

# Assignment 6

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## 0.1 Assignment 6

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### 0.1.1 6.1

```
[35]: # Import libraries

from keras import layers
from keras import models
from keras.datasets import mnist
from keras.utils import to_categorical
from pathlib import Path
import os
import matplotlib.pyplot as plt
import numpy as np
from keras import losses
from keras import metrics
```

```
[36]: # 5.1

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

```
[37]: model.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_6 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_10 (Conv2D)	(None, 11, 11, 64)	18496

```

-----
max_pooling2d_7 (MaxPooling2 (None, 5, 5, 64)          0
-----
conv2d_11 (Conv2D)          (None, 3, 3, 64)          36928
=====
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
-----

```

[38]: # 5.2

```

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

```

[39]: model.summary()

Model: "sequential\_3"

```

-----
Layer (type)                 Output Shape          Param #
=====
conv2d_9 (Conv2D)            (None, 26, 26, 32)    320
-----
max_pooling2d_6 (MaxPooling2 (None, 13, 13, 32)    0
-----
conv2d_10 (Conv2D)           (None, 11, 11, 64)    18496
-----
max_pooling2d_7 (MaxPooling2 (None, 5, 5, 64)     0
-----
conv2d_11 (Conv2D)           (None, 3, 3, 64)      36928
-----
flatten_3 (Flatten)          (None, 576)           0
-----
dense_6 (Dense)              (None, 64)            36928
-----
dense_7 (Dense)              (None, 10)            650
=====
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
-----

```

[40]: # 5.3

```

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images.reshape((60000, 28, 28, 1))

```

```

train_images = train_images.astype('float32') / 255

test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255

train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(train_images, train_labels, epochs=5, batch_size=64,
                    validation_split=0.1)

```

```

Epoch 1/5
844/844 [=====] - 12s 13ms/step - loss: 0.4310 -
accuracy: 0.8617 - val_loss: 0.0472 - val_accuracy: 0.9867
Epoch 2/5
844/844 [=====] - 11s 13ms/step - loss: 0.0536 -
accuracy: 0.9832 - val_loss: 0.0392 - val_accuracy: 0.9887
Epoch 3/5
844/844 [=====] - 11s 13ms/step - loss: 0.0360 -
accuracy: 0.9888 - val_loss: 0.0442 - val_accuracy: 0.9875
Epoch 4/5
844/844 [=====] - 11s 13ms/step - loss: 0.0270 -
accuracy: 0.9919 - val_loss: 0.0340 - val_accuracy: 0.9895
Epoch 5/5
844/844 [=====] - 11s 13ms/step - loss: 0.0190 -
accuracy: 0.9935 - val_loss: 0.0396 - val_accuracy: 0.9913

```

```

[41]: train_loss, train_acc = model.evaluate(train_images, train_labels)
print('Test Accuracy:', train_acc)
print('Test Loss:', train_loss)

```

```

1875/1875 [=====] - 9s 4ms/step - loss: 0.0159 -
accuracy: 0.9952
Test Accuracy: 0.9952499866485596
Test Loss: 0.015877896919846535

```

```

[42]: test_loss, test_acc = model.evaluate(test_images, test_labels)
print('Test Accuracy:', test_acc)
print('Test Loss:', test_loss)

```

```

313/313 [=====] - 1s 4ms/step - loss: 0.0304 -
accuracy: 0.9906
Test Accuracy: 0.9905999898910522
Test Loss: 0.030374450609087944

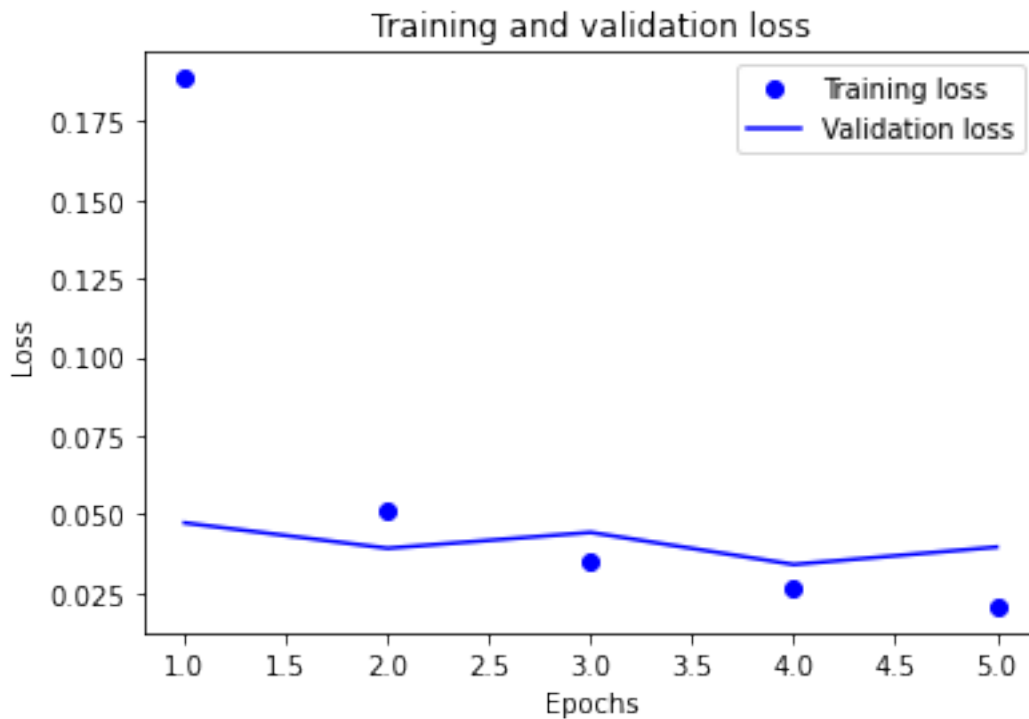
```

```
[43]: history_dict = history.history
acc_values = history_dict['accuracy']
val_acc_values = history_dict['val_accuracy']
val_loss = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(acc_values) + 1)

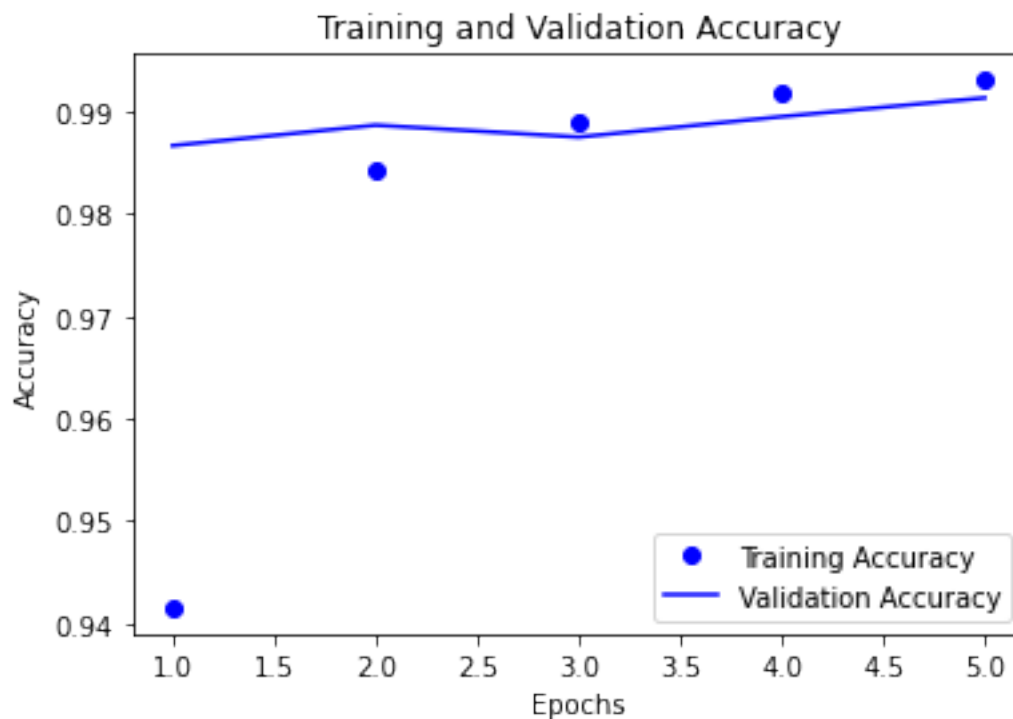
plt.plot(epochs, val_loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



