## image-classification-resnet

March 11, 2024

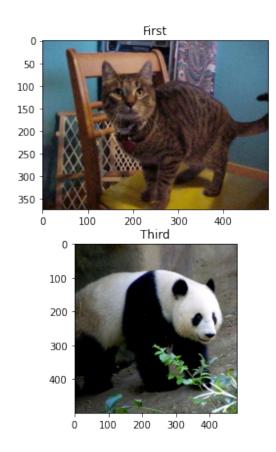
## 0.0.1 Import Libraries

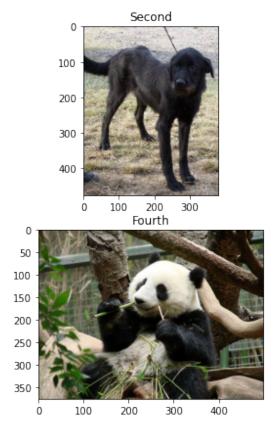
```
[1]: import numpy as np
     import pandas as pd
     from tensorflow.keras.preprocessing.image import ImageDataGenerator
     # Models
     import tensorflow as tf
     from tensorflow.keras.layers import Input
     from tensorflow.keras.layers import Flatten, Dense, Dropout, Conv2D, __
      →MaxPooling2D
     import os
     folder_path = '../input/animal-image-datasetdog-cat-and-panda/animals/'
     for dirname, _, filenames in os.walk(folder_path):
        print(dirname)
    ../input/animal-image-datasetdog-cat-and-panda/animals/animals/
    ../input/animal-image-datasetdog-cat-and-panda/animals/animals/dogs
    ../input/animal-image-datasetdog-cat-and-panda/animals/animals/panda
    ../input/animal-image-datasetdog-cat-and-panda/animals/animals/cats
[2]: print('Total cats images:', len(os.listdir(folder_path + 'cats')))
     print('Total dogs images:', len(os.listdir(folder_path + 'dogs')))
     print('Total pandas images:', len(os.listdir(folder_path + 'panda')))
    Total cats images: 1000
    Total dogs images: 1000
    Total pandas images: 1000
[3]: from keras.preprocessing import image
     import matplotlib.pyplot as plt
     import matplotlib.image as mpimg
     %matplotlib inline
```

## 0.0.2 Show some images

```
[4]: fig = plt.figure(figsize=(10, 7))
     # setting values to rows and column variables
     rows = 2
     columns = 2
     # reading images
     Image1 = image.load_img(folder_path + 'cats/cats_00001.jpg')
     Image2 = image.load_img(folder_path + 'dogs/dogs_00001.jpg')
     Image3 = image.load_img(folder_path + 'panda/panda_00001.jpg')
     Image4 = image.load_img(folder_path + 'panda/panda_00003.jpg')
     fig.add_subplot(rows, columns, 1)
     plt.imshow(Image1)
     plt.title("First")
     fig.add_subplot(rows, columns, 2)
     plt.imshow(Image2)
     plt.title("Second")
     fig.add_subplot(rows, columns, 3)
     plt.imshow(Image3)
     plt.title("Third")
     fig.add_subplot(rows, columns, 4)
     plt.imshow(Image4)
     plt.title("Fourth")
```

```
[4]: Text(0.5, 1.0, 'Fourth')
```





## Split data : 80% train, 20% validation

```
[5]: train_datagen = ImageDataGenerator(
                     fill_mode = 'nearest',
                     validation_split=0.2
     )
[6]: train_generator=train_datagen.flow_from_directory(
         folder_path,
         target_size=(108,108),
         color_mode='rgb',
         class_mode='categorical',
         subset='training',
     validation_generator=train_datagen.flow_from_directory(
         folder_path,
         target_size=(108,108),
         color_mode='rgb',
         class_mode='categorical',
         subset='validation',
```

