='ball_tree',n_jobs=-1)
knn.fit(np.array(data),np.array(labels))
```

Out[21]:
```
KNeighborsClassifier(algorithm='ball_tree', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=-1, n_neighbors=9, p=2,
                     weights='uniform')
```

**Storing the model for future reference:**

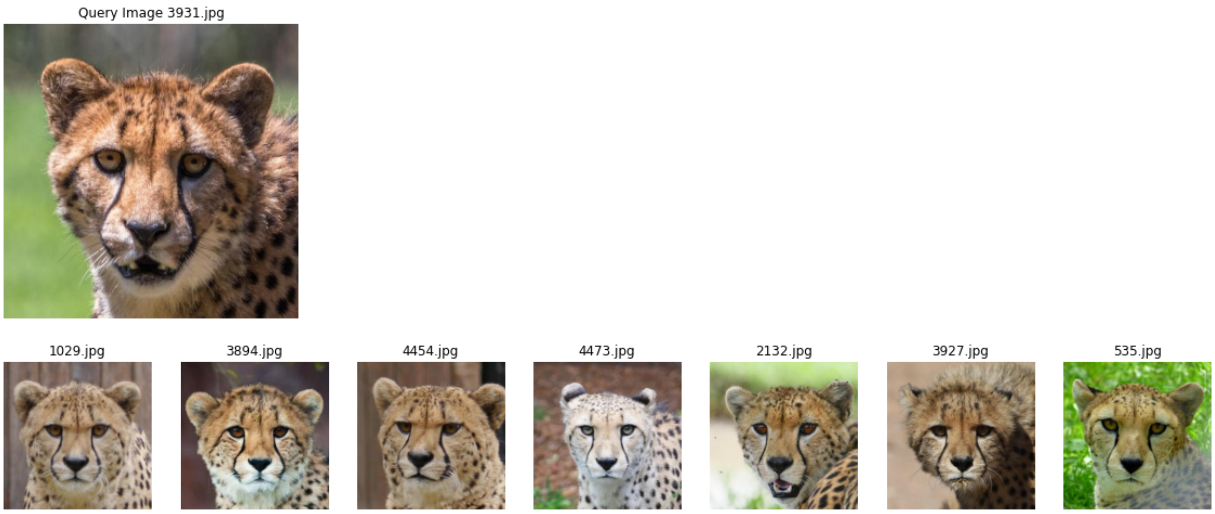
In [ ]:
```
knn_file = '/content/drive/My Drive/knn_model.pkl'
joblib.dump(knn,knn_file)
```

In [ ]:
```
def results_(query,result):

    """
    Plotting the N similar images from the dataset with query image.
    Arguments:
    query - (string) - filename of the query image
    result - (list) - filenames of similar images
    """

    def read(img):
        image = cv2.imread('/content/dataset/'+img)
        image = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
        return image
    plt.figure(figsize=(10,5))
    if type(query)!=type(30):
        plot_(query,"","",1,1,1,"Query Image","","","",True)
    else:
        plot_(read(files[query]),"","",1,1,1,"Query Image "+files[query],"","","",True)
    plt.show()
    plt.figure(figsize=(20,5))
    for iter,i in enumerate(result):
        plot_(read(files[i]),"","",1,len(result),iter+1,files[i],"","","",True)
    plt.show()
```

## Image Similarity Model

**Making predictions:**

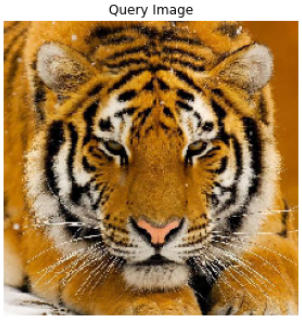
In [ ]:
```
num = 10 #datapoint
res = knn.kneighbors(data[num].reshape(1,-1),return_distance=True,n_neighbors=8)
results_(num,list(res[1][0])[1:])
```




In [ ]:
```
def predictions(label,N=8,isurl=False):

    """
    Making predictions for the query images and returns N similar images from the dataset.
    We can either pass filename or the url for the image.
    Arguments:
    label - (string) - file name of the query image.
