

Transfer Learning with VGG and Cats vs. Dogs dataset

1. Prepare & Explore Dataset

```
In [1]: # import packages
from tensorflow import keras
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Dense, Dropout, Activation, Flatten, BatchNormalization
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
from keras.utils import to_categorical
from keras.applications import VGG19, ResNet50
from keras.optimizers import SGD, Adam
```

```
In [2]: from tensorflow.keras.preprocessing import image_dataset_from_directory

train_ds = image_dataset_from_directory(
    directory='dogs-vs-cats/train/',
    labels='inferred',
    label_mode='categorical',
    batch_size=32,
    image_size=(160, 160),
    validation_split=0.1,
    subset="training",
    seed=1024
)

val_ds = image_dataset_from_directory(
    directory='dogs-vs-cats/train/',
    labels='inferred',
    label_mode='categorical',
    batch_size=32,
    image_size=(160, 160),
    validation_split=0.1,
    subset="validation",
    seed=1024
)
```

Found 25000 files belonging to 2 classes.
Using 22500 files for training.
Found 25000 files belonging to 2 classes.
Using 2500 files for validation.

```
In [3]: class_names = train_ds.class_names
```

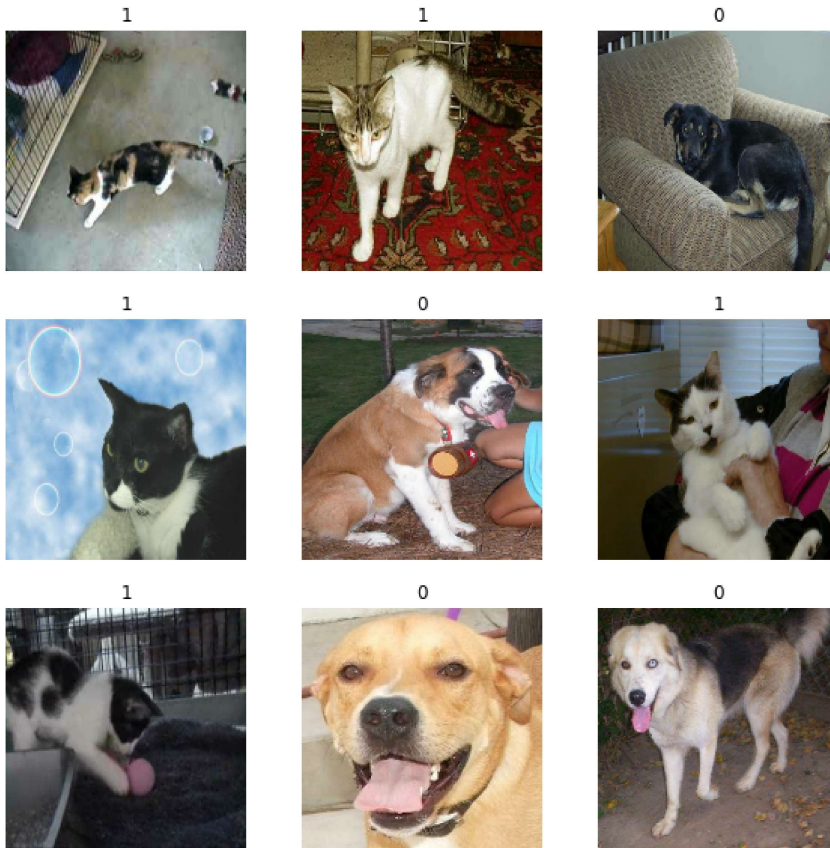
```
In [4]: print(train_ds)
print(val_ds)
print(class_names)
```

```
<BatchDataset shapes: ((None, 160, 160, 3), (None, 2)), types: (tf.float32, tf.float32)>
<BatchDataset shapes: ((None, 160, 160, 3), (None, 2)), types: (tf.float32, tf.float32)>
['cat', 'dog']
```

```
In [5]: #Visualize the data

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(int(list(labels[i])[0]))
        plt.axis("off")
```