```
[44]: plt.plot(epochs, acc_values, 'bo', label='Training Accuracy')
plt.plot(epochs, val_acc_values, 'b', label = 'Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```
plt.show()
```



## 0.2 6.2

### 0.2.1 6.2.a

```
[45]: from keras import layers
      from keras import models
      from keras import optimizers
      from keras.datasets import cifar10
      from matplotlib import pyplot
      from keras.utils import to_categorical
      from pathlib import Path
      import os
      import matplotlib.pyplot as plt
      import numpy as np
      from keras import losses
      from keras import metrics
```

```
[46]: model12 = models.Sequential()
      model12.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
```

```
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(128, (3, 3), activation='relu'))
```

```
[47]: model2.summary()
```

Model: "sequential\_4"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_8 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_13 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_9 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_14 (Conv2D)	(None, 4, 4, 128)	73856
Total params: 93,248		
Trainable params: 93,248		
Non-trainable params: 0		

```
[48]: model2.add(layers.Flatten())
model2.add(layers.Dense(512, activation='relu'))
model2.add(layers.Dense(10, activation='softmax'))
```

```
[49]: model2.summary()
```

Model: "sequential\_4"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_8 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_13 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_9 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_14 (Conv2D)	(None, 4, 4, 128)	73856
flatten_4 (Flatten)	(None, 2048)	0

```

-----
dense_8 (Dense)                (None, 512)                1049088
-----
dense_9 (Dense)                (None, 10)                 5130
=====
Total params: 1,147,466
Trainable params: 1,147,466
Non-trainable params: 0
-----

```

```

[50]: (train_images2, train_labels2), (test_images2, test_labels2) = cifar10.
      ↪load_data()

train_images2 = train_images2.reshape((50000, 32, 32, 3))
test_images2 = test_images2.reshape((10000, 32, 32, 3))

train_labels2 = to_categorical(train_labels2)
test_labels2 = to_categorical(test_labels2)

```

```

[51]: # 5.6

model2.compile(optimizer='rmsprop',
               loss='categorical_crossentropy',
               metrics=['accuracy'])
history2 = model2.fit(train_images2, train_labels2, epochs=20, batch_size=64,
                    ↪validation_data=(test_images2, test_labels2))

```

```

Epoch 1/20
782/782 [=====] - 15s 18ms/step - loss: 4.6486 -
accuracy: 0.2602 - val_loss: 1.5164 - val_accuracy: 0.4936
Epoch 2/20
782/782 [=====] - 14s 17ms/step - loss: 1.3386 -
accuracy: 0.5394 - val_loss: 1.5250 - val_accuracy: 0.4803
Epoch 3/20
782/782 [=====] - 14s 18ms/step - loss: 1.1760 -
accuracy: 0.6056 - val_loss: 1.5269 - val_accuracy: 0.5511
Epoch 4/20
782/782 [=====] - 14s 18ms/step - loss: 1.0932 -
accuracy: 0.6346 - val_loss: 1.3283 - val_accuracy: 0.5431
Epoch 5/20
782/782 [=====] - 14s 18ms/step - loss: 1.0515 -
accuracy: 0.6537 - val_loss: 1.4941 - val_accuracy: 0.5598
Epoch 6/20
782/782 [=====] - 13s 17ms/step - loss: 1.0046 -
accuracy: 0.6672 - val_loss: 1.3641 - val_accuracy: 0.5289
Epoch 7/20
782/782 [=====] - 14s 18ms/step - loss: 0.9975 -
accuracy: 0.6722 - val_loss: 1.5585 - val_accuracy: 0.5759

```