    N - (int) - Number of images to be returned
    isurl - (string) - if query image is from google is set to True else False(By default = False)
    """

    if isurl:
        img = io.imread(label)
        img = cv2.resize(img,(224,224))
    else:
        img_path = '/content/dataset/'+label
        img = image.load_img(img_path, target_size=(224,224))
    img_data = image.img_to_array(img)
    img_data = np.expand_dims(img_data,axis=0)
    img_data = preprocess_input(img_data)
    feature = K.function([model.layers[0].input],[model.layers[12].output])
    feature = np.array(feature).flatten().reshape(1,-1)
    res = knn.kneighbors(feature.reshape(1,-1),return_distance=True,n_neighbors=N)
    results_(img,list(res[1][0])[1:])
```

In [ ]:
```
query_path = '2427.jpg'
predictions(query_path)
```

Query Image



3639.jpg

2575.jpg

4337.jpg

3652.jpg

3373.jpg

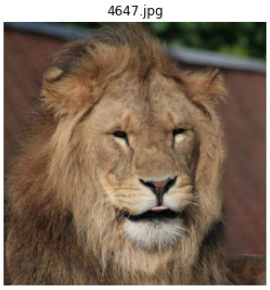
1502.jpg

116.jpg

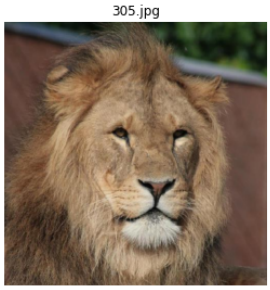
In [ ]:
```
query_path = '4160.jpg'
predictions(query_path,5)
```

Query Image

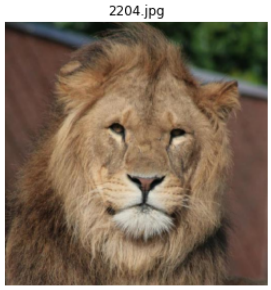
4647.jpg



305.jpg



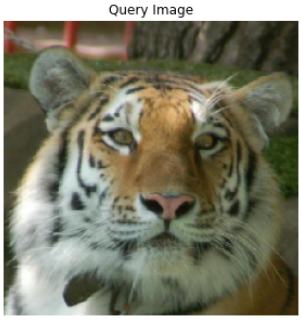
2204.jpg



3124.jpg

In [ ]:
```
query_path = '1127.jpg'
predictions(query_path)
```

Query Image



3284.jpg

1694.jpg

554.jpg

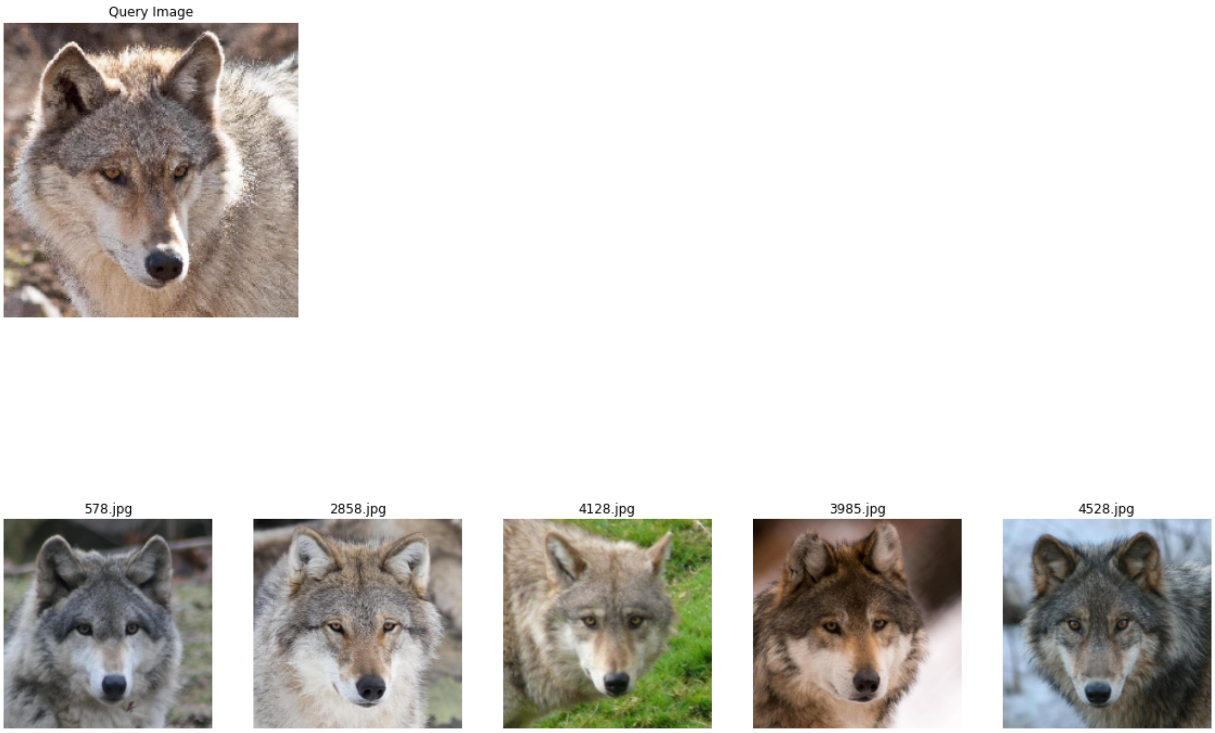
116.jpg

4083.jpg

3664.jpg

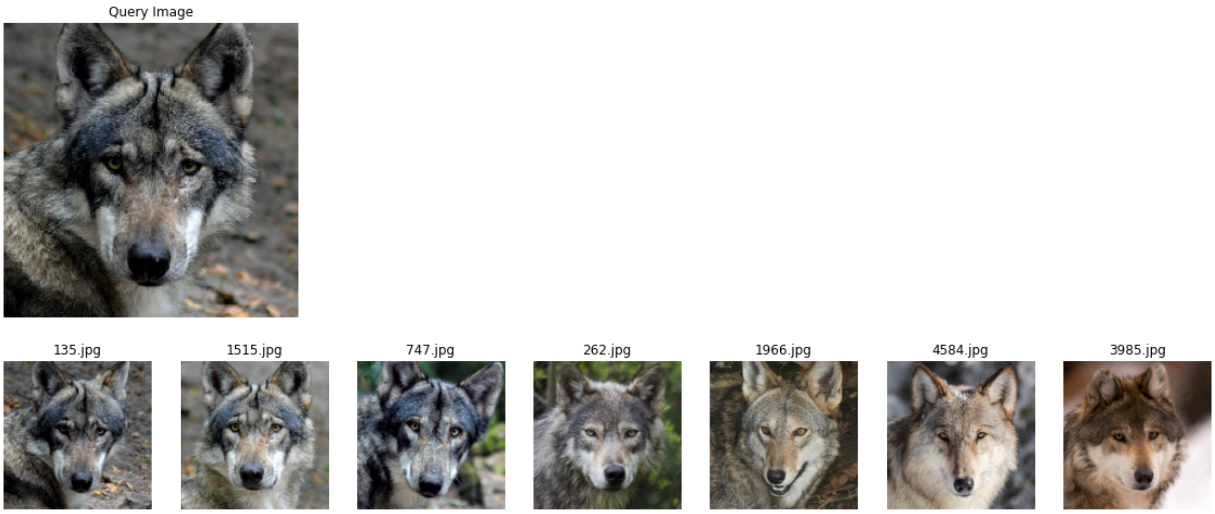
132.jpg

In [ ]:
```
query_path = '1379.jpg'
predictions(query_path,6)
```

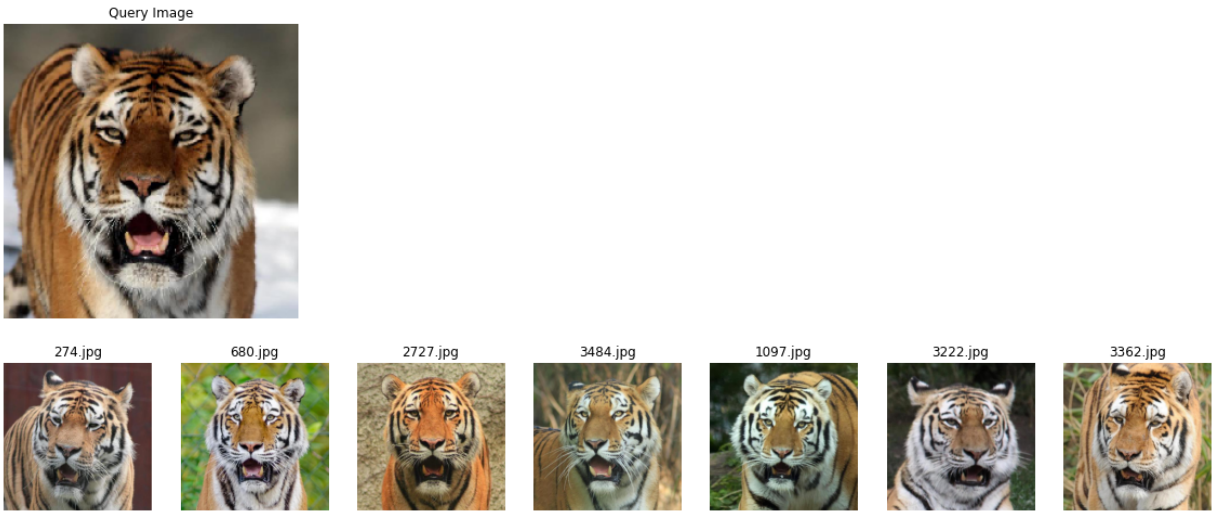



In [ ]:
```
query_path = '608.jpg'
predictions(query_path)
```

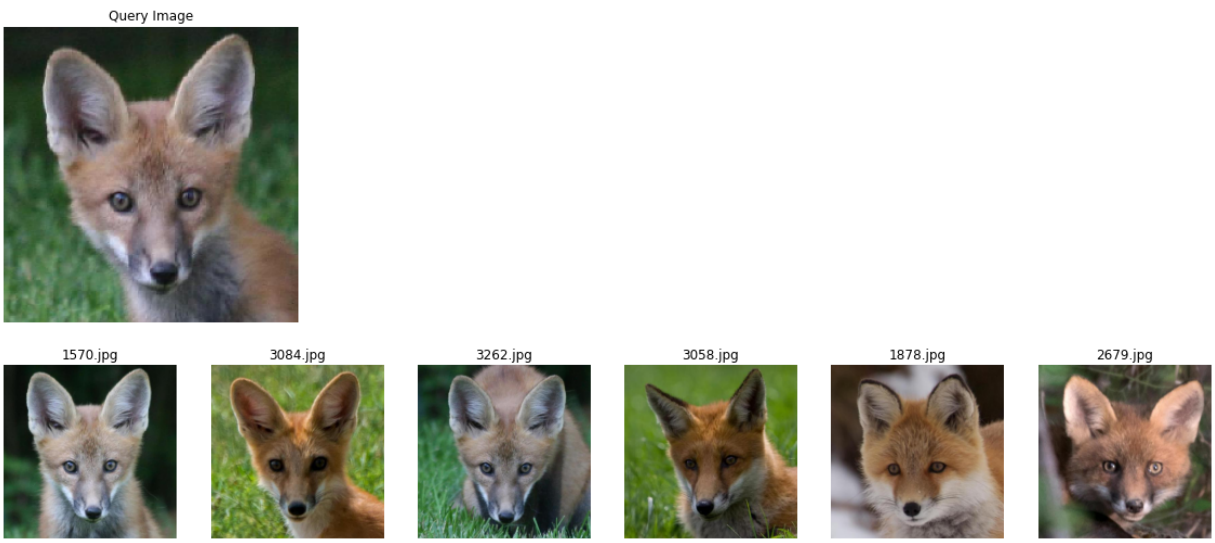
In [ ]:
```
query_path = '2550.jpg'
predictions(query_path)
```




In [ ]:
```
query_path = '167.jpg'