We can now begin the actual process of model building. The following a set process and following consistently makes learning this easier :

- Define the Data Augmentation (ImageDataGenerator)
- Build the model (Base Model + Flatten + Dense)
- Check model summary
- Initialize Batch Size, Number of Epochs
- Compile model
- Fit the model
- Evaluate the model

2. Define the neural network architecture

```
In [8]: # define the CNN model
        'The first base model used is VGG19. The pretrained weights from the imagenet challenge are used'
        base_model_1 = VGG19(include_top=False, weights='imagenet', input_shape=(160,160,3), classes=class_names)
```

```
In [9]: #Lets add the final layers to these base models where the actual classification is done in the dense Layer
        model_1 = Sequential()
        model_1.add(base_model_1)
        model_1.add(Flatten())
```

```
In [10]: model_1.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====	=====	=====
vgg19 (Functional)	(None, 5, 5, 512)	20024384
flatten (Flatten)	(None, 12800)	0
=====	=====	=====
Total params: 20,024,384		
Trainable params: 20,024,384		
Non-trainable params: 0		

```
In [11]: #Add the Dense Layers along with activation and batch normalization
        model_1.add(Dense(1024,activation=('relu'),input_dim=512))
        model_1.add(BatchNormalization())
        model_1.add(Dense(512,activation=('relu')))
        model_1.add(BatchNormalization())
        model_1.add(Dense(256,activation=('relu')))
        model_1.add(BatchNormalization())
        model_1.add(Dropout(.3))#Adding a dropout layer that will randomly drop 30% of the weights
        model_1.add(Dense(128,activation=('relu')))
        model_1.add(BatchNormalization())
        model_1.add(Dropout(.2))
        model_1.add(Dense(2, activation=('softmax')))) #This is the classification layer
```

```
In [12]: #Check final model summary
        model_1.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====	=====	=====
vgg19 (Functional)	(None, 5, 5, 512)	20024384
flatten (Flatten)	(None, 12800)	0
dense (Dense)	(None, 1024)	13108224
batch_normalization (BatchNo	(None, 1024)	4096
dense_1 (Dense)	(None, 512)	524800
batch_normalization_1 (Batch	(None, 512)	2048
dense_2 (Dense)	(None, 256)	131328
batch_normalization_2 (Batch	(None, 256)	1024
dropout (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32896
batch_normalization_3 (Batch	(None, 128)	512
dropout_1 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 2)	258
=====	=====	=====
Total params: 33,829,570		
Trainable params: 33,825,730		
Non-trainable params: 3,840		

3. Compile the neural net

```
In [13]: # compile your model
model_1.compile(loss='binary_crossentropy', optimizer=Adam(1e-3), metrics=['accuracy'])
```

```
In [14]: train_ds = train_ds.prefetch(buffer_size=32)
val_ds = val_ds.prefetch(buffer_size=32)
```

4. Fit / train the neural net

```
In [15]: callbacks = [keras.callbacks.ModelCheckpoint("save_at_{epoch}.h5"),]
model_1.fit(train_ds, validation_data = val_ds, callbacks=callbacks, epochs = 5)
```

Epoch 1/5
704/704 [=====] - 5211s 7s/step - loss: 0.7482 - accuracy: 0.5727 - val_loss: 1.055687.0000 - val_accuracy: 0.5284
Epoch 2/5
704/704 [=====] - 5020s 7s/step - loss: 0.5883 - accuracy: 0.6941 - val_loss: 4.323287.5000 - val_accuracy: 0.6888
Epoch 3/5
704/704 [=====] - 5267s 7s/step - loss: 0.4863 - accuracy: 0.7732 - val_loss: 0.4019 - val_accuracy: 0.8156
Epoch 4/5
704/704 [=====] - 5215s 7s/step - loss: 0.4073 - accuracy: 0.8184 - val_loss: 794.2145 - val_accuracy: 0.8124
Epoch 5/5
704/704 [=====] - 4965s 7s/step - loss: 0.3076 - accuracy: 0.8688 - val_loss: 0.3117 - val_accuracy: 0.8780

