

```
import numpy as np # Linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os

#for dirname, _, filenames in os.walk('/kaggle/input'):
#    for filename in filenames:
#        print(os.path.join(dirname, filename))

%matplotlib inline
import matplotlib.pyplot as plt
from PIL import Image
import tensorflow as tf
print(tf.__version__)
```

2.3.1

Ignoring the wildlife.h5 file as not needed for this exercise.

Investigate the dataset

- How many of each class of animal do we have

In [2]:

```
PATH = '../input/oregon-wildlife/oregon_wildlife/oregon_wildlife/'
animal_list = os.listdir(PATH)

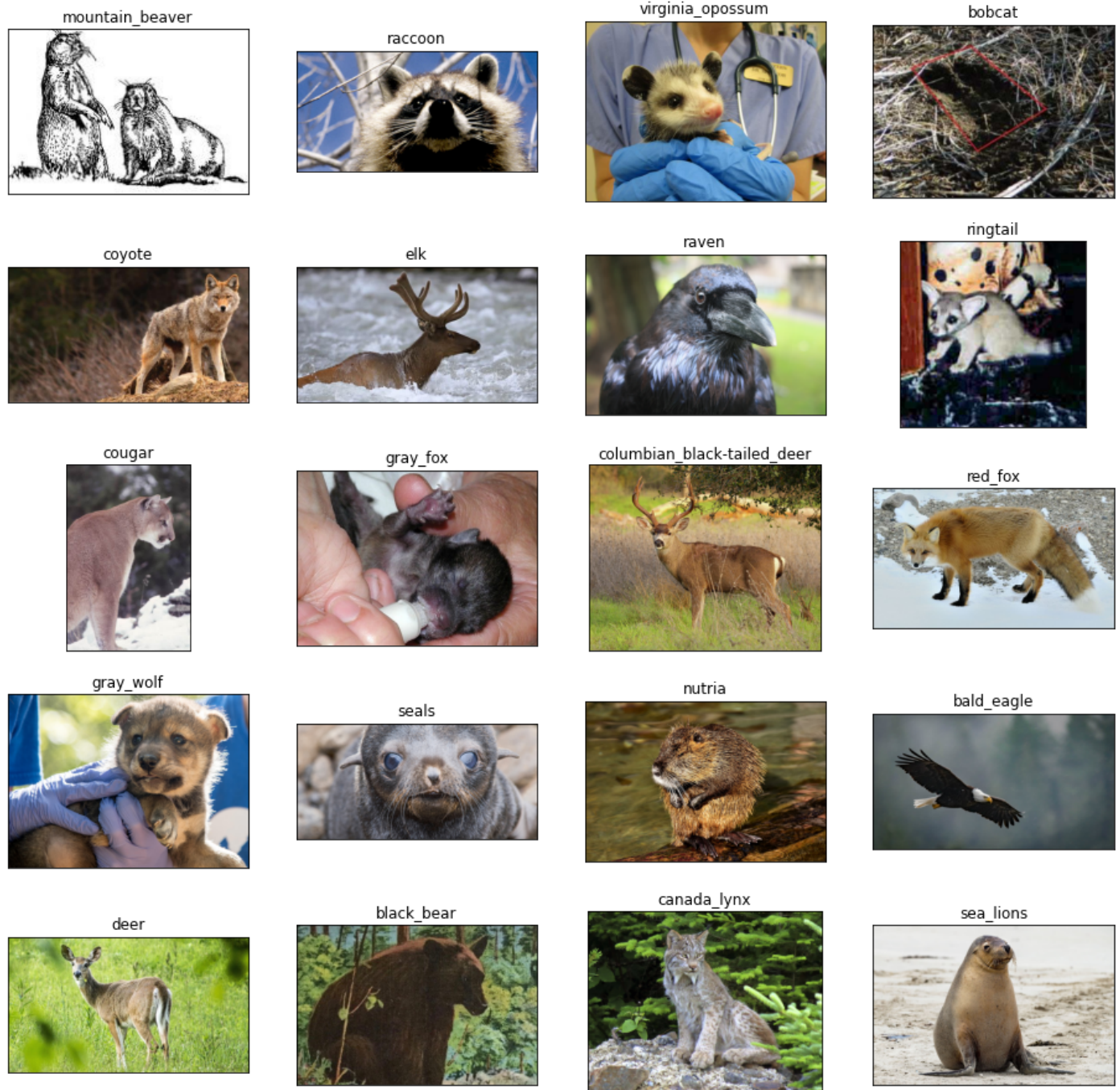
for animal in animal_list:
    number = len(os.listdir(PATH+animal))
    print('There are ', number, animal, 'images')
print('There are ', len(animal_list), 'total categories')
```

```
There are 577 mountain_beaver images
There are 728 raccoon images
There are 728 virginia_opossum images
There are 696 bobcat images
There are 736 coyote images
There are 660 elk images
There are 656 raven images
There are 588 ringtail images
There are 680 cougar images
There are 668 gray_fox images
There are 735 columbia_black-tailed_deer images
There are 759 red_fox images
There are 730 gray_wolf images
There are 698 seals images
There are 701 nutria images
There are 748 bald_eagle images
There are 764 deer images
There are 718 black_bear images
There are 717 canada_lynx images
There are 726 sea_lions images
There are 20 total categories
```

Now visualize an image from each category ¶

In [3]:

```
fig=plt.figure(figsize=(16, 16))
columns = 4
rows = 5
i=0
for animal in animal_list:
    i+=1
    file = os.listdir(PATH+animal)[0]
    img = Image.open(PATH+animal+'/' +file)
    fig.add_subplot(rows, columns, i, xticks=[], yticks=[])
    plt.title(animal)
    plt.imshow(img)
```



Load and split the data in to test, train, validation sets

Use `Keras.preprocessing.image_dataset_from_directory` to generate train, test and validation sets. The training and validation steps are from: https://github.com/tensorflow/docs/blob/master/site/en/tutorials/load_data/images.ipynb

```
In [4]: #Set the batch size, and image height and width

batch_size = 32
img_height = 224
img_width = 224
IMG_SIZE = (img_height, img_width)
```

```
In [5]: #Generate the training dataset

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    PATH,
    validation_split=0.2,
    subset="training",
    label_mode='int',
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)
```

```
Found 14013 files belonging to 20 classes.
Using 11211 files for training.
```

```
In [6]: #Generate the validation dataset

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    PATH,
    validation_split=0.2,
    subset="validation",
    label_mode='int',
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size)
```

```
Found 14013 files belonging to 20 classes.
Using 2802 files for validation.
```

