DSC650-T301 Big Data (2235-1)

4/18/2023

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conv2d 9 (Conv2D)

```
6.1
In [23]:
       from keras import layers
       from keras import models
       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'))
In [24]: # Display the architecture of the convnet so far.
       model.summary()
       Model: "sequential 3"
                                             Param #
        Layer (type)
                      Output Shape
       ______
        conv2d 9 (Conv2D)
                               (None, 26, 26, 32)
                                                    320
        max pooling2d 6 (MaxPooling (None, 13, 13, 32)
        2D)
        conv2d 10 (Conv2D) (None, 11, 11, 64) 18496
        max pooling2d 7 (MaxPooling (None, 5, 5, 64)
        2D)
        conv2d 11 (Conv2D)
                              (None, 3, 3, 64)
                                                     36928
       ______
       Total params: 55,744
       Trainable params: 55,744
       Non-trainable params: 0
In [25]: # Adding a classifier on top of the convnet
       model.add(layers.Flatten())
       model.add(layers.Dense(64, activation = 'relu'))
       model.add(layers.Dense(10, activation = 'softmax'))
In [26]: # View the summary
       model.summary()
       Model: "sequential 3"
       Layer (type)
                              Output Shape
                                                    Param #
       ______
```

(None, 26, 26, 32)

max pooling2d 6 (MaxPooling (None, 13, 13, 32)

320

```
conv2d 11 (Conv2D) (None, 3, 3, 64) 36928
       flatten 3 (Flatten) (None, 576)
       dense 6 (Dense)
                            (None, 64)
                                                36928
       dense 7 (Dense)
                            (None, 10)
                                                650
      ______
      Total params: 93,322
      Trainable params: 93,322
      Non-trainable params: 0
In [27]: # Training the convnet on MNIST images
      from keras.datasets import mnist
      from keras.utils import to categorical
      from keras import optimizers
       # set an SGD optimizer with a static learning rate.
       # opt = optimizers.SGD(learning rate=0.01)
       (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 = ['acc'
      model.fit(train images, train labels, epochs=5, batch size=64)
      Epoch 1/5
      Epoch 2/5
      Epoch 3/5
      Epoch 4/5
      938/938 [============ ] - 18s 19ms/step - loss: 0.0247 - acc: 0.9926
      Epoch 5/5
      938/938 [============== ] - 18s 19ms/step - loss: 0.0195 - acc: 0.9941
      <keras.callbacks.History at 0x251a2974d90>
Out[27]:
In [28]: # Evaluate the model
      test loss, test acc = model.evaluate(test images, test labels)
      test acc
      0.9914000034332275
Out[28]:
In [29]: from sklearn.model selection import train test split
```

18496

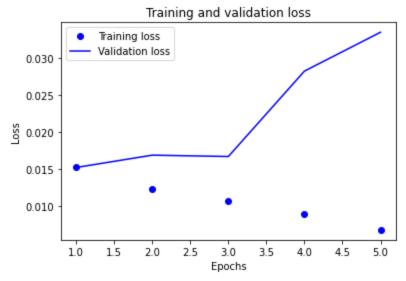
2D)

2D)

conv2d 10 (Conv2D) (None, 11, 11, 64)

max pooling2d 7 (MaxPooling (None, 5, 5, 64)

```
# Create a train-test split.
      train images, val images, train labels, val labels = train test split(train images, trai
      # Create a history object to use for plotting.
      history = model.fit(train images, train labels, epochs=5, batch size=64, validation data
      Epoch 1/5
      val loss: 0.0152 - val acc: 0.9952
      Epoch 2/5
      val loss: 0.0169 - val acc: 0.9947
      Epoch 3/5
      val loss: 0.0167 - val acc: 0.9946
      Epoch 4/5
      val loss: 0.0283 - val acc: 0.9933
     Epoch 5/5
      val loss: 0.0335 - val acc: 0.9927
In [30]: # Create a plot to view the training and validation loss
      import matplotlib.pyplot as plt
      history dict = history.history
      loss values = history dict['loss']
      val loss values = history dict['val loss']
      epochs = range(1, len(loss values) + 1)
      plt.plot(epochs, loss values, '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()
```

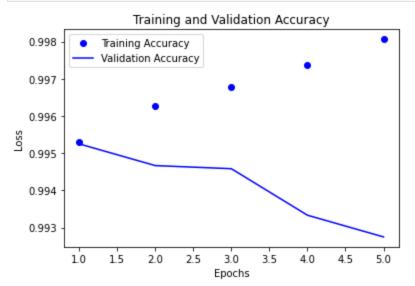


```
In [33]: # Plot the train data and validation accuracy.
plt.clf()
    acc_values = history_dict['acc']
    val_acc_values = history_dict['val_acc']

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('Loss')
plt.legend()

plt.show()
```



6.2.a

```
In [37]: from keras.datasets import cifar10
    from keras.preprocessing.image import ImageDataGenerator

(x_train, y_train), (x_test, y_test) = cifar10.load_data()

print(x_train.shape == (50000, 32, 32, 3))
    print(x_test.shape == (10000, 32, 32, 3))
    print(y_train.shape == (50000, 1))
    print(y_test.shape == (10000, 1))

# Update y values to categorical.
    num_classes = 10
    y_train = to_categorical(y_train, num_classes)
    y_test = to_categorical(y_test, num_classes)

x_train = x_train / 255
    x_test = x_test / 255
```

```
True
True
True
True
```

```
In [38]: # Set up the model
model = models.Sequential()

model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform',
    model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(layers.Dense(10, activation='relu', kernel_initializer='he_uniform'))
```

In [39]: model.summary()

Model: "sequential 4"

Layer (type)	Output Shape	Param #
	(None, 32, 32, 32)	
conv2d_13 (Conv2D)	(None, 32, 32, 32)	9248
<pre>max_pooling2d_8 (MaxPooling 2D)</pre>	(None, 16, 16, 32)	0
conv2d_14 (Conv2D)	(None, 16, 16, 64)	18496
conv2d_15 (Conv2D)	(None, 16, 16, 64)	36928
<pre>max_pooling2d_9 (MaxPooling 2D)</pre>	(None, 8, 8, 64)	0
conv2d_16 (Conv2D)	(None, 8, 8, 128)	73856
conv2d_17 (Conv2D)	(None, 8, 8, 128)	147584
<pre>max_pooling2d_10 (MaxPoolin g2D)</pre>	(None, 4, 4, 128)	0
flatten_4 (Flatten)	(None, 2048)	0
dense_8 (Dense)	(None, 128)	262272
_	(None, 10)	1290
Total params: 550,570 Trainable params: 550,570 Non-trainable params: 0		=======

```
In [40]: # Compile the model.
model.compile(loss='categorical_crossentropy', optimizer=optimizers.RMSprop(learning_rat
```

```
In [41]: train_datagen = ImageDataGenerator()
  test_datagen = ImageDataGenerator()
```

```
train_datagen.fit(x_train)
test_datagen.fit(x_test)

train_generator = train_datagen.flow(x_train, y_train, batch_size=64)

validation_generator = test_datagen.flow(x_test, y_test, batch_size=64)
```

```
In [42]: history = model.fit(train generator, steps per epoch=64, epochs=120, validation data=(va
    Epoch 1/120
    64/64 [============= ] - 11s 154ms/step - loss: 2.2837 - acc: 0.1895 - v
    al loss: 1.9515 - val acc: 0.3257
    Epoch 2/120
    al loss: 1.8593 - val acc: 0.3015
    Epoch 3/120
    64/64 [=========================] - 10s 150ms/step - loss: 1.6945 - acc: 0.3777 - v
    al loss: 1.6732 - val acc: 0.3889
    Epoch 4/120
    64/64 [============== ] - 10s 149ms/step - loss: 1.5987 - acc: 0.4109 - v
    al loss: 2.1765 - val acc: 0.3167
    Epoch 5/120
    al loss: 1.4524 - val acc: 0.4719
    Epoch 6/120
    al loss: 1.4061 - val acc: 0.5034
    Epoch 7/120
    al loss: 1.3567 - val acc: 0.5269
    Epoch 8/120
    al loss: 1.2888 - val acc: 0.5503
    Epoch 9/120
    al loss: 1.2380 - val acc: 0.5598
    Epoch 10/120
    al loss: 1.2168 - val acc: 0.5698
    Epoch 11/120
    al loss: 1.0942 - val acc: 0.6133
    Epoch 12/120
    al loss: 1.1188 - val acc: 0.6084
    Epoch 13/120
    al loss: 1.1353 - val acc: 0.6128
    Epoch 14/120
    al loss: 1.0926 - val acc: 0.6116
    Epoch 15/120
    al loss: 1.0168 - val acc: 0.6484
    Epoch 16/120
    l loss: 1.0175 - val acc: 0.6418
    Epoch 17/120
    l loss: 0.9917 - val acc: 0.6487
    Epoch 18/120
    64/64 [============== ] - 10s 156ms/step - loss: 0.8975 - acc: 0.6848 - v
    al loss: 0.9368 - val acc: 0.6653
    Epoch 19/120
```

```
al loss: 1.0231 - val acc: 0.6335
Epoch 20/120
64/64 [============== ] - 10s 153ms/step - loss: 0.8601 - acc: 0.7031 - v
al loss: 0.9920 - val acc: 0.6631
Epoch 21/120
al loss: 0.8980 - val acc: 0.6792
Epoch 22/120
al loss: 0.9026 - val acc: 0.6843
Epoch 23/120
al loss: 0.8985 - val acc: 0.7036
Epoch 24/120
al loss: 0.8631 - val acc: 0.7048
Epoch 25/120
64/64 [=============== ] - 10s 163ms/step - loss: 0.7833 - acc: 0.7327 - v
al loss: 0.8943 - val acc: 0.6882
al loss: 0.8385 - val acc: 0.7122
Epoch 27/120
al_loss: 1.2042 - val acc: 0.6296
Epoch 28/120
al loss: 0.8292 - val acc: 0.7166
Epoch 29/120
al loss: 0.9671 - val acc: 0.6895
Epoch 30/120
al loss: 0.8252 - val acc: 0.7192
Epoch 31/120
al loss: 0.8263 - val acc: 0.7231
Epoch 32/120
al loss: 0.8505 - val acc: 0.7109
Epoch 33/120
al loss: 0.7530 - val acc: 0.7427
Epoch 34/120
al loss: 0.7854 - val acc: 0.7283
Epoch 35/120
al loss: 0.8039 - val acc: 0.7231
Epoch 36/120
al loss: 0.8091 - val acc: 0.7314
Epoch 37/120
64/64 [============== ] - 10s 158ms/step - loss: 0.5950 - acc: 0.7905 - v
al loss: 0.7812 - val acc: 0.7373
Epoch 38/120
al loss: 0.7647 - val acc: 0.7429
Epoch 39/120
al loss: 0.8395 - val acc: 0.7200
Epoch 40/120
64/64 [============== ] - 10s 156ms/step - loss: 0.5751 - acc: 0.8069 - v
al loss: 0.7671 - val acc: 0.7332
```

Epoch 41/120

```
al loss: 0.7766 - val acc: 0.7351
Epoch 42/120
64/64 [============== ] - 10s 150ms/step - loss: 0.5325 - acc: 0.8252 - v
al loss: 0.7740 - val acc: 0.7422
Epoch 43/120
al loss: 0.7639 - val acc: 0.7354
Epoch 44/120
al loss: 0.8101 - val acc: 0.7390
Epoch 45/120
al loss: 0.8462 - val acc: 0.7383
Epoch 46/120
al loss: 0.8277 - val acc: 0.7388
Epoch 47/120
al loss: 0.7510 - val acc: 0.7598
Epoch 48/120
al loss: 0.7719 - val acc: 0.7490
Epoch 49/120
64/64 [============= ] - 10s 162ms/step - loss: 0.4744 - acc: 0.8391 - v
al_loss: 0.7593 - val acc: 0.7539
Epoch 50/120
al loss: 0.7569 - val acc: 0.7529
Epoch 51/120
al loss: 0.7709 - val acc: 0.7571
Epoch 52/120
al loss: 0.8849 - val acc: 0.7317
Epoch 53/120
al loss: 0.7487 - val acc: 0.7634
Epoch 54/120
64/64 [============== ] - 10s 160ms/step - loss: 0.4332 - acc: 0.8538 - v
al loss: 0.8197 - val acc: 0.7441
Epoch 55/120
al loss: 0.7916 - val acc: 0.7437
Epoch 56/120
al loss: 0.8167 - val acc: 0.7468
Epoch 57/120
al loss: 0.9146 - val acc: 0.7312
Epoch 58/120
al loss: 0.8283 - val acc: 0.7361
Epoch 59/120
al loss: 0.7530 - val acc: 0.7766
Epoch 60/120
al loss: 0.8598 - val acc: 0.7368
Epoch 61/120
al loss: 0.8168 - val acc: 0.7546
Epoch 62/120
64/64 [============== ] - 10s 154ms/step - loss: 0.4066 - acc: 0.8662 - v
al loss: 0.8689 - val acc: 0.7378
```

Epoch 63/120

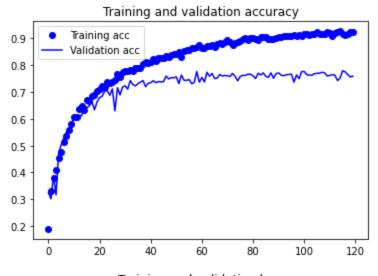
```
al loss: 0.8052 - val acc: 0.7739
Epoch 64/120
64/64 [============== ] - 10s 156ms/step - loss: 0.3867 - acc: 0.8738 - v
al loss: 0.9079 - val acc: 0.7590
Epoch 65/120
al loss: 0.7583 - val acc: 0.7695
Epoch 66/120
al loss: 0.8614 - val acc: 0.7502
Epoch 67/120
al loss: 0.8858 - val acc: 0.7527
Epoch 68/120
al loss: 0.7771 - val acc: 0.7656
Epoch 69/120
64/64 [================== ] - 11s 166ms/step - loss: 0.3370 - acc: 0.8806 - v
al loss: 0.9363 - val acc: 0.7600
Epoch 70/120
al loss: 0.8636 - val acc: 0.7620
Epoch 71/120
al_loss: 0.8711 - val acc: 0.7607
Epoch 72/120
al loss: 0.7938 - val acc: 0.7583
Epoch 73/120
al loss: 0.8092 - val acc: 0.7698
Epoch 74/120
al loss: 0.8552 - val acc: 0.7583
Epoch 75/120
al loss: 0.9377 - val acc: 0.7422
Epoch 76/120
al loss: 0.9443 - val acc: 0.7585
Epoch 77/120
al loss: 0.8843 - val acc: 0.7625
Epoch 78/120
al loss: 0.8726 - val acc: 0.7620
Epoch 79/120
al loss: 0.7875 - val acc: 0.7666
Epoch 80/120
al loss: 0.8610 - val acc: 0.7666
Epoch 81/120
64/64 [=================== ] - 10s 156ms/step - loss: 0.3053 - acc: 0.9014 - v
al loss: 0.8430 - val acc: 0.7607
Epoch 82/120
al loss: 0.8416 - val acc: 0.7505
Epoch 83/120
al loss: 0.8408 - val acc: 0.7703
Epoch 84/120
64/64 [============== ] - 10s 156ms/step - loss: 0.2961 - acc: 0.9043 - v
al loss: 0.8574 - val acc: 0.7639
```

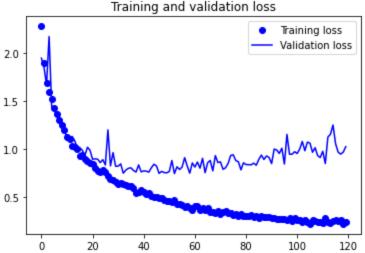
Epoch 85/120

```
al loss: 0.8362 - val acc: 0.7715
Epoch 86/120
64/64 [============== ] - 10s 156ms/step - loss: 0.2907 - acc: 0.9058 - v
al loss: 0.8960 - val acc: 0.7590
Epoch 87/120
al loss: 0.9416 - val acc: 0.7549
Epoch 88/120
al loss: 0.8958 - val acc: 0.7717
Epoch 89/120
al loss: 0.9326 - val acc: 0.7515
Epoch 90/120
al loss: 0.9165 - val acc: 0.7688
Epoch 91/120
64/64 [============== ] - 10s 162ms/step - loss: 0.2853 - acc: 0.9059 - v
al loss: 0.8531 - val acc: 0.7715
Epoch 92/120
al loss: 1.0040 - val acc: 0.7629
Epoch 93/120
al loss: 0.9948 - val acc: 0.7612
Epoch 94/120
al loss: 0.9586 - val acc: 0.7646
Epoch 95/120
l loss: 1.0135 - val acc: 0.7659
Epoch 96/120
al loss: 0.8484 - val acc: 0.7666
Epoch 97/120
al loss: 1.1568 - val acc: 0.7371
Epoch 98/120
al loss: 0.9502 - val acc: 0.7639
Epoch 99/120
al loss: 0.9511 - val acc: 0.7500
Epoch 100/120
al loss: 0.9767 - val acc: 0.7766
Epoch 101/120
al loss: 0.9581 - val acc: 0.7769
Epoch 102/120
al loss: 1.0056 - val acc: 0.7651
Epoch 103/120
al loss: 1.0832 - val acc: 0.7632
Epoch 104/120
al loss: 0.9866 - val acc: 0.7632
Epoch 105/120
al loss: 1.0767 - val acc: 0.7686
Epoch 106/120
al loss: 1.0658 - val acc: 0.7698
```

Epoch 107/120

```
al loss: 0.9711 - val acc: 0.7708
     Epoch 108/120
     al loss: 1.0187 - val acc: 0.7739
     Epoch 109/120
     al loss: 0.9365 - val acc: 0.7720
     Epoch 110/120
     al loss: 0.9160 - val acc: 0.7600
     Epoch 111/120
     al loss: 0.9809 - val acc: 0.7622
     Epoch 112/120
     64/64 [=================== ] - 10s 157ms/step - loss: 0.2838 - acc: 0.9075 - v
     al loss: 0.8533 - val acc: 0.7649
     Epoch 113/120
     al loss: 1.1290 - val acc: 0.7634
     Epoch 114/120
     al loss: 1.1578 - val acc: 0.7432
     Epoch 115/120
     al loss: 1.2551 - val acc: 0.7515
     Epoch 116/120
     al loss: 1.0616 - val acc: 0.7793
     Epoch 117/120
     al loss: 0.9726 - val acc: 0.7756
     Epoch 118/120
     64/64 [=================== ] - 10s 162ms/step - loss: 0.2656 - acc: 0.9170 - v
     al loss: 0.9519 - val acc: 0.7659
     Epoch 119/120
     al loss: 0.9725 - val acc: 0.7563
     Epoch 120/120
     al loss: 1.0291 - val acc: 0.7593
In [43]: # Display the curves of lass and accuracy during training
     acc = history.history['acc']
     val acc = history.history['val acc']
     loss = history.history['loss']
     val loss = history.history['val loss']
     epochs = range(len(acc))
     plt.plot(epochs, acc, 'bo', label='Training acc')
     plt.plot(epochs, val acc, 'b', label='Validation acc')
     plt.title('Training and validation accuracy')
     plt.legend()
     plt.figure()
     plt.plot(epochs, loss, 'bo', label='Training loss')
     plt.plot(epochs, val loss, 'b', label='Validation loss')
     plt.title('Training and validation loss')
     plt.legend()
     plt.show()
```





6.2.b

```
In [45]: (x_train, y_train), (x_test, y_test) = cifar10.load_data()

print(x_train.shape == (50000, 32, 32, 3))
print(x_test.shape == (10000, 32, 32, 3))
print(y_train.shape == (50000, 1))
print(y_test.shape == (10000, 1))

# Update y values to categorical.
num_classes = 10
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

x_train = x_train / 255
x_test = x_test / 255
```

```
True
True
True
True
```

```
In [46]: # Set up the model
        model = models.Sequential()
        model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.BatchNormalization())
        model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.MaxPooling2D((2, 2)))
        model.add(layers.Dropout(0.2))
        model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.BatchNormalization())
        model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.MaxPooling2D((2, 2)))
        model.add(layers.Dropout(0.3))
        model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.BatchNormalization())
        model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel initializer='he uniform',
        model.add(layers.MaxPooling2D((2, 2)))
        model.add(layers.Dropout(0.4))
        model.add(layers.Flatten())
        model.add(layers.Dense(128, activation='relu', kernel initializer='he uniform'))
        model.add(layers.Dropout(0.5))
        model.add(layers.Dense(10, activation='softmax'))
```

In [47]: model.summary()

Model: "sequential 5"

Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)		896
<pre>batch_normalization (BatchN ormalization)</pre>	(None, 32, 32, 32)	128
conv2d_19 (Conv2D)	(None, 32, 32, 32)	9248
<pre>max_pooling2d_11 (MaxPoolin g2D)</pre>	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0
conv2d_20 (Conv2D)	(None, 16, 16, 64)	18496
<pre>batch_normalization_1 (Batc hNormalization)</pre>	(None, 16, 16, 64)	256
conv2d_21 (Conv2D)	(None, 16, 16, 64)	36928
<pre>max_pooling2d_12 (MaxPoolin g2D)</pre>	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0
conv2d_22 (Conv2D)	(None, 8, 8, 128)	73856
<pre>batch_normalization_2 (Batc hNormalization)</pre>	(None, 8, 8, 128)	512
conv2d_23 (Conv2D)	(None, 8, 8, 128)	147584

```
g2D)
                       (None, 4, 4, 128)
      dropout 2 (Dropout)
      flatten 5 (Flatten)
                      (None, 2048)
      dense 10 (Dense)
                       (None, 128)
                                       262272
      dropout 3 (Dropout)
                       (None, 128)
     dense 11 (Dense)
                       (None, 10)
                                       1290
     ______
     Total params: 551,466
     Trainable params: 551,018
     Non-trainable params: 448
In [48]: model.compile(loss='categorical crossentropy', optimizer='rmsprop', metrics=['acc'])
In [49]: train datagen = ImageDataGenerator(
            rescale=1./255,
            rotation range=40,
            width shift range=0.2,
            height shift range=0.2,
            shear range=0.2,
            zoom range=0.2,
            horizontal flip=True)
     test datagen = ImageDataGenerator(rescale=1./255)
     train datagen.fit(x train)
     test datagen.fit(x test)
     train generator = train datagen.flow(x train, y train, batch size=64)
     validation generator = test datagen.flow(x test, y test, batch size=64)
In [50]: history = model.fit(train_generator, steps_per_epoch=64, epochs=120, validation data=(val
     al loss: 2.3342 - val acc: 0.0972
     Epoch 2/120
     al loss: 2.3555 - val acc: 0.1060
     Epoch 3/120
     al loss: 2.5423 - val acc: 0.1016
     Epoch 4/120
     al loss: 2.7448 - val acc: 0.0947
     Epoch 5/120
     al loss: 3.0198 - val acc: 0.0955
     Epoch 6/120
     al loss: 2.9739 - val acc: 0.0955
     Epoch 7/120
     al loss: 2.7050 - val acc: 0.1060
     Epoch 8/120
     al loss: 2.6081 - val acc: 0.1038
```

max pooling2d 13 (MaxPoolin (None, 4, 4, 128)

```
Epoch 9/120
al loss: 3.4202 - val acc: 0.1033
Epoch 10/120
64/64 [============== ] - 12s 189ms/step - loss: 2.0969 - acc: 0.1990 - v
al loss: 5.6036 - val acc: 0.0989
Epoch 11/120
al loss: 2.5543 - val acc: 0.0991
Epoch 12/120
al loss: 2.1136 - val acc: 0.1685
Epoch 13/120
al loss: 4.4744 - val acc: 0.0994
Epoch 14/120
al loss: 2.6532 - val acc: 0.1001
Epoch 15/120
al loss: 3.6351 - val acc: 0.1035
Epoch 16/120
al loss: 4.6778 - val acc: 0.0999
Epoch 17/120
al loss: 2.2745 - val acc: 0.1248
Epoch 18/120
al loss: 25.6225 - val acc: 0.1052
Epoch 19/120
al loss: 22.8345 - val acc: 0.0959
Epoch 20/120
al loss: 9.2863 - val acc: 0.1084
Epoch 21/120
al loss: 21.8551 - val acc: 0.0979
Epoch 22/120
al loss: 2.2366 - val acc: 0.1467
Epoch 23/120
al loss: 2.6222 - val acc: 0.1204
Epoch 24/120
al loss: 2.6817 - val acc: 0.1099
Epoch 25/120
al loss: 18.8771 - val acc: 0.0994
Epoch 26/120
al loss: 4.3199 - val acc: 0.1116
Epoch 27/120
al loss: 6.9402 - val acc: 0.1458
Epoch 28/120
al loss: 2.6702 - val acc: 0.1472
Epoch 29/120
al loss: 5.2655 - val acc: 0.1235
Epoch 30/120
```

al loss: 6.7972 - val acc: 0.1021

```
Epoch 31/120
al loss: 8.1150 - val acc: 0.0984
Epoch 32/120
al loss: 5.2472 - val acc: 0.0984
Epoch 33/120
al loss: 8.7620 - val acc: 0.0991
Epoch 34/120
al loss: 3.3961 - val acc: 0.1387
Epoch 35/120
al loss: 3.0554 - val acc: 0.1208
Epoch 36/120
al loss: 22.0960 - val acc: 0.1030
Epoch 37/120
al loss: 4.7590 - val acc: 0.1028
Epoch 38/120
al loss: 3.7109 - val acc: 0.1453
Epoch 39/120
64/64 [================== ] - 11s 178ms/step - loss: 1.6972 - acc: 0.3953 - v
al loss: 2.5095 - val acc: 0.1038
Epoch 40/120
al loss: 2.2329 - val acc: 0.2437
Epoch 41/120
al loss: 3.7691 - val acc: 0.1426
Epoch 42/120
al loss: 5.3318 - val acc: 0.1094
Epoch 43/120
al loss: 6.9960 - val acc: 0.1035
Epoch 44/120
al loss: 18.6203 - val acc: 0.0950
Epoch 45/120
al loss: 6.1255 - val acc: 0.0986
Epoch 46/120
al loss: 8.1010 - val acc: 0.1047
Epoch 47/120
al loss: 4.7100 - val acc: 0.1057
Epoch 48/120
al loss: 24.1461 - val acc: 0.1030
Epoch 49/120
al loss: 2.2656 - val acc: 0.1619
Epoch 50/120
al loss: 16.9186 - val acc: 0.1006
Epoch 51/120
al loss: 2.6770 - val acc: 0.1086
Epoch 52/120
```

al loss: 2.2710 - val acc: 0.1655

```
Epoch 53/120
al loss: 13.9716 - val acc: 0.1411
Epoch 54/120
al loss: 2.6467 - val acc: 0.1382
Epoch 55/120
al loss: 2.4264 - val acc: 0.1279
Epoch 56/120
al loss: 3.2394 - val acc: 0.1030
Epoch 57/120
al loss: 5.5914 - val acc: 0.1001
Epoch 58/120
al loss: 15.0164 - val acc: 0.1384
Epoch 59/120
al loss: 60.7235 - val acc: 0.1003
Epoch 60/120
al loss: 35.0550 - val acc: 0.1067
Epoch 61/120
al loss: 45.2798 - val acc: 0.1040
Epoch 62/120
al loss: 24.6839 - val acc: 0.1016
Epoch 63/120
al loss: 35.6904 - val acc: 0.1028
Epoch 64/120
al loss: 2.4387 - val acc: 0.1328
Epoch 65/120
al loss: 4.1101 - val acc: 0.1050
Epoch 66/120
al loss: 12.7003 - val acc: 0.0972
Epoch 67/120
al loss: 38.7816 - val acc: 0.1062
Epoch 68/120
al loss: 10.6478 - val acc: 0.0991
Epoch 69/120
al loss: 45.5764 - val acc: 0.1409
Epoch 70/120
al loss: 1.7534 - val acc: 0.4211
Epoch 71/120
al loss: 2.5413 - val acc: 0.0991
Epoch 72/120
al loss: 9.7079 - val acc: 0.1042
Epoch 73/120
al loss: 33.3889 - val acc: 0.1006
Epoch 74/120
```

al loss: 2.8972 - val acc: 0.1106

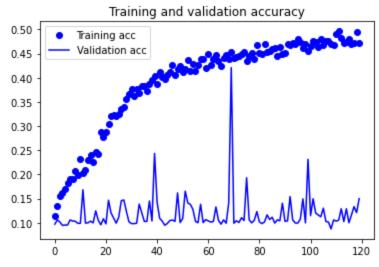
```
Epoch 75/120
al loss: 16.0890 - val acc: 0.1047
Epoch 76/120
al loss: 3.2735 - val acc: 0.1934
Epoch 77/120
64/64 [============= ] - 12s 186ms/step - loss: 1.5815 - acc: 0.4461 - v
al loss: 8.4401 - val acc: 0.1062
Epoch 78/120
al loss: 19.7906 - val acc: 0.0999
Epoch 79/120
al loss: 48.7871 - val acc: 0.1052
Epoch 80/120
al loss: 2.3215 - val acc: 0.1233
Epoch 81/120
al loss: 4.1019 - val acc: 0.1018
Epoch 82/120
al loss: 3.8959 - val acc: 0.0984
Epoch 83/120
al loss: 24.6894 - val acc: 0.1018
Epoch 84/120
al loss: 10.4061 - val acc: 0.1165
Epoch 85/120
al loss: 6.1698 - val acc: 0.1069
Epoch 86/120
al loss: 18.3342 - val acc: 0.1116
Epoch 87/120
al loss: 39.6418 - val acc: 0.0994
Epoch 88/120
64/64 [=================== ] - 11s 179ms/step - loss: 1.5719 - acc: 0.4458 - v
al loss: 22.6992 - val acc: 0.1062
Epoch 89/120
al loss: 4.3248 - val acc: 0.1042
Epoch 90/120
al loss: 2.2610 - val acc: 0.1406
Epoch 91/120
al loss: 3.7280 - val acc: 0.1030
Epoch 92/120
al loss: 62.4323 - val acc: 0.1040
Epoch 93/120
al loss: 4.3345 - val acc: 0.1543
Epoch 94/120
al loss: 5.4102 - val acc: 0.1064
Epoch 95/120
al loss: 29.8517 - val acc: 0.0996
Epoch 96/120
```

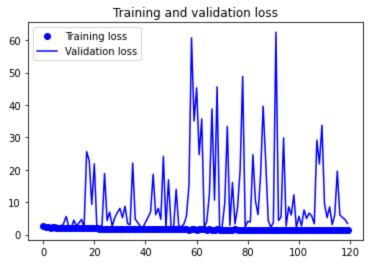
al loss: 2.6820 - val acc: 0.0994

```
Epoch 97/120
al loss: 8.5809 - val acc: 0.1077
Epoch 98/120
al loss: 6.0476 - val acc: 0.1497
Epoch 99/120
al loss: 12.2934 - val acc: 0.0999
Epoch 100/120
al loss: 2.1246 - val acc: 0.2314
Epoch 101/120
al loss: 5.6431 - val acc: 0.1150
Epoch 102/120
64/64 [=================== ] - 11s 179ms/step - loss: 1.4845 - acc: 0.4770 - v
al loss: 2.6797 - val acc: 0.1499
Epoch 103/120
al loss: 7.6049 - val acc: 0.1201
Epoch 104/120
al loss: 4.9664 - val acc: 0.1162
Epoch 105/120
al loss: 6.6424 - val acc: 0.1125
Epoch 106/120
al loss: 5.7358 - val acc: 0.1304
Epoch 107/120
al loss: 3.3516 - val acc: 0.1028
Epoch 108/120
al loss: 29.1532 - val acc: 0.1016
Epoch 109/120
al loss: 21.8093 - val acc: 0.0874
Epoch 110/120
al loss: 33.7608 - val acc: 0.1060
Epoch 111/120
al loss: 9.4681 - val acc: 0.1035
Epoch 112/120
al loss: 5.2646 - val acc: 0.1055
Epoch 113/120
al loss: 8.5561 - val acc: 0.1292
Epoch 114/120
al loss: 3.1014 - val acc: 0.1025
Epoch 115/120
al loss: 6.0575 - val acc: 0.1292
Epoch 116/120
al loss: 19.5801 - val acc: 0.1001
Epoch 117/120
al loss: 6.1042 - val acc: 0.1165
Epoch 118/120
```

al loss: 5.3027 - val acc: 0.1335

```
Epoch 119/120
       al loss: 4.6801 - val acc: 0.1211
       Epoch 120/120
       al loss: 3.4648 - val acc: 0.1499
In [51]: # Plot the data.
       acc = history.history['acc']
       val_acc = history.history['val acc']
       loss = history.history['loss']
       val loss = history.history['val loss']
       epochs = range(len(acc))
       plt.plot(epochs, acc, 'bo', label='Training acc')
       plt.plot(epochs, val acc, 'b', label='Validation acc')
       plt.title('Training and validation accuracy')
       plt.legend()
       plt.figure()
       plt.plot(epochs, loss, 'bo', label='Training loss')
       plt.plot(epochs, val loss, 'b', label='Validation loss')
       plt.title('Training and validation loss')
       plt.legend()
       plt.show()
```





6.3

```
In [54]: from tensorflow.keras.applications.resnet50 import ResNet50
        from tensorflow.keras.preprocessing import image
        from tensorflow.keras.applications.resnet50 import preprocess input, decode predictions
        model = ResNet50 (weights='imagenet')
        filepath = 'images'
        output = []
        # Loop over each image to make predictions
        for file in os.listdir(filepath):
            image path = os.path.join(filepath, file)
            img = image.load img(image path, target size=(224, 224))
            x = image.img to array(img)
            x = np.expand dims(x, axis = 0)
            x = preprocess input(x)
            # Make the predictions
            predictions = model.predict(x)
            prediction name = str(image path)
            info = str('Predicted: ' + str(decode predictions(predictions, top=5)[0]))
            output.append(prediction name)
            output.append(info)
            print(f'{prediction name} \n {info}')
        1/1 [======= ] - 1s 1s/step
        Downloading data from https://storage.googleapis.com/download.tensorflow.org/data/imagen
        et class index.json
        35363/35363 [===========] - Os lus/step
        images\amy-hirschi-szrJ3wjzOMg-unsplash.jpg
         Predicted: [('n03291819', 'envelope', 0.21261807), ('n03642806', 'laptop', 0.08052259),
        ('n04118776', 'rule', 0.080337815), ('n03179701', 'desk', 0.07715189), ('n04548280', 'wa
        ll clock', 0.07612319)]
        1/1 [======= ] - Os 117ms/step
        images\daniel-bonilla-MVZlkv G4zQ-unsplash.jpg
         Predicted: [('n03803284', 'muzzle', 0.9223493), ('n02403003', 'ox', 0.031144816), ('n03
        868863', 'oxygen mask', 0.0288808), ('n03424325', 'gasmask', 0.0042149327), ('n0209233
        9', 'Weimaraner', 0.0014808961)]
        1/1 [=======] - 0s 103ms/step
        images\dushawn-jovic-B3fgTrrgsiI-unsplash.jpg
         Predicted: [('n02807133', 'bathing cap', 0.4402964), ('n03710637', 'maillot', 0.1761608
        1), ('n02892767', 'brassiere', 0.14404574), ('n03710721', 'maillot', 0.13406157), ('n028
        37789', 'bikini', 0.07064589)]
        1/1 [======= ] - 0s 103ms/step
        images\erik-mclean-ZRns2R5azu0-unsplash.jpg
         Predicted: [('n03594945', 'jeep', 0.29830098), ('n04467665', 'trailer truck', 0.2078867
        1), ('n04037443', 'racer', 0.12850937), ('n03770679', 'minivan', 0.05470578), ('n0393063
           'pickup', 0.04988277)]
        1/1 [======= ] - 0s 101ms/step
        images\intricate-explorer-ndmaGsIr6E4-unsplash.jpg
```

```
Predicted: [('n13040303', 'stinkhorn', 0.13910884), ('n12985857', 'coral fungus', 0.038
        33431), ('n01773549', 'barn spider', 0.03268129), ('n01950731', 'sea slug', 0.03092150
        8), ('n04604644', 'worm fence', 0.02760182)]
        1/1 [======= ] - Os 101ms/step
        images\leio-mclaren-FwdZYz0yc9g-unsplash.jpg
        Predicted: [('n03888257', 'parachute', 0.44306922), ('n03773504', 'missile', 0.1711833
        8), ('n09472597', 'volcano', 0.10201463), ('n04552348', 'warplane', 0.10144949), ('n0400
        8634', 'projectile', 0.056138314)]
        1/1 [======= ] - Os 102ms/step
        images\manja-vitolic-gKXKBY-C-Dk-unsplash.jpg
        Predicted: [('n02124075', 'Egyptian cat', 0.61982495), ('n02123597', 'Siamese cat', 0.1
        3296269), ('n02909870', 'bucket', 0.052781727), ('n02123045', 'tabby', 0.03871195), ('n0
        3958227', 'plastic bag', 0.020926394)]
        images\obie-fernandez-0GFNAelMPZA-unsplash.jpg
         Predicted: [('n03250847', 'drumstick', 0.2297712), ('n04584207', 'wig', 0.129819), ('n0
        3594734', 'jean', 0.066456355), ('n02963159', 'cardigan', 0.05127348), ('n03770439', 'mi
        niskirt', 0.04637946)]
        images\quino-al-8gWEAAXJjtI-unsplash.jpg
        Predicted: [('n03187595', 'dial telephone', 0.9591948), ('n03902125', 'pay-phone', 0.03
        9810065), ('n04328186', 'stopwatch', 0.000522505), ('n04548280', 'wall clock', 0.0001079
        9182), ('n04069434', 'reflex camera', 7.302062e-05)]
        1/1 [=======] - 0s 102ms/step
        images\richard-brutyo-Sg3XwuEpybU-unsplash.jpg
        Predicted: [('n02099601', 'golden retriever', 0.9678861), ('n02099712', 'Labrador retri
        ever', 0.007136036), ('n02102318', 'cocker_spaniel', 0.0039223228), ('n02085620', 'Chihu
        ahua', 0.0025483514), ('n02113624', 'toy poodle', 0.0023548473)]
In [56]: # Save predictions to a file
        if not os.path.exists('results/predictions/resnet50'):
           os.makedirs('results/predictions/resnet50')
        outfile = 'results/predictions/resnet50/predictions-6-3.txt'
        with open(outfile, 'w') as f:
           for line in output:
               f.write("%s\n" % line)
```