Found 2400 images belonging to 3 classes. Found 600 images belonging to 3 classes.

```
[7]: from keras.applications import ResNet50
    model = tf.keras.models.Sequential([
       ResNet50(input_shape=(108,108,3), include_top=False),
    ])
    for layer in model.layers:
     layer.trainable = False
    model.add(Conv2D(64, (3,3), activation='relu'))
    model.add(MaxPooling2D(2,2))
    model.add(Flatten())
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dense(3, activation='softmax'))
    model.summary()
   Downloading data from https://storage.googleapis.com/tensorflow/keras-
   applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
   Model: "sequential"
   Layer (type) Output Shape
   _____
   resnet50 (Functional)
                           (None, 4, 4, 2048)
                                                23587712
                          (None, 2, 2, 64)
   conv2d (Conv2D)
                                               1179712
   max_pooling2d (MaxPooling2D) (None, 1, 1, 64)
   flatten (Flatten) (None, 64)
   dense (Dense)
                          (None, 64)
                                                4160
   dropout (Dropout) (None, 64)
   dense_1 (Dense) (None, 3) 195
   Total params: 24,771,779
   Trainable params: 1,184,067
   Non-trainable params: 23,587,712
[8]: model.compile(optimizer='Adam',
               loss='categorical_crossentropy',
```

```
metrics=['accuracy'])
[9]: history = model.fit(train_generator,
                 validation_data=validation_generator,
                 epochs=25,
                 verbose=1,
   Epoch 1/25
   accuracy: 0.6816 - val_loss: 0.4622 - val_accuracy: 0.8500
   Epoch 2/25
   75/75 [============ ] - 13s 174ms/step - loss: 0.3802 -
   accuracy: 0.8593 - val_loss: 0.2975 - val_accuracy: 0.8967
   Epoch 3/25
   75/75 [=========== ] - 13s 169ms/step - loss: 0.3030 -
   accuracy: 0.9205 - val_loss: 0.3336 - val_accuracy: 0.8867
   Epoch 4/25
   accuracy: 0.9296 - val_loss: 0.2697 - val_accuracy: 0.9167
   accuracy: 0.9421 - val_loss: 0.2644 - val_accuracy: 0.9233
   Epoch 6/25
   accuracy: 0.9500 - val_loss: 0.3849 - val_accuracy: 0.9017
   Epoch 7/25
   75/75 [=========== ] - 13s 173ms/step - loss: 0.0635 -
   accuracy: 0.9773 - val_loss: 0.3215 - val_accuracy: 0.9133
   Epoch 8/25
   75/75 [=========== ] - 13s 170ms/step - loss: 0.0423 -
   accuracy: 0.9842 - val_loss: 0.4613 - val_accuracy: 0.9017
   Epoch 9/25
   accuracy: 0.9852 - val_loss: 0.3908 - val_accuracy: 0.9183
   Epoch 10/25
   accuracy: 0.9869 - val_loss: 0.4905 - val_accuracy: 0.9083
   Epoch 11/25
   accuracy: 0.9818 - val_loss: 0.5380 - val_accuracy: 0.9067
   Epoch 12/25
   75/75 [============= ] - 13s 170ms/step - loss: 0.0248 -
   accuracy: 0.9899 - val_loss: 0.5889 - val_accuracy: 0.9100
   Epoch 13/25
   75/75 [============ ] - 13s 167ms/step - loss: 0.0330 -
   accuracy: 0.9934 - val_loss: 0.3782 - val_accuracy: 0.8967
```

```
accuracy: 0.9888 - val_loss: 0.4316 - val_accuracy: 0.9133
   accuracy: 0.9924 - val_loss: 0.4650 - val_accuracy: 0.9117
   accuracy: 0.9926 - val_loss: 0.5947 - val_accuracy: 0.9083
   Epoch 17/25
   accuracy: 0.9876 - val_loss: 0.4491 - val_accuracy: 0.9067
   Epoch 18/25
   accuracy: 0.9968 - val_loss: 0.5354 - val_accuracy: 0.9033
   Epoch 19/25
   75/75 [============ - 13s 177ms/step - loss: 0.0394 -
   accuracy: 0.9852 - val_loss: 0.5163 - val_accuracy: 0.9000
   Epoch 20/25
   accuracy: 0.9914 - val_loss: 0.4460 - val_accuracy: 0.9200
   Epoch 21/25
   accuracy: 0.9951 - val_loss: 0.5121 - val_accuracy: 0.9167
   Epoch 22/25
   75/75 [============= ] - 13s 169ms/step - loss: 0.0309 -
   accuracy: 0.9924 - val_loss: 0.7349 - val_accuracy: 0.9100
   Epoch 23/25
   accuracy: 0.9965 - val_loss: 0.6946 - val_accuracy: 0.9033
   Epoch 24/25
   accuracy: 0.9973 - val_loss: 0.4800 - val_accuracy: 0.9100
   Epoch 25/25
   accuracy: 0.9874 - val_loss: 0.6157 - val_accuracy: 0.9100
[13]: # Plot Model accuracy and loss
   plt.figure(figsize=(12, 6))
   # Plot Model accuracy
   plt.subplot(1, 2, 1) # 1 row, 2 columns, subplot 1
   plt.plot(history.history['accuracy'])
   plt.plot(history.history['val_accuracy'])
   plt.title('Model Accuracy')
   plt.ylabel('Accuracy')
   plt.xlabel('Epoch')
```

Epoch 14/25

```
plt.legend(['Train', 'Validation'], loc='lower right')

# Plot Model Loss
plt.subplot(1, 2, 2) # 1 row, 2 columns, subplot 2
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')

plt.tight_layout()
plt.show()
```