Since there was not test set create one from the validation dataset. In this case we are finding the cardinality `tf.data.experimental.cardinality` of the validation dataset (`val_ds`). Then create a test dataset from that by using the take `tf.data.Dataset.take()` method and 20% (`val_batches // 5`) where the `'//'` is a floor division. Then takes the unused elements of `val_ds` to remain in the `val_ds`.

```
In [7]: val_batches = tf.data.experimental.cardinality(val_ds)
test_ds = val_ds.take(val_batches // 5)
val_sd = val_ds.skip(val_batches // 5)
```

Verification that the class names are valid and there are the correct number.

```
In [8]: class_names = train_ds.class_names
num_classes = len(class_names)
print('Class names are: ', class_names, '/n The number of classes is: ', num_classes)
```

```
Class names are: ['bald_eagle', 'black_bear', 'bobcat', 'canada_lynx', 'columbian_black-tailed_deer', 'cougar', 'coyote', 'deer', 'elk', 'gray_fox', 'gray_wolf', 'mountain_beaver', 'nutria', 'raccoon', 'raven', 'red_fox', 'ringtail', 'sea_lions', 'seals', 'virginia_opossum'] /n The number of classes is: 20
```

1. In the next few steps we will load the `tf.keras.applications.MobileNetV2` base model. This model needs to be preprocessed with values between `[-1,1]` so we will process the inputs to it with `tf.keras.applications.mobilenet_v2.preprocess_input`.

```
In [9]: from tensorflow.keras import layers

preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
```

Setup buffering and prefetching of the training and validation datasets

```
In [10]:
AUTOTUNE = tf.data.experimental.AUTOTUNE #This sets up the runtime to dynamically tune the buffersize

train_ds = train_ds.cache().prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

- **Here I'm loading the MobileNetV2 model from Keras. I'm not including the top layer, so I can create a custom classification layer.**

```
In [11]:
# Create the base model from the pre-trained model MobileNet V2
IMG_SHAPE = IMG_SIZE + (3,)
base_model = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
                                                include_top=False,
                                                weights='imagenet')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h5
9412608/9406464 [=====] - 0s 0us/step
```

This feature extractor converts each 160x160x3 image into a n x n x p block of features in order to always be able to get the correct size for the new feature extraction layer we'll measure the shape of a batch of data from the train_dataset. The output will be a tensor of shape (batch_size, n, n, p).

```
In [12]:
image_batch, label_batch = next(iter(train_ds))
feature_batch = base_model(image_batch)
print(feature_batch.shape)
```

```
(32, 7, 7, 1280)
```

Feature Extraction

In this section we freeze the base model layers so the pre-learned weights and biases aren't updated during training and then add the new classifier on top and train.

In [13]:

```
base_model.trainable = False
```

The base model layers need to be frozen, this way the weights in the layers, except for the top layer won't be updated during training. The top layer is not included in order to add a custom classifier layer with the 20 classes we're training on. See this [TensorFlow Tutorial](#). As we'll see MobilNet contains batch normalization layers, and special care should be taken as described here: [BatchNorm Description](#)

In [14]:

```
base_model.summary() #Look at the model architecture
```


Model: "mobilenetv2_1.00_224"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 224, 224, 3)] 0		
Conv1_pad (ZeroPadding2D)	(None, 225, 225, 3) 0		input_1[0][0]
Conv1 (Conv2D)	(None, 112, 112, 32) 864		Conv1_pad[0][0]
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32) 128		Conv1[0][0]
Conv1_relu (ReLU)	(None, 112, 112, 32) 0		bn_Conv1[0][0]
expanded_conv_depthwise (Depthwise Conv2D)	(None, 112, 112, 32) 288		Conv1_relu[0][0]
expanded_conv_depthwise_BN (Batch Normalization)	(None, 112, 112, 32) 128		expanded_conv_depthwise[0][0]
expanded_conv_depthwise_relu (ReLU)	(None, 112, 112, 32) 0		expanded_conv_depthwise_BN[0][0]
expanded_conv_project (Conv2D)	(None, 112, 112, 16) 512		expanded_conv_depthwise_relu[0][0]
expanded_conv_project_BN (Batch Normalization)	(None, 112, 112, 16) 64		expanded_conv_project[0][0]
block_1_expand (Conv2D)	(None, 112, 112, 96) 1536		expanded_conv_project_BN[0][0]
block_1_expand_BN (Batch Normalization)	(None, 112, 112, 96) 384		block_1_expand[0][0]

block_1_expand_relu (ReLU)	(None, 112, 112, 96)	0	block_1_expand_BN[0][0]
block_1_pad (ZeroPadding2D)	(None, 113, 113, 96)	0	block_1_expand_relu[0][0]
block_1_depthwise (DepthwiseConv2D)	(None, 56, 56, 96)	864	block_1_pad[0][0]
block_1_depthwise_BN (BatchNormalization)	(None, 56, 56, 96)	384	block_1_depthwise[0][0]
block_1_depthwise_relu (ReLU)	(None, 56, 56, 96)	0	block_1_depthwise_BN[0][0]
block_1_project (Conv2D)	(None, 56, 56, 24)	2304	block_1_depthwise_relu[0][0]
block_1_project_BN (BatchNormalization)	(None, 56, 56, 24)	96	block_1_project[0][0]
block_2_expand (Conv2D)	(None, 56, 56, 144)	3456	block_1_project_BN[0][0]
block_2_expand_BN (BatchNormalization)	(None, 56, 56, 144)	576	block_2_expand[0][0]
block_2_expand_relu (ReLU)	(None, 56, 56, 144)	0	block_2_expand_BN[0][0]
block_2_depthwise (DepthwiseConv2D)	(None, 56, 56, 144)	1296	block_2_expand_relu[0][0]
block_2_depthwise_BN (BatchNormalization)	(None, 56, 56, 144)	576	block_2_depthwise[0][0]

block_2_depthwise_relu (ReLU)	(None, 56, 56, 144)	0	block_2_depthwise_BN [0][0]
block_2_project (Conv2D)	(None, 56, 56, 24)	3456	block_2_depthwise_relu [0][0]
block_2_project_BN (BatchNormal	(None, 56, 56, 24)	96	block_2_project[0][0]
block_2_add (Add)	(None, 56, 56, 24)	0	block_1_project_BN[0] [0] block_2_project_BN[0] [0]
block_3_expand (Conv2D)	(None, 56, 56, 144)	3456	block_2_add[0][0]
block_3_expand_BN (BatchNormali	(None, 56, 56, 144)	576	block_3_expand[0][0]
block_3_expand_relu (ReLU)	(None, 56, 56, 144)	0	block_3_expand_BN[0] [0]
block_3_pad (ZeroPadding2D)	(None, 57, 57, 144)	0	block_3_expand_relu[0] [0]
block_3_depthwise (DepthwiseCon	(None, 28, 28, 144)	1296	block_3_pad[0][0]
block_3_depthwise_BN (BatchNorm	(None, 28, 28, 144)	576	block_3_depthwise[0] [0]
block_3_depthwise_relu (ReLU)	(None, 28, 28, 144)	0	block_3_depthwise_BN [0][0]
block_3_project (Conv2D)	(None, 28, 28, 32)	4608	block_3_depthwise_relu [0][0]

block_3_project_BN (BatchNormal	(None, 28, 28, 32)	128	block_3_project[0][0]
block_4_expand (Conv2D)	(None, 28, 28, 192)	6144	block_3_project_BN[0] [0]
block_4_expand_BN (BatchNormali	(None, 28, 28, 192)	768	block_4_expand[0][0]
block_4_expand_relu (ReLU)	(None, 28, 28, 192)	0	block_4_expand_BN[0] [0]
block_4_depthwise (DepthwiseCon	(None, 28, 28, 192)	1728	block_4_expand_relu[0] [0]
block_4_depthwise_BN (BatchNorm	(None, 28, 28, 192)	768	block_4_depthwise[0] [0]
block_4_depthwise_relu (ReLU)	(None, 28, 28, 192)	0	block_4_depthwise_BN [0][0]
block_4_project (Conv2D)	(None, 28, 28, 32)	6144	block_4_depthwise_relu [0][0]
block_4_project_BN (BatchNormal	(None, 28, 28, 32)	128	block_4_project[0][0]
block_4_add (Add)	(None, 28, 28, 32)	0	block_3_project_BN[0] [0] block_4_project_BN[0] [0]
block_5_expand (Conv2D)	(None, 28, 28, 192)	6144	block_4_add[0][0]
block_5_expand_BN (BatchNormali	(None, 28, 28, 192)	768	block_5_expand[0][0]

block_5_expand_relu (ReLU)	(None, 28, 28, 192)	0	block_5_expand_BN[0]
<hr/>			
block_5_depthwise (DepthwiseConv2D)	(None, 28, 28, 192)	1728	block_5_expand_relu[0]
<hr/>			
block_5_depthwise_BN (BatchNormali	(None, 28, 28, 192)	768	block_5_depthwise[0]
<hr/>			
block_5_depthwise_relu (ReLU)	(None, 28, 28, 192)	0	block_5_depthwise_BN[0][0]
<hr/>			
block_5_project (Conv2D)	(None, 28, 28, 32)	6144	block_5_depthwise_relu[0][0]
<hr/>			
block_5_project_BN (BatchNormali	(None, 28, 28, 32)	128	block_5_project[0][0]
<hr/>			
block_5_add (Add)	(None, 28, 28, 32)	0	block_4_add[0][0] block_5_project_BN[0]
<hr/>			
block_6_expand (Conv2D)	(None, 28, 28, 192)	6144	block_5_add[0][0]
<hr/>			
block_6_expand_BN (BatchNormali	(None, 28, 28, 192)	768	block_6_expand[0][0]
<hr/>			
block_6_expand_relu (ReLU)	(None, 28, 28, 192)	0	block_6_expand_BN[0]
<hr/>			
block_6_pad (ZeroPadding2D)	(None, 29, 29, 192)	0	block_6_expand_relu[0]
<hr/>			
block_6_depthwise (DepthwiseConv2D)	(None, 14, 14, 192)	1728	block_6_pad[0][0]
<hr/>			
block_6_depthwise_BN (BatchNorm	(None, 14, 14, 192)	768	block_6_depthwise[0]

[0]			
<hr/>			
block_6_depthwise_relu (ReLU)	(None, 14, 14, 192)	0	block_6_depthwise_BN[0][0]
<hr/>			
block_6_project (Conv2D)	(None, 14, 14, 64)	12288	block_6_depthwise_relu[0][0]
<hr/>			
block_6_project_BN (BatchNormal	(None, 14, 14, 64)	256	block_6_project[0][0]
<hr/>			
block_7_expand (Conv2D)	(None, 14, 14, 384)	24576	block_6_project_BN[0][0]
<hr/>			
block_7_expand_BN (BatchNormali	(None, 14, 14, 384)	1536	block_7_expand[0][0]
<hr/>			
block_7_expand_relu (ReLU)	(None, 14, 14, 384)	0	block_7_expand_BN[0][0]
<hr/>			
block_7_depthwise (DepthwiseCon	(None, 14, 14, 384)	3456	block_7_expand_relu[0][0]
<hr/>			
block_7_depthwise_BN (BatchNorm	(None, 14, 14, 384)	1536	block_7_depthwise[0][0]
<hr/>			
block_7_depthwise_relu (ReLU)	(None, 14, 14, 384)	0	block_7_depthwise_BN[0][0]
<hr/>			
block_7_project (Conv2D)	(None, 14, 14, 64)	24576	block_7_depthwise_relu[0][0]
<hr/>			
block_7_project_BN (BatchNormal	(None, 14, 14, 64)	256	block_7_project[0][0]
<hr/>			
block_7_add (Add)	(None, 14, 14, 64)	0	block_6_project_BN[0][0]

			block_7_project_BN[0]
[0]			