```

Epoch 8/20
782/782 [=====] - 14s 17ms/step - loss: 0.9793 -
accuracy: 0.6756 - val_loss: 1.4979 - val_accuracy: 0.5467
Epoch 9/20
782/782 [=====] - 14s 18ms/step - loss: 0.9722 -
accuracy: 0.6876 - val_loss: 2.0705 - val_accuracy: 0.5072
Epoch 10/20
782/782 [=====] - 15s 19ms/step - loss: 0.9759 -
accuracy: 0.6842 - val_loss: 3.1018 - val_accuracy: 0.4191
Epoch 11/20
782/782 [=====] - 14s 19ms/step - loss: 0.9734 -
accuracy: 0.6877 - val_loss: 1.4568 - val_accuracy: 0.5247
Epoch 12/20
782/782 [=====] - 15s 19ms/step - loss: 0.9555 -
accuracy: 0.6935 - val_loss: 1.6071 - val_accuracy: 0.5782
Epoch 13/20
782/782 [=====] - 14s 18ms/step - loss: 0.9536 -
accuracy: 0.6953 - val_loss: 1.3725 - val_accuracy: 0.6028
Epoch 14/20
782/782 [=====] - 14s 18ms/step - loss: 0.9395 -
accuracy: 0.6990 - val_loss: 1.6724 - val_accuracy: 0.5883
Epoch 15/20
782/782 [=====] - 14s 19ms/step - loss: 0.9676 -
accuracy: 0.6914 - val_loss: 1.7113 - val_accuracy: 0.5964
Epoch 16/20
782/782 [=====] - 15s 19ms/step - loss: 0.9465 -
accuracy: 0.7005 - val_loss: 1.4506 - val_accuracy: 0.5782
Epoch 17/20
782/782 [=====] - 14s 18ms/step - loss: 0.9461 -
accuracy: 0.7006 - val_loss: 2.5139 - val_accuracy: 0.4644
Epoch 18/20
782/782 [=====] - 15s 19ms/step - loss: 0.9695 -
accuracy: 0.6888 - val_loss: 1.5570 - val_accuracy: 0.6305
Epoch 19/20
782/782 [=====] - 15s 19ms/step - loss: 0.9790 -
accuracy: 0.6903 - val_loss: 2.2056 - val_accuracy: 0.6279
Epoch 20/20
782/782 [=====] - 15s 19ms/step - loss: 0.9641 -
accuracy: 0.6975 - val_loss: 1.4994 - val_accuracy: 0.5927

```

```

[52]: test_loss2, test_acc2 = model2.evaluate(test_images2, test_labels2)
      print('Test Accuracy:', test_acc2)
      print('Test Loss:', test_loss2)

```

```

313/313 [=====] - 2s 5ms/step - loss: 1.4994 -
accuracy: 0.5927
Test Accuracy: 0.5927000045776367
Test Loss: 1.4994142055511475

```

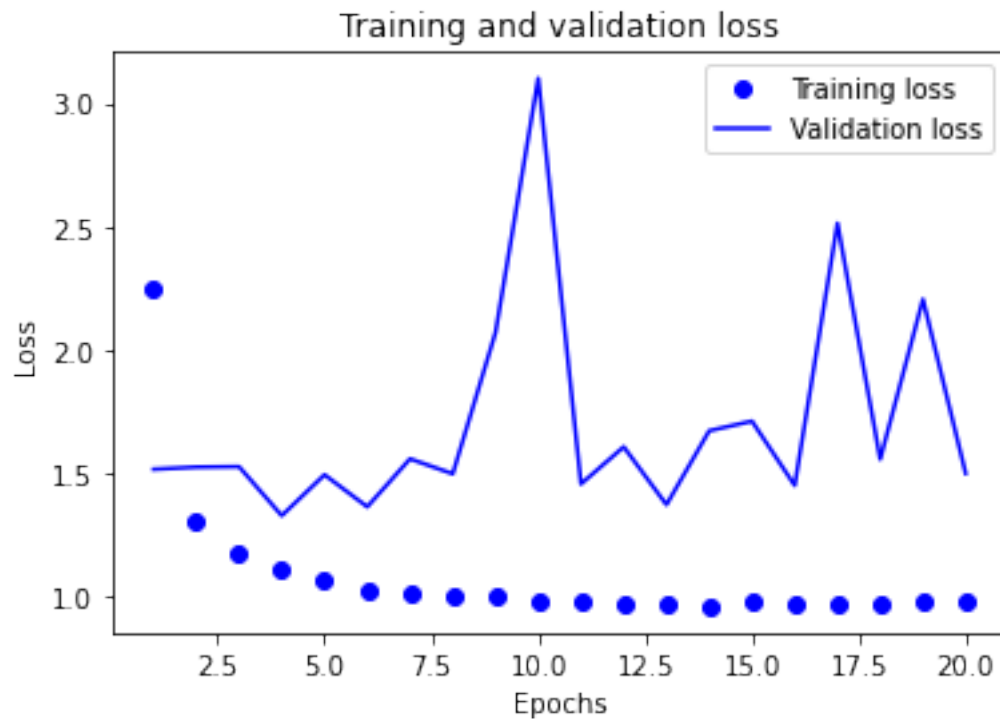


```
[53]: history_dict2 = history2.history
acc_values2 = history_dict2['accuracy']
val_acc_values2 = history_dict2['val_accuracy']
val_loss2 = history_dict2['loss']
val_loss_values2 = history_dict2['val_loss']

epochs2 = range(1, len(val_loss2) + 1)