predictions(query_path)
```




In [ ]:
```
query_path = '543.jpg'
predictions(query_path,7)
```

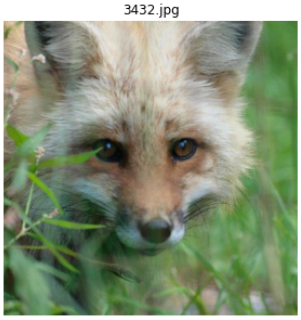



**Testing with google images:**

In [ ]:
```
import imageio as io
query_path = 'https://tse4.mm.bing.net/th?id=OIP.NIMP0bTfhF3898t_ZYLB8QHaE8&pid=Api&P=0&w=248&h=166'
predictions(query_path,4,isurl=True)
```

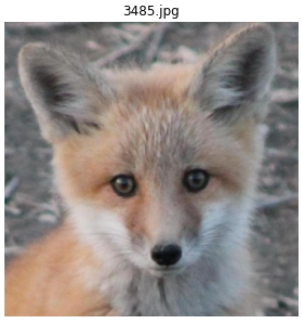
Query Image

3432.jpg



3899.jpg

3485.jpg



In [ ]:
```
query_path = 'https://tse4.mm.bing.net/th?id=OIP.dr7YkzR28BFJerLKJc4cLgHaE7&pid=Api&P=0&w=242&h=162'
predictions(query_path,5,isurl=True)
```

Query Image

4439.jpg

1846.jpg

1337.jpg

1017.jpg

In [ ]:
```
query_path = 'https://tse2.mm.bing.net/th?id=OIP.EkSb6SADo3WRj2WFQWTBvgHaFj&pid=Api&P=0&w=216&h=163'
predictions(query_path,6,isurl=True)
```

Query Image

1738.jpg

4178.jpg

3955.jpg

2277.jpg

978.jpg

In [ ]:
```
```

/