Out[15]: <tensorflow.python.keras.callbacks.History at 0x261c0dd9be0>

5. Evaluate the neural net

```
In [16]: score = model_1.evaluate(val_ds, verbose=1)
print('Validation accuracy:', score[1])
```

79/79 [=====] - 121s 2s/step - loss: 0.3117 - accuracy: 0.8780
Validation accuracy: 0.878000020980835

Define model_2 using ResNet

```
In [6]: # define the CNN model
        'For the 2nd base model we will use Resnet 50 and compare the performance against the previous one'
        'The hypothesis is that Resnet 50 should perform better because of its deeper architecture'
        base_model_2 = ResNet50(include_top=False, weights='imagenet', input_shape=(160,160,3), classes=class_name)

        #Lets add the final layers to these base models where the actual classification is done in the dense layer
        model_2 = Sequential()
        model_2.add(base_model_2)
        model_2.add(Flatten())

        #Add the Dense layers along with activation and batch normalization
        model_2.add(Dense(1024, activation='relu', input_dim=512))
        model_2.add(BatchNormalization())
        model_2.add(Dense(512,activation='relu'))
        model_2.add(BatchNormalization())
        model_2.add(Dense(256,activation='relu'))
        model_2.add(BatchNormalization())
        model_2.add(Dropout(.3))
        model_2.add(Dense(128,activation='relu'))
        model_2.add(BatchNormalization())
        model_2.add(Dropout(.2))
        model_2.add(Dense(2, activation='softmax')) #This is the classification layer

        model_2.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 5, 5, 2048)	23587712
flatten (Flatten)	(None, 51200)	0
dense (Dense)	(None, 1024)	52429824
batch_normalization (Batch Normalization)	(None, 1024)	4096
dense_1 (Dense)	(None, 512)	524800
batch_normalization_1 (Batch Normalization)	(None, 512)	2048
dense_2 (Dense)	(None, 256)	131328
batch_normalization_2 (Batch Normalization)	(None, 256)	1024
dropout (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 128)	32896
batch_normalization_3 (Batch Normalization)	(None, 128)	512
dropout_1 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 2)	258
Total params: 76,714,498		
Trainable params: 76,657,538		
Non-trainable params: 56,960		

```
In [7]: ▶ model_2.compile(loss='binary_crossentropy', optimizer=Adam(1e-3), metrics=['accuracy'])
callbacks = [keras.callbacks.ModelCheckpoint("model_2_save_at_{epoch}.h5"),]
model_2.fit(train_ds, validation_data = val_ds, callbacks=callbacks, epochs = 5)

Epoch 1/5
704/704 [=====] - 3331s 5s/step - loss: 0.6972 - accuracy: 0.6238 - val_loss:
0.7290 - val_accuracy: 0.6032
Epoch 2/5
704/704 [=====] - 3281s 5s/step - loss: 0.6265 - accuracy: 0.6480 - val_loss:
0.5622 - val_accuracy: 0.7056
Epoch 3/5
704/704 [=====] - 3197s 5s/step - loss: 0.4450 - accuracy: 0.7943 - val_loss:
4.4500 - val_accuracy: 0.4900
Epoch 4/5
704/704 [=====] - 3192s 5s/step - loss: 0.3323 - accuracy: 0.8473 - val_loss:
0.3709 - val_accuracy: 0.8528
Epoch 5/5
704/704 [=====] - 3204s 5s/step - loss: 0.2511 - accuracy: 0.8874 - val_loss:
0.5892 - val_accuracy: 0.6984
```

Out[7]: <tensorflow.python.keras.callbacks.History at 0x19a9a1d7fd0>

```
In [8]: ▶ score = model_2.evaluate(val_ds, verbose=1)
print('Validation accuracy:', score[1])

79/79 [=====] - 60s 753ms/step - loss: 0.5892 - accuracy: 0.6984
Validation accuracy: 0.6984000205993652
```