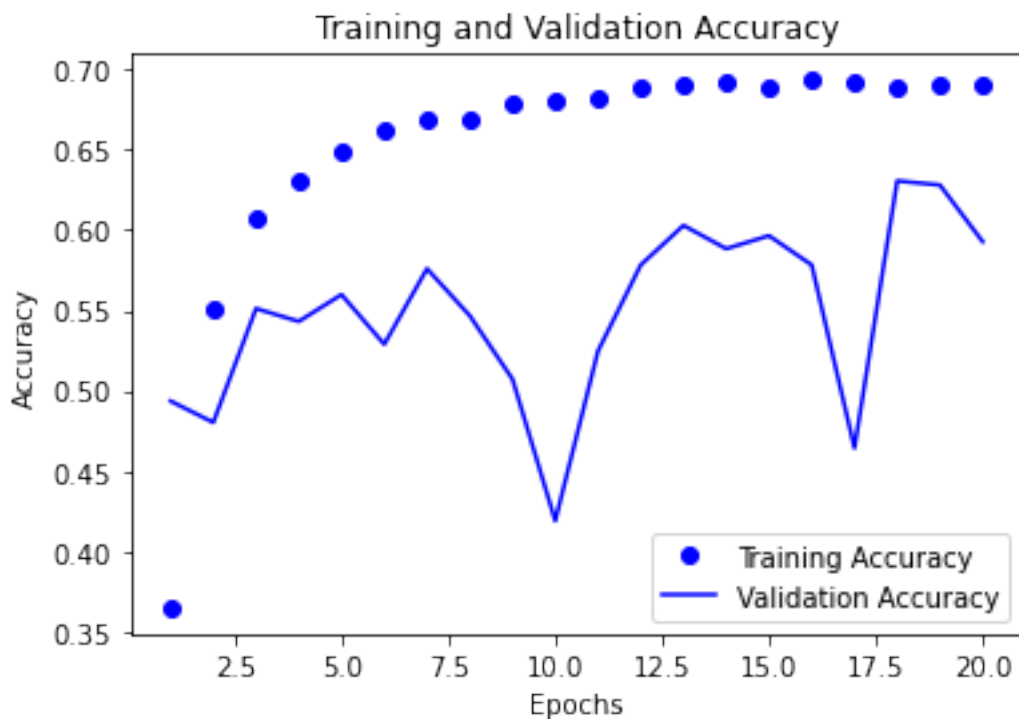
plt.plot(epochs2, val_loss2, 'bo', label='Training loss')
plt.plot(epochs2, val_loss_values2, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



```
[54]: plt.plot(epochs2, acc_values2, 'bo', label='Training Accuracy')
plt.plot(epochs2, val_acc_values2, 'b', label = 'Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```
plt.show()
```



### 0.2.2 6.2.b

```
[55]: # Import libraries
from keras import layers
from keras import models
from keras import optimizers
from keras.datasets import cifar10
from matplotlib import pyplot
from keras.utils import to_categorical
from pathlib import Path
import os
import matplotlib.pyplot as plt
import numpy as np
from keras import losses
from keras import metrics
from keras.preprocessing.image import ImageDataGenerator
```

```
[56]: model3 = models.Sequential()
model3.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
```

```

model3.add(layers.MaxPooling2D((2, 2)))
model3.add(layers.Dropout(0.2))
model3.add(layers.Conv2D(64, (3, 3), activation='relu'))
model3.add(layers.MaxPooling2D((2, 2)))
model3.add(layers.Dropout(0.2))
model3.add(layers.Conv2D(128, (3, 3), activation='relu'))

```

[57]: `model3.summary()`

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_10 (MaxPooling)	(None, 15, 15, 32)	0
dropout_2 (Dropout)	(None, 15, 15, 32)	0
conv2d_16 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_11 (MaxPooling)	(None, 6, 6, 64)	0
dropout_3 (Dropout)	(None, 6, 6, 64)	0
conv2d_17 (Conv2D)	(None, 4, 4, 128)	73856
Total params: 93,248		
Trainable params: 93,248		
Non-trainable params: 0		

[58]: `model3.add(layers.Flatten())`  
`model3.add(layers.Dense(512, activation='relu'))`  
`model3.add(layers.Dense(10, activation='softmax'))`

[59]: `model3.summary()`

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_10 (MaxPooling)	(None, 15, 15, 32)	0
dropout_2 (Dropout)	(None, 15, 15, 32)	0

```

-----
conv2d_16 (Conv2D)          (None, 13, 13, 64)      18496
-----
max_pooling2d_11 (MaxPooling) (None, 6, 6, 64)        0
-----
dropout_3 (Dropout)         (None, 6, 6, 64)        0
-----
conv2d_17 (Conv2D)          (None, 4, 4, 128)       73856
-----
flatten_5 (Flatten)         (None, 2048)             0
-----
dense_10 (Dense)            (None, 512)             1049088
-----
dense_11 (Dense)            (None, 10)              5130
=====
Total params: 1,147,466
Trainable params: 1,147,466
Non-trainable params: 0
-----

```

```
[60]: (train_images3, train_labels3), (test_images3, test_labels3) = cifar10.
      ↪load_data()
```

```

train_images3 = train_images3.reshape((50000, 32, 32, 3))
test_images3 = test_images3.reshape((10000, 32, 32, 3))

train_labels3 = to_categorical(train_labels3)
test_labels3 = to_categorical(test_labels3)

```

```
[61]: model3.compile(optimizer='rmsprop',
                    loss='categorical_crossentropy',
                    metrics=['accuracy'])

train_datagen = ImageDataGenerator(width_shift_range=0.1, height_shift_range=0.
    ↪1, horizontal_flip = True)
train_generator = train_datagen.flow(train_images3, train_labels3, batch_size =
    ↪64)
```

```
[62]: history3 = model3.fit(train_generator, epochs = 20, validation_data =
    ↪(test_images3, test_labels3))
```

```

Epoch 1/20
782/782 [=====] - 36s 45ms/step - loss: 7.0143 -
accuracy: 0.1753 - val_loss: 1.6006 - val_accuracy: 0.4108
Epoch 2/20
782/782 [=====] - 35s 45ms/step - loss: 1.6302 -
accuracy: 0.4178 - val_loss: 1.3813 - val_accuracy: 0.5129
Epoch 3/20

```

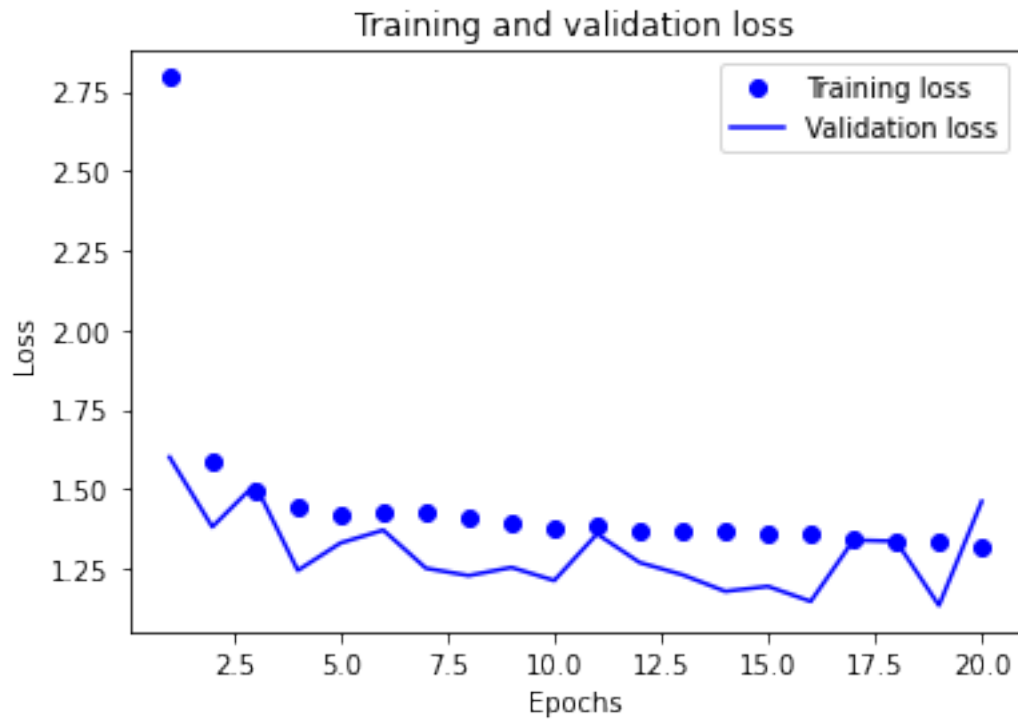
782/782 [=====] - 35s 45ms/step - loss: 1.4982 - accuracy: 0.4720 - val\_loss: 1.5150 - val\_accuracy: 0.4575  
Epoch 4/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4530 - accuracy: 0.4928 - val\_loss: 1.2444 - val\_accuracy: 0.5622  
Epoch 5/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4269 - accuracy: 0.4973 - val\_loss: 1.3307 - val\_accuracy: 0.5223  
Epoch 6/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4219 - accuracy: 0.5038 - val\_loss: 1.3711 - val\_accuracy: 0.5296  
Epoch 7/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4240 - accuracy: 0.5055 - val\_loss: 1.2511 - val\_accuracy: 0.5584  
Epoch 8/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4124 - accuracy: 0.5076 - val\_loss: 1.2283 - val\_accuracy: 0.5725  
Epoch 9/20  
782/782 [=====] - 35s 45ms/step - loss: 1.4001 - accuracy: 0.5156 - val\_loss: 1.2538 - val\_accuracy: 0.5602  
Epoch 10/20  
782/782 [=====] - 35s 44ms/step - loss: 1.3632 - accuracy: 0.5258 - val\_loss: 1.2127 - val\_accuracy: 0.5774  
Epoch 11/20  
782/782 [=====] - 36s 46ms/step - loss: 1.3844 - accuracy: 0.5238 - val\_loss: 1.3592 - val\_accuracy: 0.5215  
Epoch 12/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3546 - accuracy: 0.5331 - val\_loss: 1.2691 - val\_accuracy: 0.5760  
Epoch 13/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3653 - accuracy: 0.5280 - val\_loss: 1.2308 - val\_accuracy: 0.5804  
Epoch 14/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3646 - accuracy: 0.5301 - val\_loss: 1.1787 - val\_accuracy: 0.5873  
Epoch 15/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3533 - accuracy: 0.5323 - val\_loss: 1.1943 - val\_accuracy: 0.5826  
Epoch 16/20  
782/782 [=====] - 35s 44ms/step - loss: 1.3561 - accuracy: 0.5302 - val\_loss: 1.1471 - val\_accuracy: 0.6032  
Epoch 17/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3360 - accuracy: 0.5426 - val\_loss: 1.3397 - val\_accuracy: 0.5394  
Epoch 18/20  
782/782 [=====] - 35s 45ms/step - loss: 1.3419 - accuracy: 0.5442 - val\_loss: 1.3360 - val\_accuracy: 0.5361  
Epoch 19/20

```
782/782 [=====] - 35s 45ms/step - loss: 1.3351 -  
accuracy: 0.5474 - val_loss: 1.1342 - val_accuracy: 0.5984  
Epoch 20/20  
782/782 [=====] - 35s 44ms/step - loss: 1.3137 -  
accuracy: 0.5539 - val_loss: 1.4613 - val_accuracy: 0.5291
```

```
[63]: test_loss3, test_acc3 = model3.evaluate(test_images3, test_labels3)  
      print('Test Accuracy:', test_acc3)  
      print('Test Loss:', test_loss3)
```

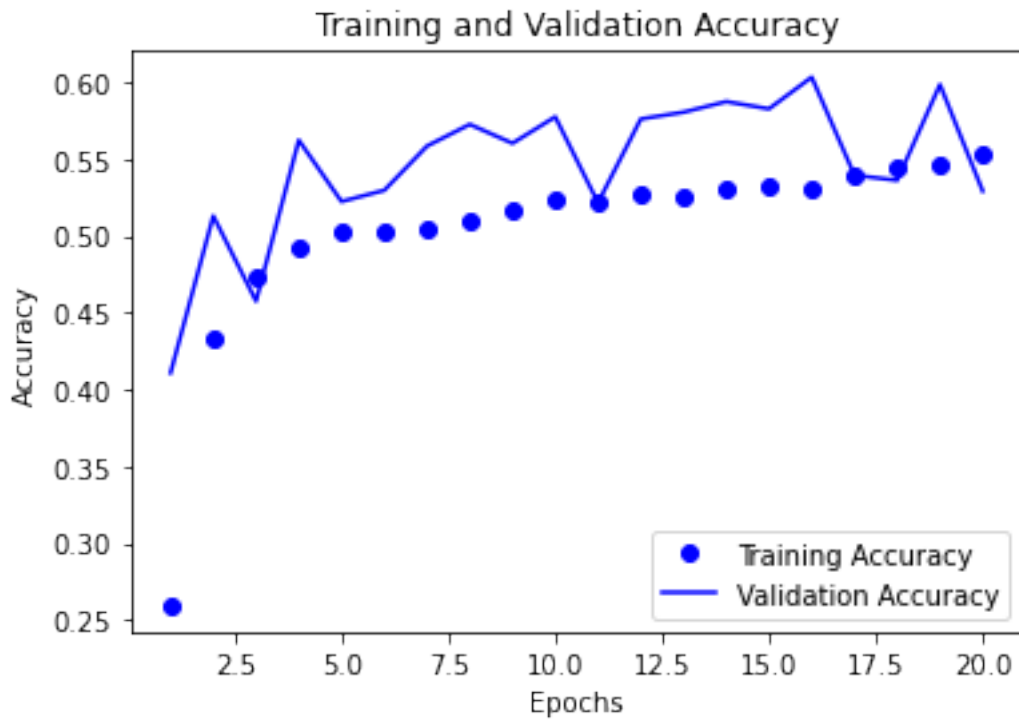
```
313/313 [=====] - 2s 5ms/step - loss: 1.4613 -  
accuracy: 0.5291  
Test Accuracy: 0.5291000008583069  
Test Loss: 1.4613064527511597
```

```
[64]: history_dict3 = history3.history  
      acc_values3 = history_dict3['accuracy']  
      val_acc_values3 = history_dict3['val_accuracy']  
      val_loss3 = history_dict3['loss']  
      val_loss_values3 = history_dict3['val_loss']  
  
      epochs3 = range(1, len(val_loss3) + 1)  
  
      plt.plot(epochs3, val_loss3, 'bo', label='Training loss')  
      plt.plot(epochs3, val_loss_values3, 'b', label='Validation loss')  
      plt.title('Training and validation loss')  
      plt.xlabel('Epochs')  
      plt.ylabel('Loss')  
      plt.legend()  
  
      plt.show()
```



```
[65]: plt.plot(epochs3, acc_values3, 'bo', label='Training Accuracy')
plt.plot(epochs3, val_acc_values3, 'b', label = 'Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



### 0.3 6.3

```
[66]: # Import libraries
import os
from pathlib import Path

import numpy as np

from keras.preprocessing import image
from keras.preprocessing.image import img_to_array
from keras.applications.resnet50 import ResNet50
from keras.applications.resnet50 import preprocess_input
from keras.applications.imagenet_utils import decode_predictions
import matplotlib.pyplot as plt
```

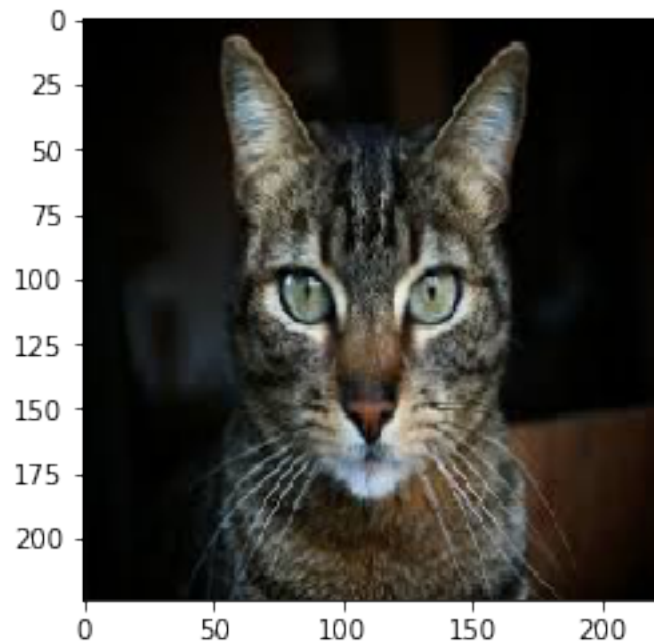
```
[67]: current_dir = Path(os.getcwd()).absolute()
images_dir = current_dir.joinpath('images')
images_dir.mkdir(parents=True, exist_ok = True)
```

```
[68]: img1 = image.load_img('images/cat.jpg', target_size = (224, 224))

plt.imshow(img1)
```



[68]: <matplotlib.image.AxesImage at 0x7f44d8530340>



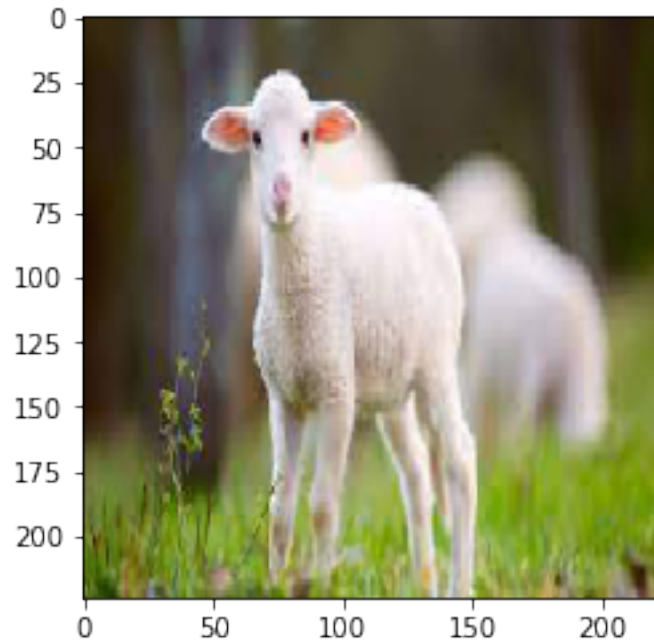
```
[69]: img1 = image.img_to_array(img1)
img1 = np.expand_dims(img1, axis = 0)
img1 = preprocess_input(img1)
model = ResNet50(weights = 'imagenet')
preds1 = model.predict(img1)
print('Predicted:', decode_predictions(preds1, top = 1)[0])
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels.h5](https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels.h5)  
102973440/102967424 [=====] - 16s 0us/step  
Downloading data from [https://storage.googleapis.com/download.tensorflow.org/data/imagenet\\_class\\_index.json](https://storage.googleapis.com/download.tensorflow.org/data/imagenet_class_index.json)  
40960/35363 [=====] - 0s 1us/step  
Predicted: [('n02124075', 'Egyptian\_cat', 0.48118547)]

```
[70]: img2 = image.load_img('images/sheep.jpg', target_size = (224, 224))

plt.imshow(img2)
```

[70]: <matplotlib.image.AxesImage at 0x7f44e0084d30>



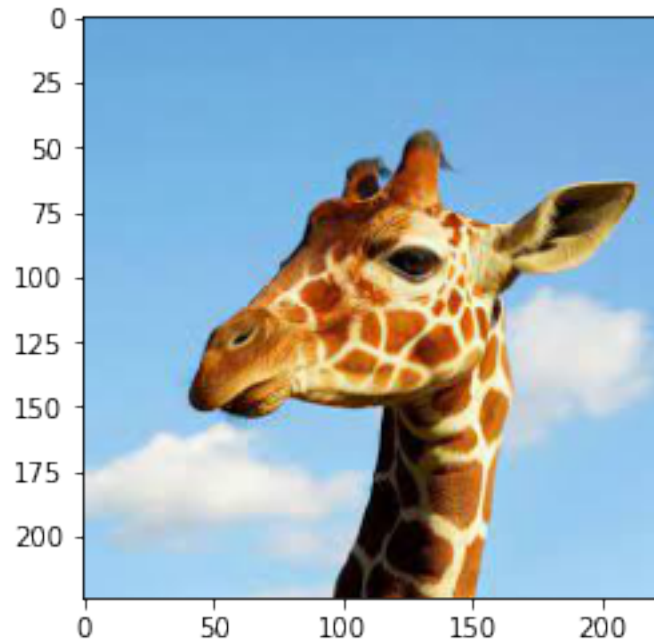
```
[71]: img2 = image.img_to_array(img2)
img2 = np.expand_dims(img2, axis = 0)
img2 = preprocess_input(img2)
model2 = ResNet50(weights = 'imagenet')
preds2 = model.predict(img2)
print('Predicted:', decode_predictions(preds2, top = 1)[0])
```

Predicted: [('n02412080', 'ram', 0.5580335)]

```
[72]: img3 = image.load_img('images/girrafe.jpg', target_size = (224, 224))

plt.imshow(img3)
```

```
[72]: <matplotlib.image.AxesImage at 0x7f44d032fa60>
```



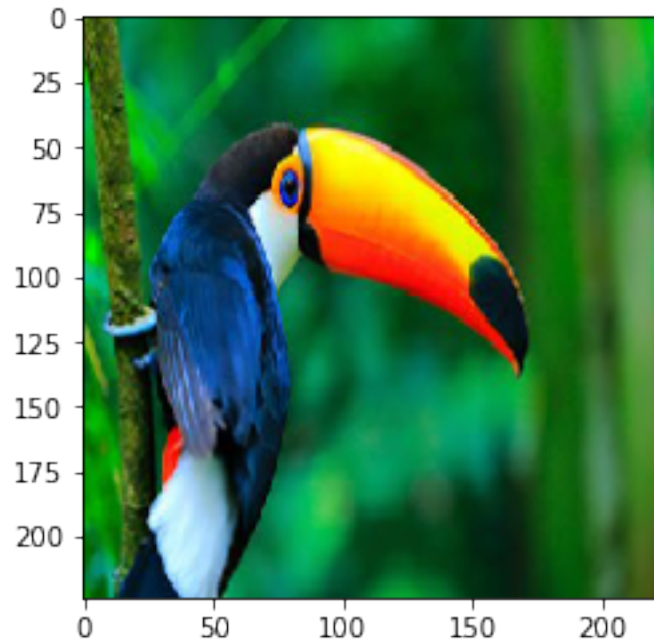
```
[73]: img3 = image.img_to_array(img3)
img3 = np.expand_dims(img3, axis = 0)
img3 = preprocess_input(img3)
model3 = ResNet50(weights = 'imagenet')
preds3 = model.predict(img3)
print('Predicted:', decode_predictions(preds3, top = 1)[0])
```

Predicted: [('n02422699', 'impala', 0.3296979)]

```
[74]: img4 = image.load_img('images/bird-toucan.jpg', target_size = (224, 224))

plt.imshow(img4)
```

```
[74]: <matplotlib.image.AxesImage at 0x7f44f04117f0>
```



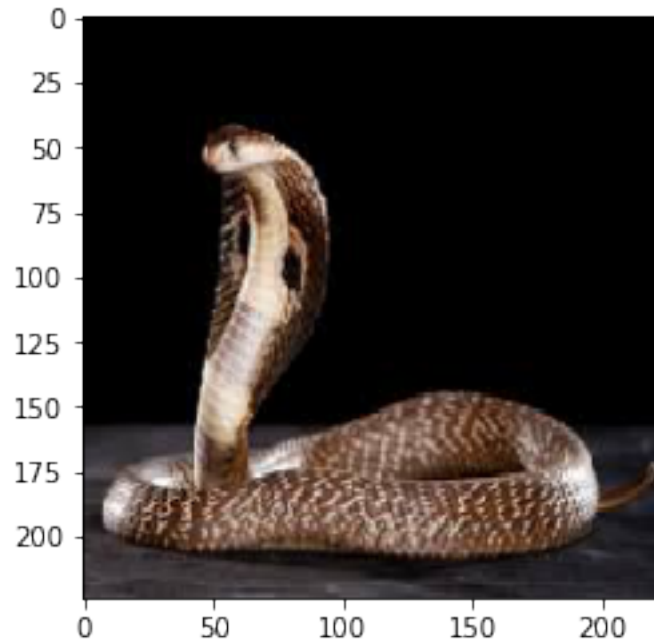
```
[75]: img4 = image.img_to_array(img4)
img4 = np.expand_dims(img4, axis = 0)
img4 = preprocess_input(img4)
model4 = ResNet50(weights = 'imagenet')
preds4 = model.predict(img4)
print('Predicted:', decode_predictions(preds4, top = 1)[0])
```

Predicted: [('n01843383', 'toucan', 0.99644655)]

```
[76]: img5 = image.load_img('images/snake.jpg', target_size = (224, 224))

plt.imshow(img5)
```

```
[76]: <matplotlib.image.AxesImage at 0x7f44d00c0df0>
```



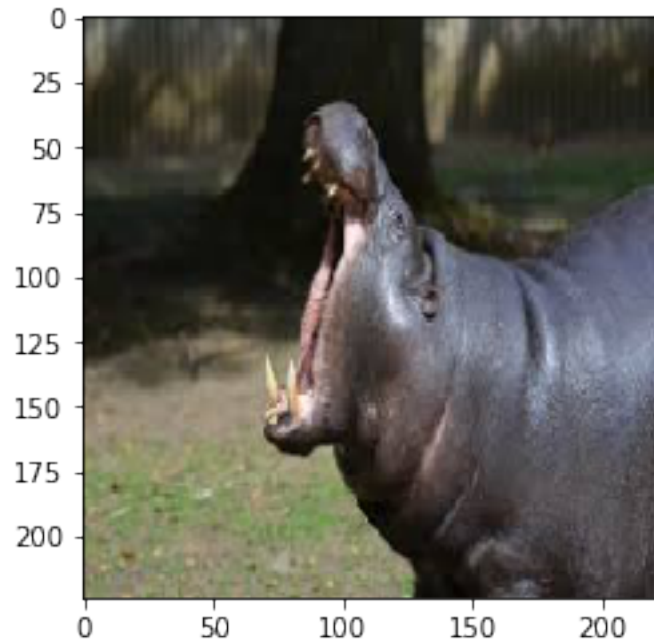
```
[77]: img5 = image.img_to_array(img5)
img5 = np.expand_dims(img5, axis = 0)
img5 = preprocess_input(img5)
model5 = ResNet50(weights = 'imagenet')
preds5 = model.predict(img5)
print('Predicted:', decode_predictions(preds5, top = 1)[0])
```

Predicted: [('n01748264', 'Indian\_cobra', 0.9999243)]

```
[78]: img6 = image.load_img('images/hippo.jpg', target_size = (224, 224))

plt.imshow(img6)
```

[78]: <matplotlib.image.AxesImage at 0x7f4494672220>



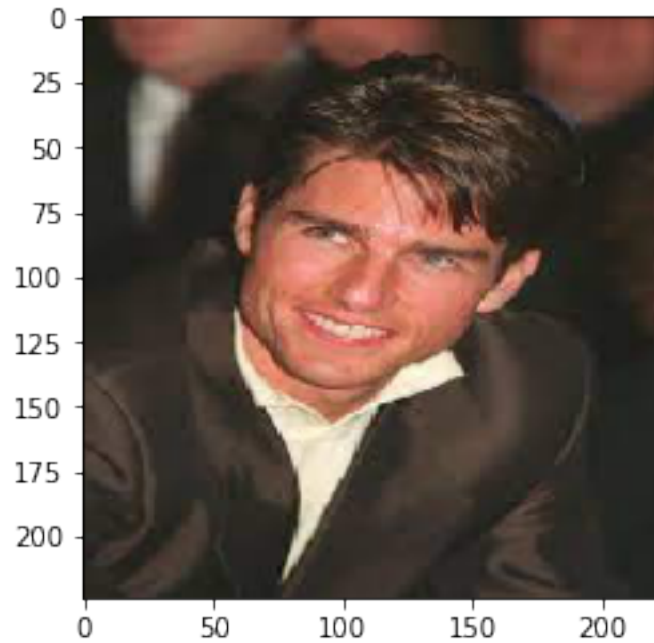
```
[79]: img6 = image.img_to_array(img6)
img6 = np.expand_dims(img6, axis = 0)
img6 = preprocess_input(img6)
model6 = ResNet50(weights = 'imagenet')
preds6 = model.predict(img6)
print('Predicted:', decode_predictions(preds6, top = 1)[0])
```

Predicted: [('n02398521', 'hippopotamus', 0.99706525)]

```
[80]: img7 = image.load_img('images/tomcruise.jpg', target_size = (224, 224))

plt.imshow(img7)
```

```
[80]: <matplotlib.image.AxesImage at 0x7f44943de6d0>
```



```
[81]: img7 = image.img_to_array(img7)
      img7 = np.expand_dims(img7, axis = 0)
      img7 = preprocess_input(img7)
      model7 = ResNet50(weights = 'imagenet')
      preds7 = model7.predict(img7)
      print('Predicted:', decode_predictions(preds7, top = 1)[0])
```

Predicted: [('n04350905', 'suit', 0.17670709)]

```
[ ]:
```