block_8_expand (Conv2D)	(None, 14, 14, 384)	24576	block_7_add[0][0]
block_8_expand_BN (BatchNormali	(None, 14, 14, 384)	1536	block_8_expand[0][0]
block_8_expand_relu (ReLU)	(None, 14, 14, 384)	0	block_8_expand_BN[0]
[0]			
block_8_depthwise (DepthwiseCon	(None, 14, 14, 384)	3456	block_8_expand_relu[0]
[0]			
block_8_depthwise_BN (BatchNorm	(None, 14, 14, 384)	1536	block_8_depthwise[0]
[0]			
block_8_depthwise_relu (ReLU)	(None, 14, 14, 384)	0	block_8_depthwise_BN
[0][0]			
block_8_project (Conv2D)	(None, 14, 14, 64)	24576	block_8_depthwise_relu
[0][0]			
block_8_project_BN (BatchNormal	(None, 14, 14, 64)	256	block_8_project[0][0]
block_8_add (Add)	(None, 14, 14, 64)	0	block_7_add[0][0]
			block_8_project_BN[0]
[0]			
block_9_expand (Conv2D)	(None, 14, 14, 384)	24576	block_8_add[0][0]
block_9_expand_BN (BatchNormali	(None, 14, 14, 384)	1536	block_9_expand[0][0]
block_9_expand_relu (ReLU)	(None, 14, 14, 384)	0	block_9_expand_BN[0]
[0]			

block_9_depthwise (DepthwiseCon	(None, 14, 14, 384)	3456	block_9_expand_relu[0][0]
block_9_depthwise_BN (BatchNorm	(None, 14, 14, 384)	1536	block_9_depthwise[0][0]
block_9_depthwise_relu (ReLU)	(None, 14, 14, 384)	0	block_9_depthwise_BN[0][0]
block_9_project (Conv2D)	(None, 14, 14, 64)	24576	block_9_depthwise_relu[0][0]
block_9_project_BN (BatchNormal	(None, 14, 14, 64)	256	block_9_project[0][0]
block_9_add (Add)	(None, 14, 14, 64)	0	block_8_add[0][0] block_9_project_BN[0][0]
block_10_expand (Conv2D)	(None, 14, 14, 384)	24576	block_9_add[0][0]
block_10_expand_BN (BatchNormal	(None, 14, 14, 384)	1536	block_10_expand[0][0]
block_10_expand_relu (ReLU)	(None, 14, 14, 384)	0	block_10_expand_BN[0][0]
block_10_depthwise (DepthwiseCo	(None, 14, 14, 384)	3456	block_10_expand_relu[0][0]
block_10_depthwise_BN (BatchNor	(None, 14, 14, 384)	1536	block_10_depthwise[0][0]
block_10_depthwise_relu (ReLU)	(None, 14, 14, 384)	0	block_10_depthwise_BN[0][0]

block_10_project (Conv2D)	(None, 14, 14, 96)	36864	block_10_depthwise_relu[0][0]
block_10_project_BN (BatchNormal	(None, 14, 14, 96)	384	block_10_project[0][0]
block_11_expand (Conv2D)	(None, 14, 14, 576)	55296	block_10_project_BN[0][0]
block_11_expand_BN (BatchNormal	(None, 14, 14, 576)	2304	block_11_expand[0][0]
block_11_expand_relu (ReLU)	(None, 14, 14, 576)	0	block_11_expand_BN[0][0]
block_11_depthwise (DepthwiseCo	(None, 14, 14, 576)	5184	block_11_expand_relu[0][0]
block_11_depthwise_BN (BatchNor	(None, 14, 14, 576)	2304	block_11_depthwise[0][0]
block_11_depthwise_relu (ReLU)	(None, 14, 14, 576)	0	block_11_depthwise_BN[0][0]
block_11_project (Conv2D)	(None, 14, 14, 96)	55296	block_11_depthwise_relu[0][0]
block_11_project_BN (BatchNorma	(None, 14, 14, 96)	384	block_11_project[0][0]
block_11_add (Add)	(None, 14, 14, 96)	0	block_10_project_BN[0][0]
			block_11_project_BN[0][0]
block_12_expand (Conv2D)	(None, 14, 14, 576)	55296	

block_12_expand_BN (BatchNormal	(None, 14, 14, 576)	2304	block_12_expand[0][0]
block_12_expand_relu (ReLU)	(None, 14, 14, 576)	0	block_12_expand_BN[0][0]
block_12_depthwise (DepthwiseCo	(None, 14, 14, 576)	5184	block_12_expand_relu[0][0]
block_12_depthwise_BN (BatchNor	(None, 14, 14, 576)	2304	block_12_depthwise[0][0]
block_12_depthwise_relu (ReLU)	(None, 14, 14, 576)	0	block_12_depthwise_BN[0][0]
block_12_project (Conv2D)	(None, 14, 14, 96)	55296	block_12_depthwise_relu[0][0]
block_12_project_BN (BatchNorma	(None, 14, 14, 96)	384	block_12_project[0][0]
block_12_add (Add)	(None, 14, 14, 96)	0	block_11_add[0][0] block_12_project_BN[0][0]
block_13_expand (Conv2D)	(None, 14, 14, 576)	55296	block_12_add[0][0]
block_13_expand_BN (BatchNormal	(None, 14, 14, 576)	2304	block_13_expand[0][0]
block_13_expand_relu (ReLU)	(None, 14, 14, 576)	0	block_13_expand_BN[0][0]
block_13_pad (ZeroPadding2D)	(None, 15, 15, 576)	0	block_13_expand_relu[0][0]

block_13_depthwise (DepthwiseCo	(None, 7, 7, 576)	5184	block_13_pad[0][0]
block_13_depthwise_BN (BatchNor	(None, 7, 7, 576)	2304	block_13_depthwise[0][0]
block_13_depthwise_relu (ReLU)	(None, 7, 7, 576)	0	block_13_depthwise_BN[0][0]
block_13_project (Conv2D)	(None, 7, 7, 160)	92160	block_13_depthwise_relu[0][0]
block_13_project_BN (BatchNorma	(None, 7, 7, 160)	640	block_13_project[0][0]
block_14_expand (Conv2D)	(None, 7, 7, 960)	153600	block_13_project_BN[0][0]
block_14_expand_BN (BatchNormal	(None, 7, 7, 960)	3840	block_14_expand[0][0]
block_14_expand_relu (ReLU)	(None, 7, 7, 960)	0	block_14_expand_BN[0][0]
block_14_depthwise (DepthwiseCo	(None, 7, 7, 960)	8640	block_14_expand_relu[0][0]
block_14_depthwise_BN (BatchNor	(None, 7, 7, 960)	3840	block_14_depthwise[0][0]
block_14_depthwise_relu (ReLU)	(None, 7, 7, 960)	0	block_14_depthwise_BN[0][0]
block_14_project (Conv2D)	(None, 7, 7, 160)	153600	block_14_depthwise_relu[0][0]

block_14_project_BN (BatchNormal	(None, 7, 7, 160)	640	block_14_project[0][0]
<hr/>			
block_14_add (Add)	(None, 7, 7, 160)	0	block_13_project_BN[0]
[0]			block_14_project_BN[0]
[0]			
<hr/>			
block_15_expand (Conv2D)	(None, 7, 7, 960)	153600	block_14_add[0][0]
<hr/>			
block_15_expand_BN (BatchNormal	(None, 7, 7, 960)	3840	block_15_expand[0][0]
<hr/>			
block_15_expand_relu (ReLU)	(None, 7, 7, 960)	0	block_15_expand_BN[0]
[0]			
<hr/>			
block_15_depthwise (DepthwiseCo	(None, 7, 7, 960)	8640	block_15_expand_relu
[0][0]			
<hr/>			
block_15_depthwise_BN (BatchNor	(None, 7, 7, 960)	3840	block_15_depthwise[0]
[0]			
<hr/>			
block_15_depthwise_relu (ReLU)	(None, 7, 7, 960)	0	block_15_depthwise_BN
[0][0]			
<hr/>			
block_15_project (Conv2D)	(None, 7, 7, 160)	153600	block_15_depthwise_relu[0][0]
<hr/>			
block_15_project_BN (BatchNorma	(None, 7, 7, 160)	640	block_15_project[0][0]
<hr/>			
block_15_add (Add)	(None, 7, 7, 160)	0	block_14_add[0][0]
[0]			block_15_project_BN[0]
[0]			
<hr/>			
block_16_expand (Conv2D)	(None, 7, 7, 960)	153600	block_15_add[0][0]
<hr/>			
<hr/>			

Help and inputs at this step are from [Adding a Classification Head](#) In order to use the output to create a classification layer the output of the base model is, n,n,p. Need to convert this to a single 1280 element vector so this is done by using a average pooling layer.

