Project name - Animal classification using deep learning

Objective - Animal classification(Dog and cat) into two parts using Deep Lerning.

Attribute Information -

- Dog images -1000
- cat image - 1000
- total image is -2000

```
!wget --no-check-certificate \
    https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip \
    -O /tmp/cats_and_dogs_filtered.zip
```

```
--2024-04-18 03:11:48--  https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip
Resolving storage.googleapis.com (storage.googleapis.com)... 74.125.128.207, 74.125.143.207, 173.194.69.207, ...
Connecting to storage.googleapis.com (storage.googleapis.com)|74.125.128.207|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 68606236 (65M) [application/zip]
Saving to: '/tmp/cats_and_dogs_filtered.zip'

/tmp/cats_and_dogs_ 100%[===================>]  65.43M  28.7MB/s    in 2.3s

2024-04-18 03:11:51 (28.7 MB/s) - '/tmp/cats_and_dogs_filtered.zip' saved [68606236/68606236]
```

```
import os
import zipfile

local_zip = '/tmp/cats_and_dogs_filtered.zip'
zip_ref = zipfile.ZipFile(local_zip, 'r')
zip_ref.extractall('/tmp')
zip_ref.close()
```

```
base_dir = '/tmp/cats_and_dogs_filtered'
train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')

# Directory with our training cat pictures
train_cats_dir = os.path.join(train_dir, 'cats')

# Directory with our training dog pictures
train_dogs_dir = os.path.join(train_dir, 'dogs')

# Directory with our validation cat pictures
validation_cats_dir = os.path.join(validation_dir, 'cats')

# Directory with our validation dog pictures
validation_dogs_dir = os.path.join(validation_dir, 'dogs')
```

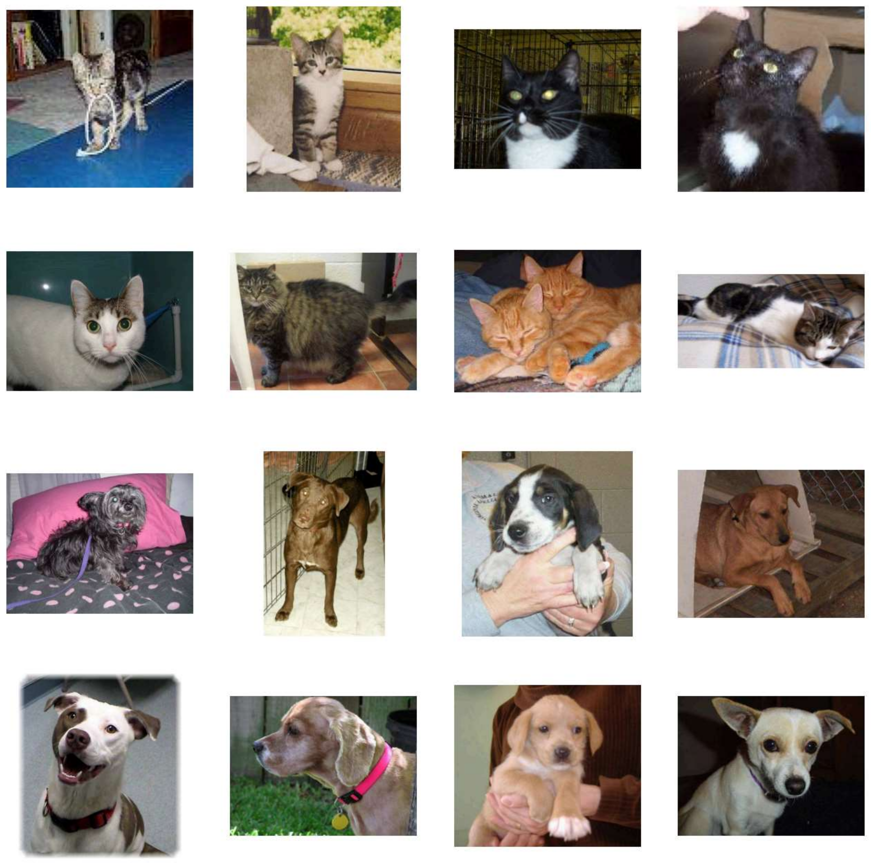
```
train_cat_fnames = os.listdir(train_cats_dir)
print(train_cat_fnames[:10])

train_dog_fnames = os.listdir(train_dogs_dir)
train_dog_fnames.sort()
print(train_dog_fnames[:10])
```

```
['cat.44.jpg', 'cat.277.jpg', 'cat.630.jpg', 'cat.822.jpg', 'cat.403.jpg', 'cat.919.jpg', 'cat.686.jpg', 'cat.153.jpg', 'cat.886.jp
['dog.0.jpg', 'dog.1.jpg', 'dog.10.jpg', 'dog.100.jpg', 'dog.101.jpg', 'dog.102.jpg', 'dog.103.jpg', 'dog.104.jpg', 'dog.105.jpg',
```

```
print('total training cat images:', len(os.listdir(train_cats_dir)))
print('total training dog images:', len(os.listdir(train_dogs_dir)))
print('total validation cat images:', len(os.listdir(validation_cats_dir)))
print('total validation dog images:', len(os.listdir(validation_dogs_dir)))
```

```
total training cat images: 1000
total training dog images: 1000
total validation cat images: 500
total validation dog images: 500
```

```
%matplotlib inline

import matplotlib.pyplot as plt
import matplotlib.image as mpimg

# Parameters for our graph; we'll output images in a 4x4 configuration
nrows = 4
ncols = 4

# Index for iterating over images
pic_index = 0


# Set up matplotlib fig, and size it to fit 4x4 pics
fig = plt.gcf()
fig.set_size_inches(ncols * 4, nrows * 4)

pic_index += 8
next_cat_pix = [os.path.join(train_cats_dir, fname)
                for fname in train_cat_fnames[pic_index-8:pic_index]]
next_dog_pix = [os.path.join(train_dogs_dir, fname)
                for fname in train_dog_fnames[pic_index-8:pic_index]]

for i, img_path in enumerate(next_cat_pix+next_dog_pix):
  # Set up subplot; subplot indices start at 1
  sp = plt.subplot(nrows, ncols, i + 1)
  sp.axis('Off') # Don't show axes (or gridlines)

  img = mpimg.imread(img_path)
  plt.imshow(img)

plt.show()
```



```
from tensorflow.keras import layers
from tensorflow.keras import Model
```

```
# Our input feature map is 150x150x3: 150x150 for the image pixels, and 3 for
# the three color channels: R, G, and B
img_input = layers.Input(shape=(150, 150, 3))

# First convolution extracts 16 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
x = layers.Conv2D(16, 3, activation='relu')(img_input)
x = layers.MaxPooling2D(2)(x)

# Second convolution extracts 32 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
x = layers.Conv2D(32, 3, activation='relu')(x)
x = layers.MaxPooling2D(2)(x)

# Third convolution extracts 64 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
x = layers.Conv2D(64, 3, activation='relu')(x)
x = layers.MaxPooling2D(2)(x)


# Flatten feature map to a 1-dim tensor so we can add fully connected layers
x = layers.Flatten()(x)

# Create a fully connected layer with ReLU activation and 512 hidden units
x = layers.Dense(512, activation='relu')(x)

# Create output layer with a single node and sigmoid activation
output = layers.Dense(1, activation='sigmoid')(x)

# Create model:
# input = input feature map
# output = input feature map + stacked convolution/maxpooling layers + fully
# connected layer + sigmoid output layer
model = Model(img_input, output)
```

```
model.summary()
```

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

 conv2d (Conv2D)             (None, 148, 148, 16)      448

 max_pooling2d (MaxPooling2  (None, 74, 74, 16)        0
 D)

 conv2d_1 (Conv2D)           (None, 72, 72, 32)        4640

 max_pooling2d_1 (MaxPoolin  (None, 36, 36, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 64)        18496

 max_pooling2d_2 (MaxPoolin  (None, 17, 17, 64)        0
 g2D)

 flatten (Flatten)           (None, 18496)             0

 dense (Dense)               (None, 512)               9470464

 dense_1 (Dense)             (None, 1)                 513

=================================================================
Total params: 9494561 (36.22 MB)
Trainable params: 9494561 (36.22 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
from tensorflow.keras.optimizers import RMSprop

model.compile(loss='binary_crossentropy',
              optimizer=RMSprop(lr=0.001),
              metrics=['acc'])
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimizers
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1./255)
val_datagen = ImageDataGenerator(rescale=1./255)

# Flow training images in batches of 20 using train_datagen generator
train_generator = train_datagen.flow_from_directory(
        train_dir,  # This is the source directory for training images
        target_size=(150, 150),  # All images will be resized to 150x150
        batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels
        class_mode='binary')

# Flow validation images in batches of 20 using val_datagen generator
validation_generator = val_datagen.flow_from_directory(
        validation_dir,
        target_size=(150, 150),
        batch_size=20,
        class_mode='binary')
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
```

```
history = model.fit_generator(
      train_generator,
      steps_per_epoch=100,  # 2000 images = batch_size * steps
      epochs=15,
      validation_data=validation_generator,
      validation_steps=50,  # 1000 images = batch_size * steps
      verbose=2)
```

```
Epoch 1/15
<ipython-input-14-91d346d1b720>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please
  history = model.fit_generator(
100/100 - 10s - loss: 0.7851 - acc: 0.5295 - val_loss: 0.6577 - val_acc: 0.5940 - 10s/epoch - 101ms/step
Epoch 2/15
100/100 - 5s - loss: 0.6580 - acc: 0.6270 - val_loss: 0.6227 - val_acc: 0.6640 - 5s/epoch - 45ms/step
Epoch 3/15
100/100 - 6s - loss: 0.6146 - acc: 0.6785 - val_loss: 0.6719 - val_acc: 0.5940 - 6s/epoch - 55ms/step
Epoch 4/15
100/100 - 5s - loss: 0.5644 - acc: 0.7040 - val_loss: 0.5824 - val_acc: 0.6960 - 5s/epoch - 46ms/step
Epoch 5/15
100/100 - 6s - loss: 0.5189 - acc: 0.7405 - val_loss: 0.5684 - val_acc: 0.7010 - 6s/epoch - 56ms/step
Epoch 6/15
100/100 - 5s - loss: 0.4564 - acc: 0.7875 - val_loss: 0.5967 - val_acc: 0.6990 - 5s/epoch - 46ms/step
Epoch 7/15
100/100 - 6s - loss: 0.3957 - acc: 0.8250 - val_loss: 0.5472 - val_acc: 0.7420 - 6s/epoch - 56ms/step
Epoch 8/15
100/100 - 5s - loss: 0.3220 - acc: 0.8540 - val_loss: 0.5881 - val_acc: 0.7430 - 5s/epoch - 49ms/step
Epoch 9/15
100/100 - 5s - loss: 0.2627 - acc: 0.8935 - val_loss: 0.6764 - val_acc: 0.7160 - 5s/epoch - 53ms/step
Epoch 10/15
100/100 - 5s - loss: 0.2058 - acc: 0.9160 - val_loss: 0.8787 - val_acc: 0.6690 - 5s/epoch - 46ms/step
Epoch 11/15
100/100 - 6s - loss: 0.1375 - acc: 0.9505 - val_loss: 0.9153 - val_acc: 0.6950 - 6s/epoch - 56ms/step
Epoch 12/15
100/100 - 5s - loss: 0.0887 - acc: 0.9720 - val_loss: 0.9716 - val_acc: 0.7120 - 5s/epoch - 46ms/step
Epoch 13/15
100/100 - 6s - loss: 0.0545 - acc: 0.9810 - val_loss: 1.1245 - val_acc: 0.7260 - 6s/epoch - 64ms/step
Epoch 14/15
100/100 - 5s - loss: 0.0772 - acc: 0.9820 - val_loss: 1.1373 - val_acc: 0.7180 - 5s/epoch - 45ms/step
Epoch 15/15
100/100 - 6s - loss: 0.0971 - acc: 0.9905 - val_loss: 1.2668 - val_acc: 0.7350 - 6s/epoch - 55ms/step
```

```
import numpy as np
import random
from tensorflow.keras.preprocessing.image import img_to_array, load_img

# Let's define a new Model that will take an image as input, and will output
# intermediate representations for all layers in the previous model after
# the first.
successive_outputs = [layer.output for layer in model.layers[1:]]
visualization_model = Model(img_input, successive_outputs)

# Let's prepare a random input image of a cat or dog from the training set.
cat_img_files = [os.path.join(train_cats_dir, f) for f in train_cat_fnames]
dog_img_files = [os.path.join(train_dogs_dir, f) for f in train_dog_fnames]
img_path = random.choice(cat_img_files + dog_img_files)

img = load_img(img_path, target_size=(150, 150))  # this is a PIL image
x = img_to_array(img)  # Numpy array with shape (150, 150, 3)
x = x.reshape((1,) + x.shape)  # Numpy array with shape (1, 150, 150, 3)

# Rescale by 1/255
x /= 255

# Let's run our image through our network, thus obtaining all
# intermediate representations for this image.
successive_feature_maps = visualization_model.predict(x)

# These are the names of the layers, so can have them as part of our plot
layer_names = [layer.name for layer in model.layers[1:]]

# Now let's display our representations
for layer_name, feature_map in zip(layer_names, successive_feature_maps):
  if len(feature_map.shape) == 4:
    # Just do this for the conv / maxpool layers, not the fully-connected layers
    n_features = feature_map.shape[-1]  # number of features in feature map
    # The feature map has shape (1, size, size, n_features)
    size = feature_map.shape[1]
    # We will tile our images in this matrix
    display_grid = np.zeros((size, size * n_features))
    for i in range(n_features):
      # Postprocess the feature to make it visually palatable
      x = feature_map[0, :, :, i]
      x -= x.mean()
      x /= x.std()
      x *= 64
      x += 128
      x = np.clip(x, 0, 255).astype('uint8')
      # We'll tile each filter into this big horizontal grid
      display_grid[:, i * size : (i + 1) * size] = x
    # Display the grid
    scale = 20. / n_features
    plt.figure(figsize=(scale * n_features, scale))
    plt.title(layer_name)
    plt.grid(False)
    plt.imshow(display_grid, aspect='auto', cmap='viridis')
```

```
# Retrieve a list of accuracy results on training and validation data
# sets for each training epoch
acc = history.history['acc']
val_acc = history.history['val_acc']

# Retrieve a list of list results on training and validation data
# sets for each training epoch
loss = history.history['loss']
val_loss = history.history['val_loss']

# Get number of epochs
epochs = range(len(acc))

# Plot training and validation accuracy per epoch
plt.plot(epochs, acc)
plt.plot(epochs, val_acc)
plt.title('Training and validation accuracy')
```