```
In [15]:
global_average_layer = tf.keras.layers.GlobalAveragePooling2D()
feature_batch_average = global_average_layer(feature_batch)
prediction_layer = tf.keras.layers.Dense(num_classes, activation='softmax', name='prediction')
prediction_batch = prediction_layer(feature_batch_average)
print(prediction_batch.shape)
```

(32, 20)

```
In [16]:
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.experimental.preprocessing.RandomFlip('horizontal'),
    tf.keras.layers.experimental.preprocessing.RandomRotation(0.2),
])
```

```
In [17]:
inputs = tf.keras.Input(shape=(img_height, img_width, 3))
x = data_augmentation(inputs)
x = preprocess_input(inputs)
x = base_model(x)
x = global_average_layer(x)
x = tf.keras.layers.Dropout(0.2)(x)
outputs = prediction_layer(x)
model = tf.keras.models.Model(inputs, outputs)
```

Compile the Model

Compile the model before training. There are two classes, uses sparse_categorical_crossentropy

```
In [18]:
base_learning_rate = 0.0001
model.compile(optimizer=tf.keras.optimizers.Adam(lr=base_learning_rate),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

```
In [19]: model.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 224, 224, 3)]	0

tf_op_layer_RealDiv (TensorF	[(None, 224, 224, 3)]	0

tf_op_layer_Sub (TensorFlow0	[(None, 224, 224, 3)]	0

mobilenetv2_1.00_224 (Functi	(None, 7, 7, 1280)	2257984

global_average_pooling2d (Gl	(None, 1280)	0

dropout (Dropout)	(None, 1280)	0

prediction (Dense)	(None, 20)	25620
=====		
Total params: 2,283,604		
Trainable params: 25,620		
Non-trainable params: 2,257,984		

Train the model

Setup initial training parameters and evaluation criterial

```
In [20]: epochs = 10
```

In [21]:

```
history = model.fit(train_ds,  
                    validation_data=val_ds,  
                    epochs=epochs)
```

Epoch 1/10

351/351 [=====] - 288s 820ms/step - loss: 2.8024 - accuracy: 0.4012 - val_loss: 2.5764 - val_accuracy: 0.6542

Epoch 2/10

351/351 [=====] - 12s 35ms/step - loss: 2.4804 - accuracy: 0.7135 - val_loss: 2.4323 - val_accuracy: 0.7355

Epoch 3/10

351/351 [=====] - 12s 35ms/step - loss: 2.3897 - accuracy: 0.7700 - val_loss: 2.3794 - val_accuracy: 0.7698

Epoch 4/10

351/351 [=====] - 13s 36ms/step - loss: 2.3513 - accuracy: 0.7911 - val_loss: 2.3528 - val_accuracy: 0.7862

Epoch 5/10

351/351 [=====] - 12s 35ms/step - loss: 2.3309 - accuracy: 0.8038 - val_loss: 2.3357 - val_accuracy: 0.7941

Epoch 6/10

351/351 [=====] - 12s 35ms/step - loss: 2.3153 - accuracy: 0.8111 - val_loss: 2.3239 - val_accuracy: 0.8009

Epoch 7/10

351/351 [=====] - 12s 35ms/step - loss: 2.3039 - accuracy: 0.8180 - val_loss: 2.3141 - val_accuracy: 0.8084

Epoch 8/10

351/351 [=====] - 12s 35ms/step - loss: 2.2958 - accuracy: 0.8217 - val_loss: 2.3069 - val_accuracy: 0.8130

Epoch 9/10

351/351 [=====] - 13s 36ms/step - loss: 2.2858 - accuracy: 0.8313 - val_loss: 2.2885 - val_accuracy: 0.8312

Epoch 10/10

351/351 [=====] - 12s 35ms/step - loss: 2.2589 - accuracy: 0.8601 - val_loss: 2.2658 - val_accuracy: 0.8555

In [22]:

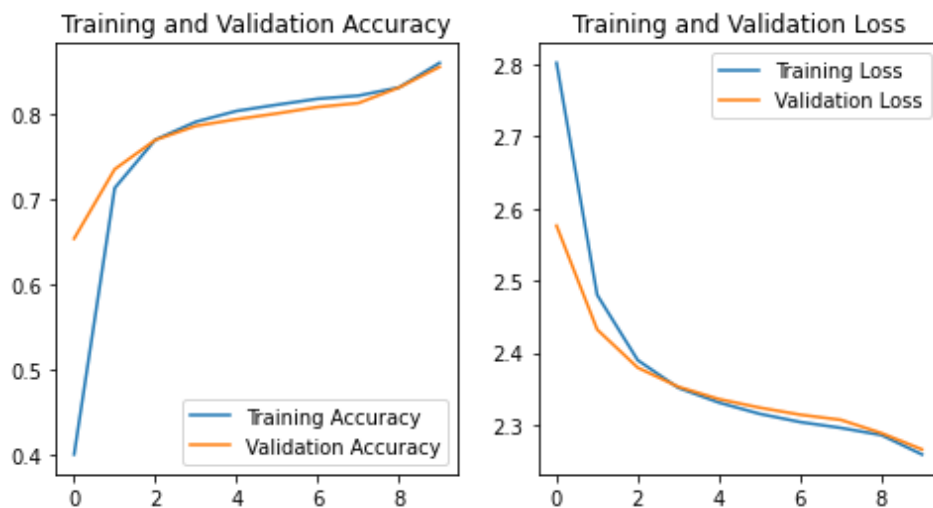
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



Baseline Model Performance

The baseline model, which contained no augmentation or fine tuning had a validation dataset accuracy of 85%.

In [23]:

```
#This will evaluate the baseline model against the test dataset.  
test_loss, test_accuracy = model.evaluate(test_ds)  
print('Test dataset loss: ', test_loss, 'Test dataset accuracy: ', test_accuracy)
```

```
17/17 [=====] - 6s 349ms/step - loss: 2.2477 - accuracy: 0.873  
2
```

```
Test dataset loss: 2.2477364540100098 Test dataset accuracy: 0.873161792755127
```

Visualize the feature maps for an example image

In [24]:

```
from keras.models import Model
```

```
#This will create a model that outputs the feature maps generated the output of block 1
```

```
feature_model = Model(inputs=base_model.inputs, outputs=base_model.layers[17].output)
```

```
feature_model.summary()
```

Model: "functional_3"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
<hr/>		
Conv1_pad (ZeroPadding2D)	(None, 225, 225, 3)	0
<hr/>		
Conv1 (Conv2D)	(None, 112, 112, 32)	864
<hr/>		
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)	128
<hr/>		
Conv1_relu (ReLU)	(None, 112, 112, 32)	0
<hr/>		
expanded_conv_depthwise (DepthwiseConv2D)	(None, 112, 112, 32)	288
<hr/>		
expanded_conv_depthwise_BN (BatchNormalization)	(None, 112, 112, 32)	128
<hr/>		
expanded_conv_depthwise_relu (ReLU)	(None, 112, 112, 32)	0
<hr/>		
expanded_conv_project (Conv2D)	(None, 112, 112, 16)	512
<hr/>		
expanded_conv_project_BN (BatchNormalization)	(None, 112, 112, 16)	64
<hr/>		
block_1_expand (Conv2D)	(None, 112, 112, 96)	1536
<hr/>		
block_1_expand_BN (BatchNormalization)	(None, 112, 112, 96)	384
<hr/>		
block_1_expand_relu (ReLU)	(None, 112, 112, 96)	0
<hr/>		
block_1_pad (ZeroPadding2D)	(None, 113, 113, 96)	0
<hr/>		
block_1_depthwise (DepthwiseConv2D)	(None, 56, 56, 96)	864
<hr/>		
block_1_depthwise_BN (BatchNormalization)	(None, 56, 56, 96)	384
<hr/>		
block_1_depthwise_relu (ReLU)	(None, 56, 56, 96)	0
<hr/>		
block_1_project (Conv2D)	(None, 56, 56, 24)	2304
=====		
Total params: 7,456		
Trainable params: 0		
Non-trainable params: 7,456		
<hr/>		

In [25]:

```
#Here a single image is loaded in order to generate the feature maps
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from numpy import expand_dims
animal = 'elk'
file = os.listdir(PATH+animal)[3]
#Load a sample image and size resize to the shape expected by the model (img_height, img_width)
img = load_img(PATH+animal+'/' +file, target_size=(img_height, img_width))
#Convert to an array
img = img_to_array(img)
#Expand dimension so that it represents a single 'sample'
img = expand_dims(img, axis=0)
#Prepare the image for Mobilnet
img = preprocess_input(img)
```

In [26]:

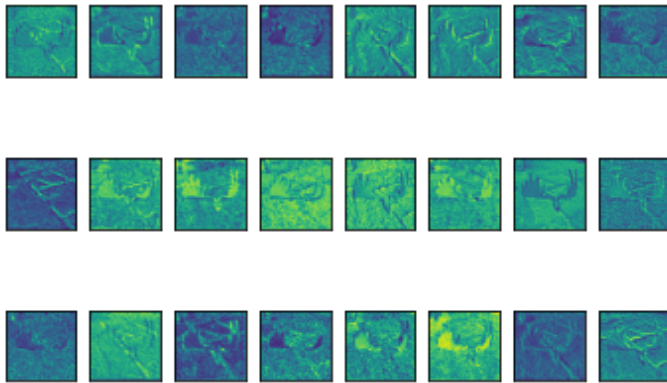
```
#This will process the single image loaded above through the base model
feature_maps = feature_model.predict(img)
```

It is interesting to note the fine details identified in the first block of MobileNet. Upon changing to be the last output block the feature maps are very generalized.

In [27]:

```
#plot 24 maps on the output of the first block in MobileNet
rows = 3
columns = 8
ix = 1
for _ in range(rows):
    for _ in range(columns):
        ax = plt.subplot(rows, columns, ix)

        ax.set_xticks([])
        ax.set_yticks([])
        plt.imshow(feature_maps[0,:,:ix-1], cmap='viridis')
        ix += 1
plt.rcParams["figure.figsize"] = (20,20)
plt.show()
```



Fine Tuning

This next section Block 16 of the base model will be set as trainable. The model will then be trained to see if improvements can be made on the model performance.

In [28]:

```
base_model.trainable = True
```

In [29]:

```
num_layers = len(base_model.layers)
print('Number of layers in the base model: ', num_layers)

fine_tune_at = num_layers-16 #this will unfreeze the block15 and block16

for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False
```

```
Number of layers in the base model: 155
```

Re-compile the model

Since I'm changing the trainable parameter of some layers of the model it needs to be re-compiled before retraining in order that the changes take effect.

In [30]:

```
base_learning_rate = 0.0001
model.compile(optimizer=tf.keras.optimizers.Adam(lr=base_learning_rate/10),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

In [31]:

```
model.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 224, 224, 3)]	0
<hr/>		
tf_op_layer_RealDiv (TensorF	[(None, 224, 224, 3)]	0
<hr/>		
tf_op_layer_Sub (TensorFlow0	[(None, 224, 224, 3)]	0
<hr/>		
mobilenetv2_1.00_224 (Functi	(None, 7, 7, 1280)	2257984
<hr/>		
global_average_pooling2d (Gl	(None, 1280)	0
<hr/>		
dropout (Dropout)	(None, 1280)	0
<hr/>		
prediction (Dense)	(None, 20)	25620
=====		
Total params: 2,283,604		
Trainable params: 1,067,540		
Non-trainable params: 1,216,064		
<hr/>		

In [32]:

```
fine_tune_epochs = 20
total_epochs = epochs + fine_tune_epochs
history_fine = model.fit(train_ds,
                        validation_data=val_ds,
                        initial_epoch = history.epoch[-1],
                        epochs=total_epochs)
```

Epoch 10/30

351/351 [=====] - 14s 41ms/step - loss: 2.2912 - accuracy: 0.8
317 - val_loss: 2.2538 - val_accuracy: 0.8569

Epoch 11/30

351/351 [=====] - 13s 38ms/step - loss: 2.2510 - accuracy: 0.8
659 - val_loss: 2.2391 - val_accuracy: 0.8683

Epoch 12/30

351/351 [=====] - 13s 38ms/step - loss: 2.2303 - accuracy: 0.8
842 - val_loss: 2.2277 - val_accuracy: 0.8772

Epoch 13/30

351/351 [=====] - 13s 38ms/step - loss: 2.2138 - accuracy: 0.8
952 - val_loss: 2.2196 - val_accuracy: 0.8847

Epoch 14/30

351/351 [=====] - 13s 38ms/step - loss: 2.2018 - accuracy: 0.9
057 - val_loss: 2.2114 - val_accuracy: 0.8911

Epoch 15/30

351/351 [=====] - 13s 38ms/step - loss: 2.1921 - accuracy: 0.9
140 - val_loss: 2.2042 - val_accuracy: 0.8983

Epoch 16/30

351/351 [=====] - 13s 38ms/step - loss: 2.1822 - accuracy: 0.9
220 - val_loss: 2.1990 - val_accuracy: 0.9036

Epoch 17/30

351/351 [=====] - 13s 38ms/step - loss: 2.1743 - accuracy: 0.9
286 - val_loss: 2.1938 - val_accuracy: 0.9079

Epoch 18/30

351/351 [=====] - 13s 38ms/step - loss: 2.1679 - accuracy: 0.9
326 - val_loss: 2.1890 - val_accuracy: 0.9101

Epoch 19/30

351/351 [=====] - 14s 39ms/step - loss: 2.1610 - accuracy: 0.9
384 - val_loss: 2.1854 - val_accuracy: 0.9104

Epoch 20/30

351/351 [=====] - 13s 38ms/step - loss: 2.1550 - accuracy: 0.9
423 - val_loss: 2.1818 - val_accuracy: 0.9154

Epoch 21/30

351/351 [=====] - 13s 38ms/step - loss: 2.1501 - accuracy: 0.9
461 - val_loss: 2.1788 - val_accuracy: 0.9172

Epoch 22/30

351/351 [=====] - 13s 38ms/step - loss: 2.1456 - accuracy: 0.9
490 - val_loss: 2.1761 - val_accuracy: 0.9197

Epoch 23/30

351/351 [=====] - 14s 40ms/step - loss: 2.1411 - accuracy: 0.9
520 - val_loss: 2.1735 - val_accuracy: 0.9201

Epoch 24/30

351/351 [=====] - 13s 38ms/step - loss: 2.1376 - accuracy: 0.9
540 - val_loss: 2.1712 - val_accuracy: 0.9215

```
Epoch 25/30
351/351 [=====] - 13s 37ms/step - loss: 2.1346 - accuracy: 0.9
558 - val_loss: 2.1687 - val_accuracy: 0.9229
Epoch 26/30
351/351 [=====] - 13s 37ms/step - loss: 2.1315 - accuracy: 0.9
577 - val_loss: 2.1665 - val_accuracy: 0.9247
Epoch 27/30
351/351 [=====] - 13s 37ms/step - loss: 2.1289 - accuracy: 0.9
593 - val_loss: 2.1640 - val_accuracy: 0.9254
Epoch 28/30
351/351 [=====] - 13s 38ms/step - loss: 2.1264 - accuracy: 0.9
608 - val_loss: 2.1619 - val_accuracy: 0.9265
Epoch 29/30
351/351 [=====] - 13s 37ms/step - loss: 2.1243 - accuracy: 0.9
628 - val_loss: 2.1607 - val_accuracy: 0.9279
Epoch 30/30
351/351 [=====] - 13s 37ms/step - loss: 2.1221 - accuracy: 0.9
633 - val_loss: 2.1590 - val_accuracy: 0.9272
```

In [33]:

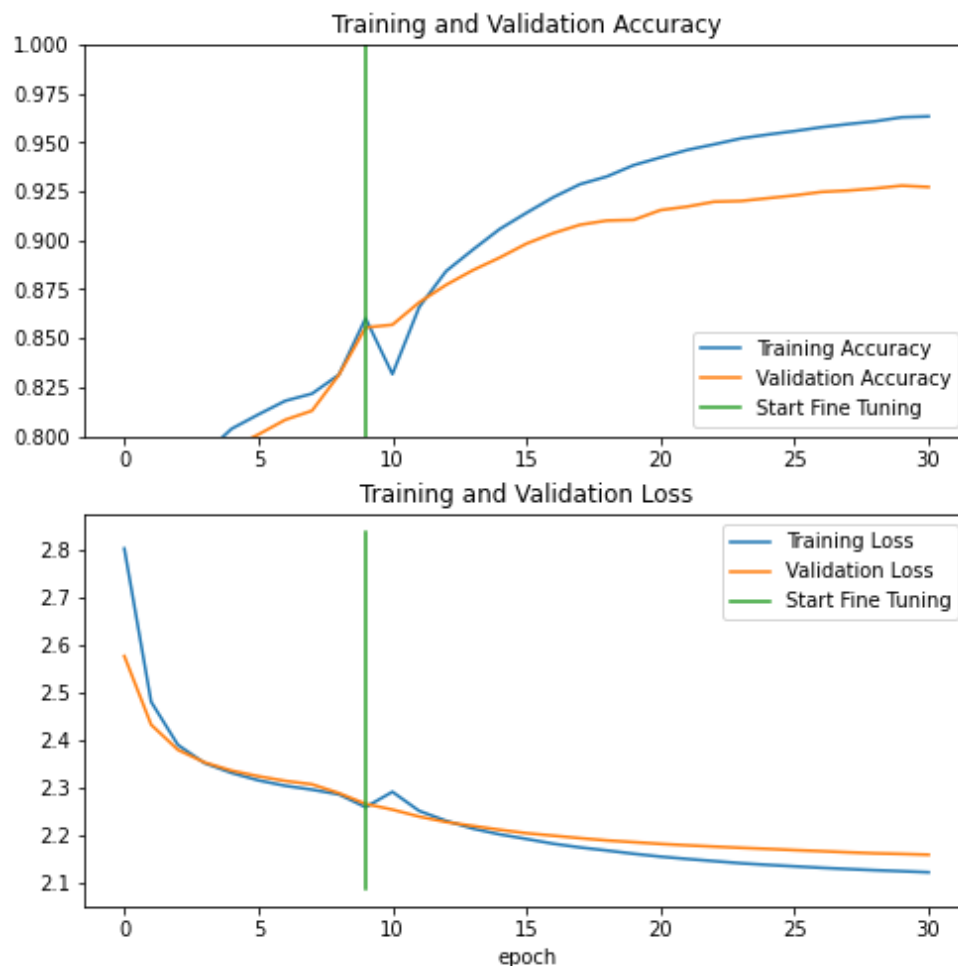
```
acc += history_fine.history['accuracy']
val_acc += history_fine.history['val_accuracy']

loss += history_fine.history['loss']
val_loss += history_fine.history['val_loss']
```

In [34]:

```
plt.figure(figsize=(8, 8))
plt.subplot(2, 1, 1)
plt.plot(acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.ylim([0.8, 1])
plt.plot([epochs-1, epochs-1],
         plt.ylim(), label='Start Fine Tuning')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(2, 1, 2)
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.plot([epochs-1, epochs-1],
         plt.ylim(), label='Start Fine Tuning')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.xlabel('epoch')
plt.show()
```



In [35]:

```
loss, accuracy = model.evaluate(test_ds)
print('Test dataset loss: ', loss, 'Test dataset accuracy: ', accuracy)
```

```
17/17 [=====] - 6s 370ms/step - loss: 2.1612 - accuracy: 0.9228
Test dataset loss: 2.1612000465393066 Test dataset accuracy: 0.9227941036224365
```

Thanks to the following website for hints on converting the tensorflow confusion matrix to the dataframe and plotting: [TensorFlow Keras Confusion Matrix in TensorBoard](#)

In [36]:

```
predictions = np.array([])
labels = np.array([])
for x, y in test_ds:
    predictions = np.concatenate([predictions, np.argmax(model.predict(x), axis=1)])
    labels = np.concatenate([labels, y.numpy()])
    #print('predict= ', predictions, 'label= ', labels)
con_mat = tf.math.confusion_matrix(labels=labels, predictions=predictions).numpy()
con_mat_norm = np.around(con_mat.astype('float')/con_mat.sum(axis=1)[:, np.newaxis], decimals=2)
con_mat_df = pd.DataFrame(con_mat_norm, index=class_names, columns=class_names)
```

In [37]:

```
import seaborn as sns

figure = plt.figure(figsize=(15,15))

sns.heatmap(con_mat_df, annot=True, cmap=plt.cm.Blues)

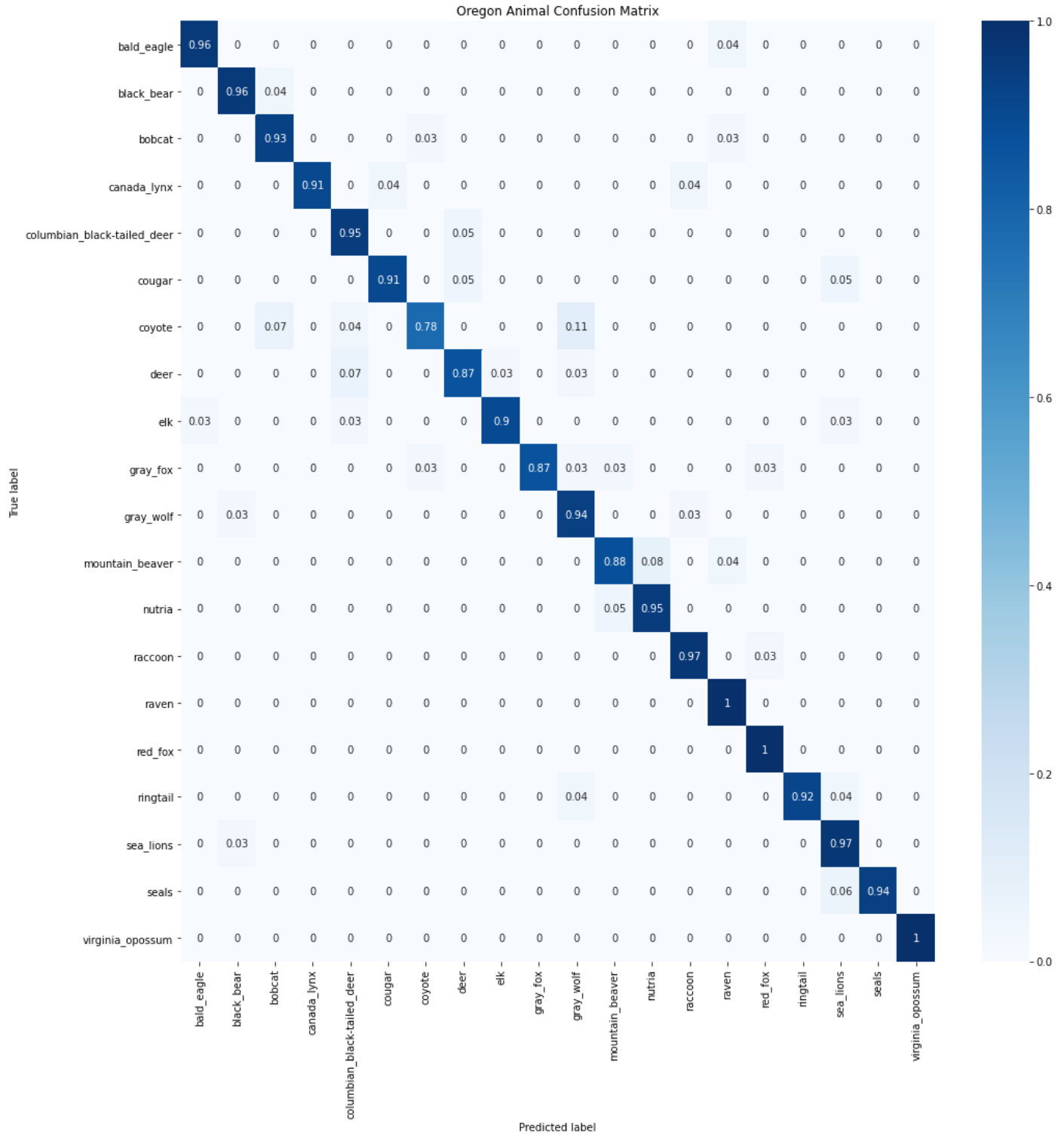
plt.tight_layout()

plt.ylabel('True label')

plt.xlabel('Predicted label')

plt.title('Oregon Animal Confusion Matrix')

plt.show()
```



Save the model and the weights that could be used later.

```
In [38]:  
# serialize model to JSON  
model_json = model.to_json()  
with open("model.json", "w") as json_file:  
    json_file.write(model_json)  
# serialize weights to HDF5  
model.save_weights("model.h5")
```

In []: