CNN_Lab_2023_final

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Presented By

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1 CNN Image Classification Laboration

Images used in this laboration are from CIFAR 10 (https://en.wikipedia.org/wiki/CIFAR-10). The CIFAR-10 dataset contains 60,000 32x32 color images in 10 different classes. The 10 different classes represent airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. There are 6,000 images of each class. Your task is to make a classifier, using a convolutional neural network, that can correctly classify each image into the correct class.

You need to answer all questions in this notebook.

1.1 Part 1: What is a convolution

To understand a bit more about convolutions, we will first test the convolution function in scipy using a number of classical filters.

Convolve the image with Gaussian filter, a Sobel X filter, and a Sobel Y filter, using the function 'convolve2d' in 'signal' from scipy.

https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.convolve2d.html

In a CNN, many filters are applied in each layer, and the filter coefficients are learned through back propagation (which is in contrast to traditional image processing, where the filters are designed by an expert).

[2]:
```
# This cell is finished

from scipy import signal
import numpy as np

# Get a test image
from scipy import misc
image = misc.ascent()

# Define a help function for creating a Gaussian filter
```

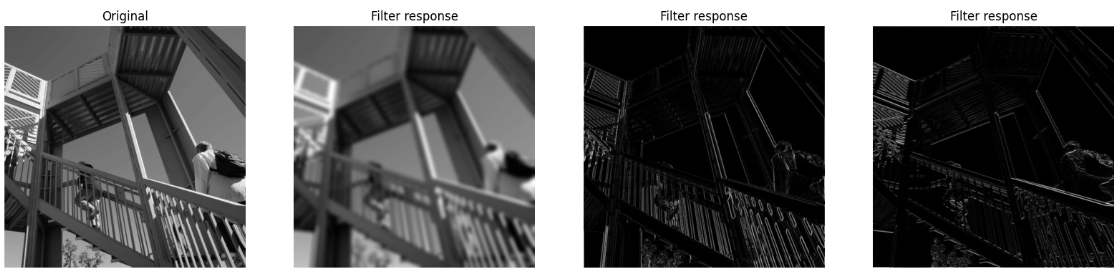
```
def matlab_style_gauss2D(shape=(3,3),sigma=0.5):
    """
    2D gaussian mask - should give the same result as MATLAB's
    fspecial('gaussian',[shape],[sigma])
    """
    m,n = [(ss-1.)/2. for ss in shape]
    y,x = np.ogrid[-m:m+1,-n:n+1]
    h = np.exp( -(x*x + y*y) / (2.*sigma*sigma) )
    h[ h < np.finfo(h.dtype).eps*h.max() ] = 0
    sumh = h.sum()
    if sumh != 0:
        h /= sumh
    return h

# Create Gaussian filter with certain size and standard deviation
gaussFilter = matlab_style_gauss2D((15,15),4)

# Define filter kernels for SobelX and Sobely
sobelX = np.array([[ 1, 0,  -1],
                    [2, 0, -2],
                    [1, 0, -1]])

sobelY = np.array([[ 1, 2,  1],
                    [0, 0, 0],
                    [-1, -2, -1]])
```

```
<ipython-input-2-01738d8e7eae>:8: DeprecationWarning: scipy.misc.ascent has been
deprecated in SciPy v1.10.0; and will be completely removed in SciPy v1.12.0.
Dataset methods have moved into the scipy.datasets module. Use
scipy.datasets.ascent instead.
  image = misc.ascent()
```

[3]:
```
# Perform convolution using the function 'convolve2d' for the different filters
filterResponseGauss = signal.convolve2d(image, gaussFilter, mode='same',␣
 ↪boundary='symm')
# mode='same' and boundary='symm' ensure that the output image has the same␣
 ↪size as the input image and that the convolution is performed symmetrically␣
 ↪at the boundaries.
filterResponseSobelX = signal.convolve2d(image, sobelX, mode='same')
filterResponseSobelY = signal.convolve2d(image, sobelY, mode='same')
```

[4]:
```
import matplotlib.pyplot as plt

# Show filter responses
fig, (ax_orig, ax_filt1, ax_filt2, ax_filt3) = plt.subplots(1, 4, figsize=(20,␣
 ↪6))
ax_orig.imshow(image, cmap='gray')
```

```
ax_orig.set_title('Original')
ax_orig.set_axis_off()
ax_filt1.imshow(np.absolute(filterResponseGauss), cmap='gray')
ax_filt1.set_title('Filter response')
ax_filt1.set_axis_off()
ax_filt2.imshow(np.absolute(filterResponseSobelX), cmap='gray')
ax_filt2.set_title('Filter response')
ax_filt2.set_axis_off()
ax_filt3.imshow(np.absolute(filterResponseSobelY), cmap='gray')
ax_filt3.set_title('Filter response')
ax_filt3.set_axis_off()
```



1.2 Part 2: Understanding convolutions

Question 1: What do the 3 different filters (Gaussian, SobelX, SobelY) do to the original image? - **Gaussian filter** This filter remove high frequency noise bluring the image. This gives a smoother version of the original image - **Sobel X filter** This filter highlihts horizontal edges of the image supressing other features - **Sobel Y filter** This filter highlihts vertical edges of the image supressing other features

Question 2: What is the size of the original image? How many channels does it have? How many channels does a color image normally have? **Size of the original image is 512x512 pixels. They have only one channel as it's a grayscale image. Color images normally have 3 channels**

Question 3: What is the size of the different filters? **Gaussian filter size is 15x15 pixels. Sobel X and Sobel Y filter size is 3x3 pixels**

Question 4: What is the size of the filter response if mode 'same' is used for the convolution ? **Filter response(output image) will be the same as input image**

Question 5: What is the size of the filter response if mode 'valid' is used for the convolution? How does the size of the valid filter response depend on the size of the filter? **filter response will be smaller than the input image.if the filter size is large the response will be small.**

Question 6: Why are 'valid' convolutions a problem for CNNs with many layers? **When you have a CNN with many layers, filter tends to reduce the size of image in each layer resulting loss of information**

[5]:
```python
# Your code for checking sizes of image and filter responses
org_image = image.shape
gaus_res = filterResponseGauss.shape
sobelx_res = filterResponseSobelX.shape
sobel_yres = filterResponseSobelY.shape

print(f'Original image size - {org_image}')
print(f'Gaussian filter response size - {gaus_res}')
print(f'SobelX filter response size - {sobelx_res}')
print(f'SobelY filter response size - {sobel_yres}')
```

```
Original image size - (512, 512)
Gaussian filter response size - (512, 512)
SobelX filter response size - (512, 512)
SobelY filter response size - (512, 512)
```

1.3 Part 3: Get a graphics card

Skip this part if you run on a CPU (recommended)

Let's make sure that our script can see the graphics card that will be used. The graphics cards will perform all the time consuming convolutions in every training iteration.

[1]:
```python
# import os
# import warnings

# # Ignore FutureWarning from numpy
# warnings.simplefilter(action='ignore', category=FutureWarning)

# import keras.backend as K
# import tensorflow as tf

# os.environ["CUDA_DEVICE_ORDER"]="PCI_BUS_ID";

# # The GPU id to use, usually either "0" or "1";
# os.environ["CUDA_VISIBLE_DEVICES"]="0";

# # Allow growth of GPU memory, otherwise it will always look like all the␣
↪memory is being used
# physical_devices = tf.config.experimental.list_physical_devices('GPU')
# tf.config.experimental.set_memory_growth(physical_devices[0], True)
```

1.4 Part 4: How fast is the graphics card?

Question 7: Why are the filters used for a color image of size 7 x 7 x 3, and not 7 x 7 ? **because the input images are color images and have 3 color channels (red, green, and blue)**

Question 8: What operation is performed by the 'Conv2D' layer? Is it a standard 2D convolution, as performed by the function signal.convolve2d we just tested? **conv2D layer in a neural network**

learns the filter weights through a training process, where the weights are adjusted to minimize a given loss function. The convolve2d function is used for general-purpose 2D convolution operations. while both scipy.signal.convolve2d and a Conv2D layer perform 2D convolution operations, they are different as the Conv2D layer is a trainable layer that can be used in a neural network.

Question 9: Do you think that a graphics card, compared to the CPU, is equally faster for convolving a batch of 1,000 images, compared to convolving a batch of 3 images? Motivate your answer. **No. GPU is much faster. It can process multiple images at the same time as it is designed to perform parallel computing. With 1000 images GPU will parallelize the computations while 3 images will be processed as a single batch.**

1.5 Part 5: Load data

Time to make a 2D CNN. Load the images and labels from keras.datasets, this cell is already finished.

[7]:
```
from keras.datasets import cifar10
import numpy as np

classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']

# Download CIFAR train and test data
(Xtrain, Ytrain), (Xtest, Ytest) = cifar10.load_data()

print("Training images have size {} and labels have size {} ".format(Xtrain.
↪shape, Ytrain.shape))
print("Test images have size {} and labels have size {} \n ".format(Xtest.
↪shape, Ytest.shape))

# Reduce the number of images for training and testing to 10000 and 2000␣
↪respectively,
# to reduce processing time for this laboration
Xtrain = Xtrain[0:10000]
Ytrain = Ytrain[0:10000]

Xtest = Xtest[0:2000]
Ytest = Ytest[0:2000]

Ytestint = Ytest

print("Reduced training images have size %s and labels have size %s " % (Xtrain.
↪shape, Ytrain.shape))
print("Reduced test images have size %s and labels have size %s \n" % (Xtest.
↪shape, Ytest.shape))

# Check that we have some training examples from each class
```

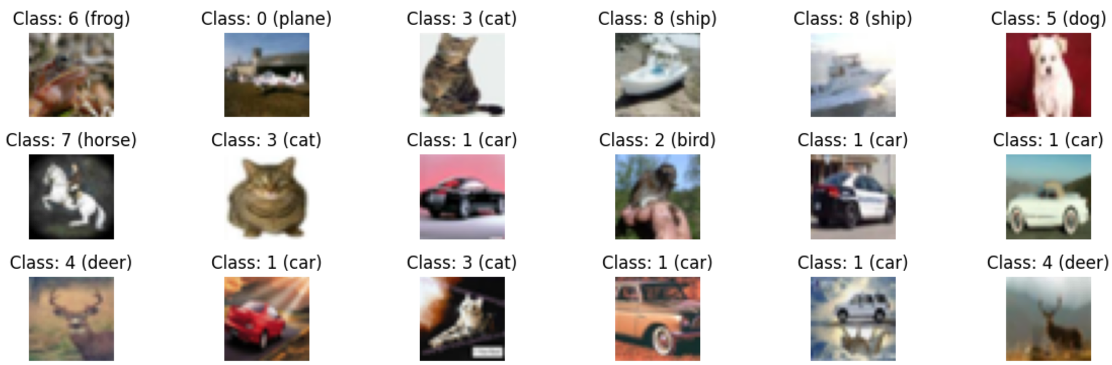
```
for i in range(10):
    print("Number of training examples for class {} is {}" .format(i,np.
 ↪sum(Ytrain == i)))
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 13s 0us/step
Training images have size (50000, 32, 32, 3) and labels have size (50000, 1)
Test images have size (10000, 32, 32, 3) and labels have size (10000, 1)

Reduced training images have size (10000, 32, 32, 3) and labels have size
(10000, 1)
Reduced test images have size (2000, 32, 32, 3) and labels have size (2000, 1)

Number of training examples for class 0 is 1005
Number of training examples for class 1 is 974
Number of training examples for class 2 is 1032
Number of training examples for class 3 is 1016
Number of training examples for class 4 is 999
Number of training examples for class 5 is 937
Number of training examples for class 6 is 1030
Number of training examples for class 7 is 1001
Number of training examples for class 8 is 1025
Number of training examples for class 9 is 981
```

1.6 Part 6: Plotting

Lets look at some of the training examples, this cell is already finished. You will see different examples every time you run the cell.

[8]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,4))
for i in range(18):
    idx = np.random.randint(7500)
    label = Ytrain[idx,0]

    plt.subplot(3,6,i+1)
    plt.tight_layout()
    plt.imshow(Xtrain[idx])
    plt.title("Class: {} ({})".format(label, classes[label]))
    plt.axis('off')
plt.show()
```



1.7 Part 7: Split data into training, validation and testing

Split your training data into training (Xtrain, Ytrain) and validation (Xval, Yval), so that we have training, validation and test datasets (as in the previous laboration). We use a function in scikit learn. Use 25% of the data for validation.

https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

[9]:
```
from sklearn.model_selection import train_test_split

# Your code for splitting the dataset
Xtrain, Xval, Ytrain, Yval = train_test_split(Xtrain, Ytrain, train_size=0.75)

# Print the size of training data, validation data and test data
print(f'Size of training data - {Xtrain.shape}')
print(f'Size of validation data - {Xval.shape}')
```

```
Size of training data - (7500, 32, 32, 3)
Size of validation data - (2500, 32, 32, 3)
```

1.8 Part 8: Preprocessing of images

Lets perform some preprocessing. The images are stored as uint8, i.e. 8 bit unsigned integers, but need to be converted to 32 bit floats. We also make sure that the range is -1 to 1, instead of 0 - 255. This cell is already finished.

[10]:
```
# Convert datatype for Xtrain, Xval, Xtest, to float32
Xtrain = Xtrain.astype('float32')
Xval = Xval.astype('float32')
Xtest = Xtest.astype('float32')

# Change range of pixel values to [-1,1]
Xtrain = Xtrain / 127.5 - 1
Xval = Xval / 127.5 - 1
Xtest = Xtest / 127.5 - 1
```

1.9 Part 9: Preprocessing of labels

The labels (Y) need to be converted from e.g. '4' to "hot encoded", i.e. to a vector of type [0, 0, 0, 1, 0, 0, 0, 0, 0] . We use a function in Keras, see https://keras.io/api/utils/python_utils/#to_categorical-function

[11]:
```
from tensorflow.keras.utils import to_categorical

# Print shapes before converting the labels
print(f'Training labels size - {Ytrain.shape}')
print(f'Validation labels size - {Yval.shape}')
print(f'Test labels size - {Ytest.shape}')

# Your code for converting Ytrain, Yval, Ytest to categorical
Ytrain = to_categorical(Ytrain)
Yval = to_categorical(Yval)
Ytest = to_categorical(Ytest)

# Print shapes after converting the labels
print('\nNew shapes after converting')
print(f'Training labels size - {Ytrain.shape}')
print(f'Validation labels size - {Yval.shape}')
print(f'Test labels size - {Ytest.shape}')
```

```
Training labels size - (7500, 1)
Validation labels size - (2500, 1)
Test labels size - (2000, 1)

New shapes after converting
Training labels size - (7500, 10)
Validation labels size - (2500, 10)
Test labels size - (2000, 10)
```

1.10 Part 10: 2D CNN

Finish this code to create the image classifier, using a 2D CNN. Each convolutional layer will contain 2D convolution, batch normalization and max pooling. After the convolutional layers comes a flatten layer and a number of intermediate dense layers. The convolutional layers should take the number of filters as an argument, use a kernel size of 3 x 3, 'same' padding, and relu activation functions. The number of filters will double with each convolutional layer. The max pooling layers should have a pool size of 2 x 2. The intermediate dense layers before the final dense layer should take the number of nodes as an argument, use relu activation functions, and be followed by batch normalization. The final dense layer should have 10 nodes (= the number of classes in this laboration) and 'softmax' activation. Here we start with the Adam optimizer.

Relevant functions are

`model.add()`, adds a layer to the network

`Dense()`, a dense network layer

`Conv2D()`, performs 2D convolutions with a number of filters with a certain size (e.g. 3 x 3).

`BatchNormalization()`, perform batch normalization

`MaxPooling2D()`, saves the max for a given pool size, results in down sampling

`Flatten()`, flatten a multi-channel tensor into a long vector

`model.compile()`, compile the model, add " metrics=['accuracy'] " to print the classification accuracy during the training

See https://keras.io/api/layers/core_layers/dense/ and https://keras.io/api/layers/reshaping_layers/flatten/ for information on how the `Dense()` and `Flatten()` functions work

See https://keras.io/layers/convolutional/ for information on how `Conv2D()` works

See https://keras.io/layers/pooling/ for information on how `MaxPooling2D()` works

Import a relevant cost function for multi-class classification from keras.losses (https://keras.io/losses/) , it relates to how many classes you have.

See the following links for how to compile, train and evaluate the model

https://keras.io/api/models/model_training_apis/#compile-method

https://keras.io/api/models/model_training_apis/#fit-method

https://keras.io/api/models/model_training_apis/#evaluate-method

[12]:
```python
from keras.models import Sequential, Model
from keras.layers import Input, Conv2D, BatchNormalization, MaxPooling2D,␣
 ↪Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from keras.losses import CategoricalCrossentropy

# Set seed from random number generator, for better comparisons
from numpy.random import seed
seed(123)

def build_CNN(input_shape, n_conv_layers=2, n_filters=16, n_dense_layers=0,␣
 ↪n_nodes=50, use_dropout=False, learning_rate=0.01):

    # Setup a sequential model
    model = Sequential()

    # Add first convolutional layer to the model, requires input shape
    model.add(Conv2D(filters=n_filters, kernel_size=(3,3), padding='same',␣
 ↪activation='relu', input_shape=input_shape))
    model.add(MaxPooling2D((2, 2)))
    model.add(BatchNormalization())
```

```
    # Add remaining convolutional layers to the model, the number of filters␣
 ↪should increase a factor 2 for each layer
    for i in range(n_conv_layers-1):
        n_filters *= 2
        model.add(Conv2D(filters=n_filters, kernel_size=(3,3), padding='same',␣
 ↪activation='relu'))
        model.add(MaxPooling2D((2, 2)))
        model.add(BatchNormalization())

    # Add flatten layer
    model.add(Flatten())

    # Add intermediate dense layers
    for i in range(n_dense_layers):
        model.add(Dense(n_nodes, activation='relu'))
        model.add(BatchNormalization())
        if use_dropout:
            model.add(Dropout(0.5))

    # Add final dense layer
    model.add(Dense(10, activation='softmax'))

    # Compile model
    model.compile(optimizer=Adam(learning_rate=learning_rate),␣
 ↪loss='categorical_crossentropy', metrics=['accuracy'])

    return model
```

[13]:
```
# Lets define a help function for plotting the training results
import matplotlib.pyplot as plt
def plot_results(history):

    loss = history.history['loss']
    acc = history.history['accuracy']
    val_loss = history.history['val_loss']
    val_acc = history.history['val_accuracy']

    plt.figure(figsize=(10,4))
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.plot(loss)
    plt.plot(val_loss)
    plt.legend(['Training','Validation'])

    plt.figure(figsize=(10,4))
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
```

```
plt.plot(acc)
plt.plot(val_acc)
plt.legend(['Training','Validation'])

plt.show()
```

1.11 Part 11: Train 2D CNN

Time to train the 2D CNN, start with 2 convolutional layers, no intermediate dense layers, learning rate = 0.01. The first convolutional layer should have 16 filters (which means that the second convolutional layer will have 32 filters).

Relevant functions

`build_CNN`, the function we defined in Part 10, call it with the parameters you want to use

`model.fit()`, train the model with some training data

`model.evaluate()`, apply the trained model to some test data

See the following links for how to train and evaluate the model

https://keras.io/api/models/model_training_apis/#fit-method

https://keras.io/api/models/model_training_apis/#evaluate-method

1.12 2 convolutional layers, no intermediate dense layers

[14]:
```
# Setup some training parameters
batch_size = 100
epochs = 20
input_shape = Xtrain.shape[1:]

# Build model
model1 = build_CNN(input_shape, n_conv_layers=2, n_filters=16,␣
 ↪n_dense_layers=0, n_nodes=50, use_dropout=False, learning_rate=0.01)

# Train the model  using training data and validation data
history1 = model1.fit(Xtrain, Ytrain, batch_size=batch_size, epochs=epochs,␣
 ↪validation_data=(Xval, Yval))
```

```
Epoch 1/20
75/75 [==============================] - 14s 12ms/step - loss: 2.3756 -
accuracy: 0.3780 - val_loss: 1.7179 - val_accuracy: 0.3828
Epoch 2/20
75/75 [==============================] - 1s 7ms/step - loss: 1.2770 - accuracy:
0.5561 - val_loss: 1.6503 - val_accuracy: 0.4208
Epoch 3/20
75/75 [==============================] - 1s 8ms/step - loss: 1.0451 - accuracy:
0.6375 - val_loss: 1.5797 - val_accuracy: 0.4236
Epoch 4/20
```

```
75/75 [==============================] - 1s 8ms/step - loss: 0.9237 - accuracy:
0.6796 - val_loss: 1.6420 - val_accuracy: 0.4688
Epoch 5/20
75/75 [==============================] - 1s 9ms/step - loss: 0.8298 - accuracy:
0.7100 - val_loss: 1.3788 - val_accuracy: 0.5456
Epoch 6/20
75/75 [==============================] - 1s 7ms/step - loss: 0.7188 - accuracy:
0.7549 - val_loss: 1.4294 - val_accuracy: 0.5452
Epoch 7/20
75/75 [==============================] - 0s 6ms/step - loss: 0.6194 - accuracy:
0.7819 - val_loss: 1.6507 - val_accuracy: 0.5440
Epoch 8/20
75/75 [==============================] - 0s 5ms/step - loss: 0.5866 - accuracy:
0.7917 - val_loss: 1.7681 - val_accuracy: 0.5480
Epoch 9/20
75/75 [==============================] - 1s 10ms/step - loss: 0.5019 - accuracy:
0.8201 - val_loss: 1.8008 - val_accuracy: 0.5492
Epoch 10/20
75/75 [==============================] - 0s 6ms/step - loss: 0.4309 - accuracy:
0.8495 - val_loss: 2.3142 - val_accuracy: 0.5168
Epoch 11/20
75/75 [==============================] - 1s 9ms/step - loss: 0.3918 - accuracy:
0.8581 - val_loss: 2.1570 - val_accuracy: 0.5472
Epoch 12/20
75/75 [==============================] - 0s 6ms/step - loss: 0.3347 - accuracy:
0.8793 - val_loss: 2.4516 - val_accuracy: 0.5376
Epoch 13/20
75/75 [==============================] - 1s 10ms/step - loss: 0.3178 - accuracy:
0.8853 - val_loss: 2.5348 - val_accuracy: 0.5324
Epoch 14/20
75/75 [==============================] - 1s 11ms/step - loss: 0.2837 - accuracy:
0.9009 - val_loss: 2.6922 - val_accuracy: 0.5388
Epoch 15/20
75/75 [==============================] - 1s 7ms/step - loss: 0.2948 - accuracy:
0.8975 - val_loss: 2.8358 - val_accuracy: 0.5172
Epoch 16/20
75/75 [==============================] - 1s 10ms/step - loss: 0.2171 - accuracy:
0.9219 - val_loss: 2.8496 - val_accuracy: 0.5432
Epoch 17/20
75/75 [==============================] - 1s 7ms/step - loss: 0.1654 - accuracy:
0.9408 - val_loss: 2.8021 - val_accuracy: 0.5440
Epoch 18/20
75/75 [==============================] - 1s 10ms/step - loss: 0.1578 - accuracy:
0.9444 - val_loss: 3.1355 - val_accuracy: 0.5296
Epoch 19/20
75/75 [==============================] - 0s 5ms/step - loss: 0.1579 - accuracy:
0.9448 - val_loss: 3.2483 - val_accuracy: 0.5496
Epoch 20/20
```

```
75/75 [==============================] - 0s 7ms/step - loss: 0.2054 - accuracy:
0.9265 - val_loss: 3.4387 - val_accuracy: 0.5196
```

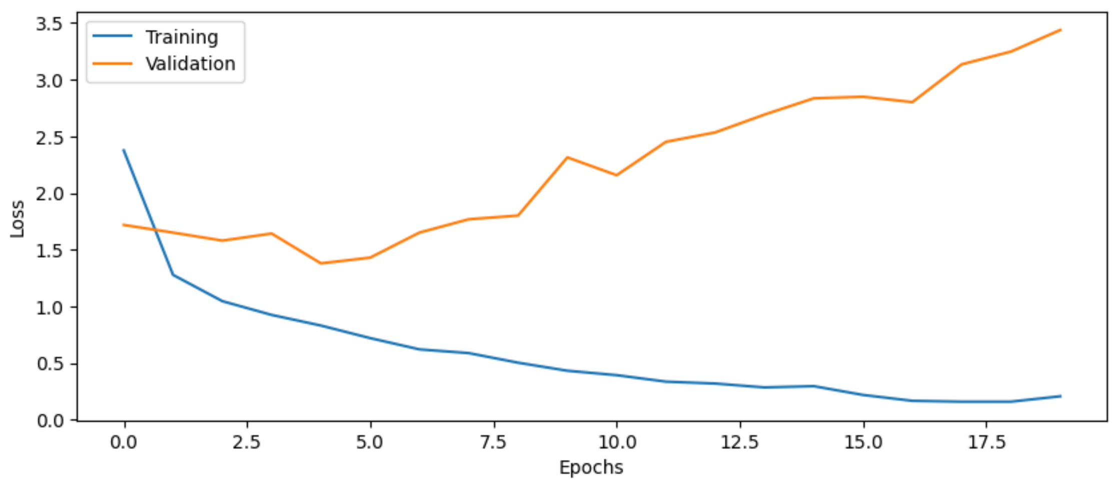
[15]:

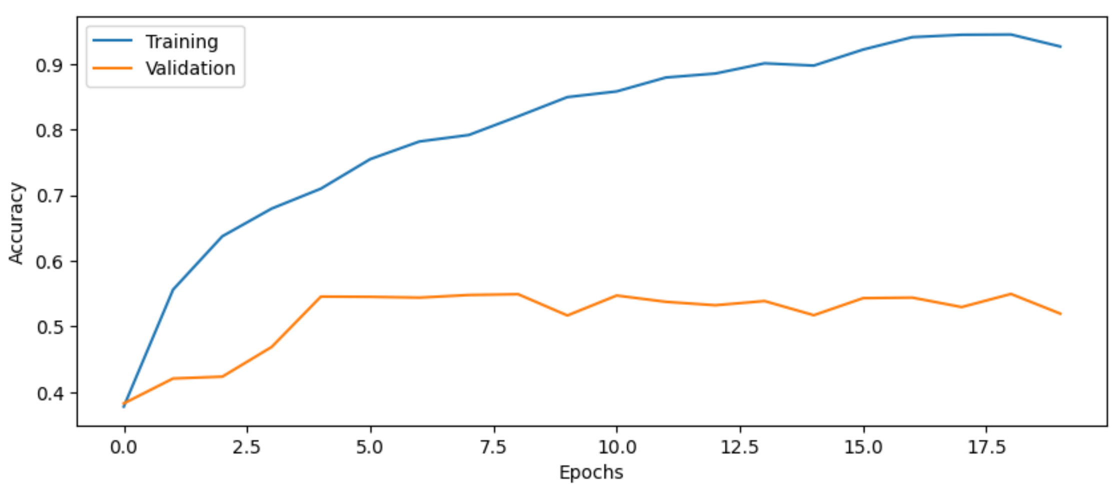
```
# Evaluate the trained model on test set, not used in training or validation
score = model1.evaluate(Xtest, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 0s 4ms/step - loss: 3.3816 - accuracy:
0.5405
Test loss: 3.3816
Test accuracy: 0.5405
```

[16]:

```
# Plot the history from the training run
plot_results(history1)
```





1.13 Part 12: Improving performance

Write down the test accuracy, are you satisfied with the classifier performance (random chance is 10%) ?

Question 10: How big is the difference between training and test accuracy? **The difference is 0.9917-0.5430=0.4487**

Question 11: For the DNN laboration we used a batch size of 10,000, why do we need to use a smaller batch size in this laboration? **That is because memory requirement for CNN is higher than memory requirement of DNN** ** correct answer: These images have 3072 values per image, while samples in DNN lab had 91 values per sample.**

1.14 2 convolutional layers, 1 intermediate dense layer (50 nodes)

[17]:
```
# Setup some training parameters
batch_size = 100
epochs = 20
input_shape = Xtrain.shape[1:]

# Build model
model2 = build_CNN(input_shape, n_conv_layers=2, n_filters=16,␣
 ↪n_dense_layers=1, n_nodes=50, use_dropout=False, learning_rate=0.01)

# Train the model  using training data and validation data
history2 = model2.fit(Xtrain, Ytrain, batch_size=batch_size, epochs=epochs,␣
 ↪validation_data=(Xval, Yval))
```

```
Epoch 1/20
75/75 [==============================] - 5s 11ms/step - loss: 1.6468 - accuracy:
0.4143 - val_loss: 2.4063 - val_accuracy: 0.2848
Epoch 2/20
75/75 [==============================] - 0s 6ms/step - loss: 1.2648 - accuracy:
0.5457 - val_loss: 2.2930 - val_accuracy: 0.2516
Epoch 3/20
75/75 [==============================] - 1s 7ms/step - loss: 1.0837 - accuracy:
0.6059 - val_loss: 1.9108 - val_accuracy: 0.3596
Epoch 4/20
75/75 [==============================] - 0s 6ms/step - loss: 0.9011 - accuracy:
0.6788 - val_loss: 1.5667 - val_accuracy: 0.4872
Epoch 5/20
75/75 [==============================] - 0s 6ms/step - loss: 0.7317 - accuracy:
0.7405 - val_loss: 1.5135 - val_accuracy: 0.5240
Epoch 6/20
75/75 [==============================] - 0s 6ms/step - loss: 0.6071 - accuracy:
0.7845 - val_loss: 1.6945 - val_accuracy: 0.5316
Epoch 7/20
```

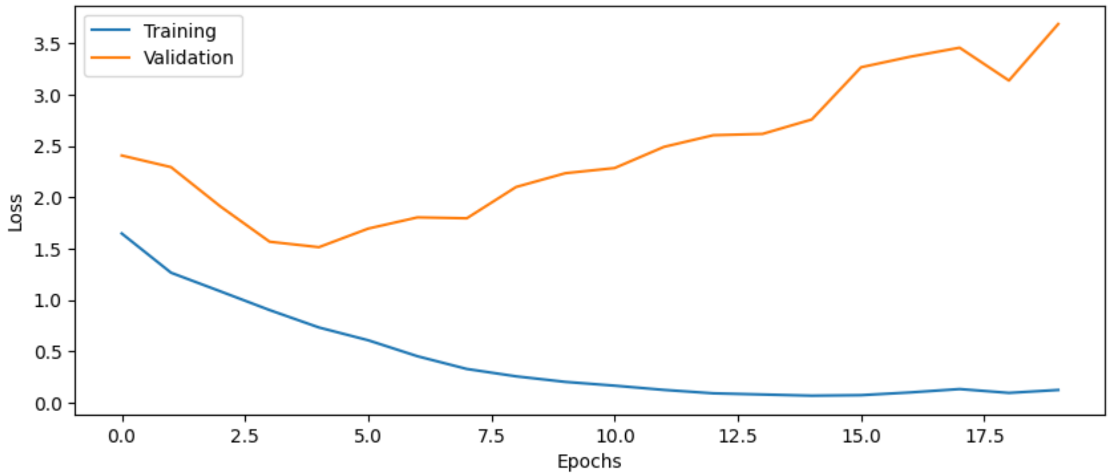
```
75/75 [==============================] - 0s 6ms/step - loss: 0.4514 - accuracy:
0.8405 - val_loss: 1.8036 - val_accuracy: 0.5440
Epoch 8/20
75/75 [==============================] - 0s 6ms/step - loss: 0.3276 - accuracy:
0.8904 - val_loss: 1.7946 - val_accuracy: 0.5524
Epoch 9/20
75/75 [==============================] - 0s 6ms/step - loss: 0.2558 - accuracy:
0.9140 - val_loss: 2.0996 - val_accuracy: 0.5472
Epoch 10/20
75/75 [==============================] - 0s 6ms/step - loss: 0.2017 - accuracy:
0.9344 - val_loss: 2.2338 - val_accuracy: 0.5628
Epoch 11/20
75/75 [==============================] - 0s 6ms/step - loss: 0.1650 - accuracy:
0.9436 - val_loss: 2.2841 - val_accuracy: 0.5544
Epoch 12/20
75/75 [==============================] - 1s 7ms/step - loss: 0.1237 - accuracy:
0.9583 - val_loss: 2.4902 - val_accuracy: 0.5516
Epoch 13/20
75/75 [==============================] - 1s 7ms/step - loss: 0.0906 - accuracy:
0.9715 - val_loss: 2.6036 - val_accuracy: 0.5412
Epoch 14/20
75/75 [==============================] - 0s 6ms/step - loss: 0.0789 - accuracy:
0.9768 - val_loss: 2.6165 - val_accuracy: 0.5448
Epoch 15/20
75/75 [==============================] - 0s 6ms/step - loss: 0.0674 - accuracy:
0.9796 - val_loss: 2.7572 - val_accuracy: 0.5368
Epoch 16/20
75/75 [==============================] - 1s 7ms/step - loss: 0.0724 - accuracy:
0.9760 - val_loss: 3.2656 - val_accuracy: 0.5332
Epoch 17/20
75/75 [==============================] - 0s 6ms/step - loss: 0.0993 - accuracy:
0.9635 - val_loss: 3.3687 - val_accuracy: 0.5504
Epoch 18/20
75/75 [==============================] - 0s 6ms/step - loss: 0.1319 - accuracy:
0.9541 - val_loss: 3.4560 - val_accuracy: 0.5264
Epoch 19/20
75/75 [==============================] - 0s 6ms/step - loss: 0.0946 - accuracy:
0.9669 - val_loss: 3.1362 - val_accuracy: 0.5544
Epoch 20/20
75/75 [==============================] - 0s 6ms/step - loss: 0.1230 - accuracy:
0.9555 - val_loss: 3.6869 - val_accuracy: 0.5368
```

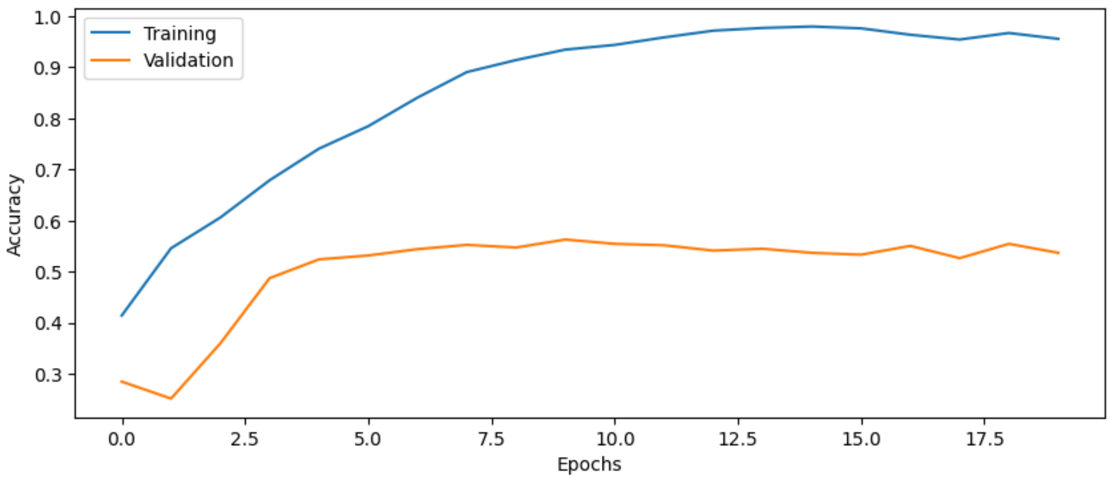
[18]:
```
# Evaluate the trained model on test set, not used in training or validation
score = model2.evaluate(Xtest, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 0s 3ms/step - loss: 3.6082 - accuracy:
```

```
0.5345
Test loss: 3.6082
Test accuracy: 0.5345
```

[19]:
```python
# Plot the history from the training run
plot_results(history2)
```





1.15 4 convolutional layers, 1 intermediate dense layer (50 nodes)

[20]:
```python
# Setup some training parameters
batch_size = 100
epochs = 20
input_shape = Xtrain.shape[1:]
```

```python
# Build model
model3 = build_CNN(input_shape, n_conv_layers=4, n_filters=16,␣
↪n_dense_layers=1, n_nodes=50, use_dropout=False, learning_rate=0.01)

# Train the model  using training data and validation data
history3 = model3.fit(Xtrain, Ytrain, batch_size=batch_size, epochs=epochs,␣
↪validation_data=(Xval, Yval))
```

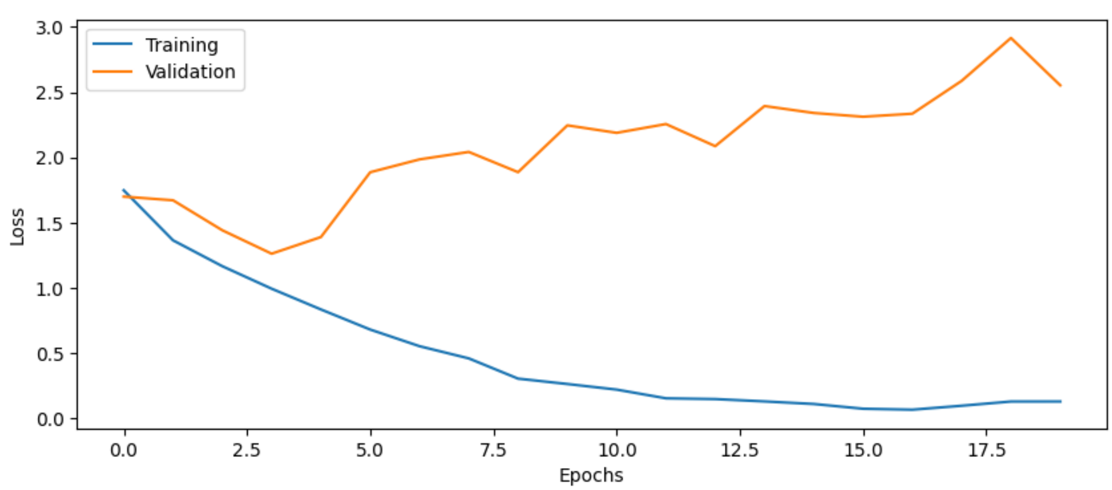
```
Epoch 1/20
75/75 [==============================] - 6s 15ms/step - loss: 1.7479 - accuracy:
0.3619 - val_loss: 1.6995 - val_accuracy: 0.3688
Epoch 2/20
75/75 [==============================] - 1s 10ms/step - loss: 1.3644 - accuracy:
0.5029 - val_loss: 1.6714 - val_accuracy: 0.4016
Epoch 3/20
75/75 [==============================] - 1s 9ms/step - loss: 1.1660 - accuracy:
0.5744 - val_loss: 1.4414 - val_accuracy: 0.5012
Epoch 4/20
75/75 [==============================] - 1s 8ms/step - loss: 0.9936 - accuracy:
0.6457 - val_loss: 1.2619 - val_accuracy: 0.5736
Epoch 5/20
75/75 [==============================] - 1s 9ms/step - loss: 0.8345 - accuracy:
0.7023 - val_loss: 1.3895 - val_accuracy: 0.5492
Epoch 6/20
75/75 [==============================] - 1s 9ms/step - loss: 0.6804 - accuracy:
0.7560 - val_loss: 1.8864 - val_accuracy: 0.4928
Epoch 7/20
75/75 [==============================] - 1s 10ms/step - loss: 0.5528 - accuracy:
0.8067 - val_loss: 1.9849 - val_accuracy: 0.5124
Epoch 8/20
75/75 [==============================] - 1s 9ms/step - loss: 0.4592 - accuracy:
0.8355 - val_loss: 2.0422 - val_accuracy: 0.5452
Epoch 9/20
75/75 [==============================] - 1s 9ms/step - loss: 0.3040 - accuracy:
0.8955 - val_loss: 1.8869 - val_accuracy: 0.5932
Epoch 10/20
75/75 [==============================] - 1s 8ms/step - loss: 0.2629 - accuracy:
0.9073 - val_loss: 2.2461 - val_accuracy: 0.5444
Epoch 11/20
75/75 [==============================] - 1s 8ms/step - loss: 0.2200 - accuracy:
0.9245 - val_loss: 2.1886 - val_accuracy: 0.5856
Epoch 12/20
75/75 [==============================] - 1s 8ms/step - loss: 0.1531 - accuracy:
0.9467 - val_loss: 2.2559 - val_accuracy: 0.5796
Epoch 13/20
75/75 [==============================] - 1s 10ms/step - loss: 0.1473 - accuracy:
0.9467 - val_loss: 2.0865 - val_accuracy: 0.6024
Epoch 14/20
```

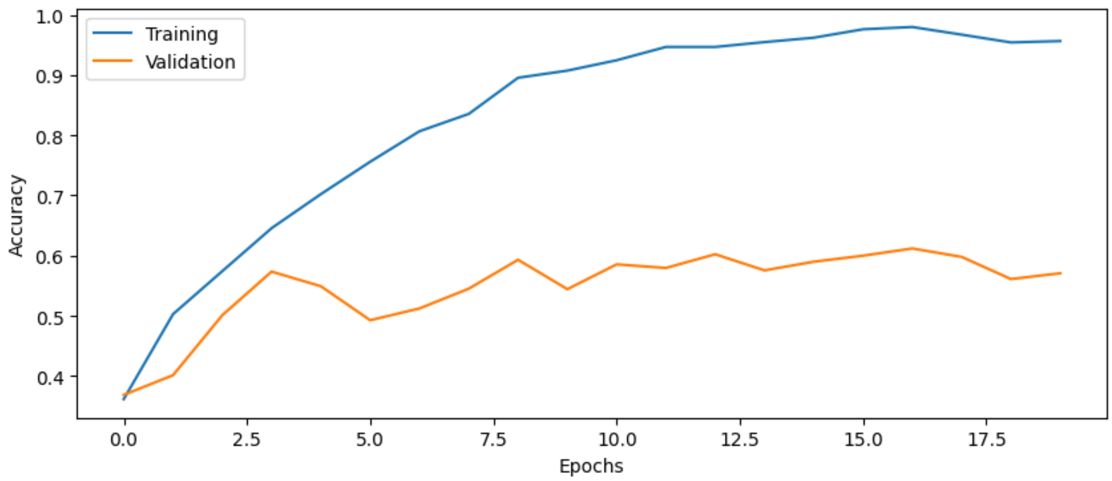
```
75/75 [==============================] - 1s 8ms/step - loss: 0.1294 - accuracy:
0.9547 - val_loss: 2.3941 - val_accuracy: 0.5756
Epoch 15/20
75/75 [==============================] - 1s 9ms/step - loss: 0.1097 - accuracy:
0.9620 - val_loss: 2.3409 - val_accuracy: 0.5900
Epoch 16/20
75/75 [==============================] - 1s 9ms/step - loss: 0.0732 - accuracy:
0.9760 - val_loss: 2.3120 - val_accuracy: 0.6000
Epoch 17/20
75/75 [==============================] - 1s 9ms/step - loss: 0.0660 - accuracy:
0.9797 - val_loss: 2.3354 - val_accuracy: 0.6120
Epoch 18/20
75/75 [==============================] - 1s 10ms/step - loss: 0.0962 - accuracy:
0.9671 - val_loss: 2.5873 - val_accuracy: 0.5980
Epoch 19/20
75/75 [==============================] - 1s 12ms/step - loss: 0.1287 - accuracy:
0.9541 - val_loss: 2.9159 - val_accuracy: 0.5612
Epoch 20/20
75/75 [==============================] - 1s 12ms/step - loss: 0.1288 - accuracy:
0.9564 - val_loss: 2.5531 - val_accuracy: 0.5708
```

[21]:
```
# Evaluate the trained model on test set, not used in training or validation
score = model3.evaluate(Xtest, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 1s 7ms/step - loss: 2.6236 - accuracy:
0.5665
Test loss: 2.6236
Test accuracy: 0.5665
```

[22]:
```
# Plot the history from the training run
plot_results(history3)
```





1.16 Part 13: Plot the CNN architecture

To understand your network better, print the architecture using `model.summary()`

Question 12: How many trainable parameters does your network have? Which part of the network contains most of the parameters? **124,180**

Question 13: What is the input to and output of a Conv2D layer? What are the dimensions of the input and output? **Input is a 4D tensor(2*2) with shape (batch_size, height, width, channels). Output is also a 4D tensor with shape (batch_size, height, width, filters).**

Question 14: Is the batch size always the first dimension of each 4D tensor? Check the documentation for Conv2D, https://keras.io/layers/convolutional/ **Depending on the data_format argument the ordering can be different, but the batch size is always the first dimension.**

Question 15: If a convolutional layer that contains 128 filters is applied to an input with 32 channels, what is the number of channels in the output? **128**

Question 16: Why is the number of parameters in each Conv2D layer *not* equal to the number of filters times the number of filter coefficients per filter (plus biases)? **This is because of parameter sharing.** ** correct answer: Conv2D learns one filter per input channel and almost performs a 3D convolution, it does not learn the same 2D filter for all channels**

Question 17: How does MaxPooling help in reducing the number of parameters to train? **Max-Pooling reduces the size of the input, which reduces the number of parameters in the next layer.**

[23]:
```
# Print network architecture

model3.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_4 (Conv2D)           (None, 32, 32, 16)        448       
                                                                 
 max_pooling2d_4 (MaxPooling  (None, 16, 16, 16)       0         
 2D)                                                             
                                                                 
 batch_normalization_5 (Batc  (None, 16, 16, 16)       64        
 hNormalization)                                                 
                                                                 
 conv2d_5 (Conv2D)           (None, 16, 16, 32)        4640      
                                                                 
 max_pooling2d_5 (MaxPooling  (None, 8, 8, 32)         0         
 2D)                                                             
                                                                 
 batch_normalization_6 (Batc  (None, 8, 8, 32)         128       
 hNormalization)                                                 
                                                                 
 conv2d_6 (Conv2D)           (None, 8, 8, 64)          18496     
                                                                 
 max_pooling2d_6 (MaxPooling  (None, 4, 4, 64)         0         
 2D)                                                             
                                                                 
 batch_normalization_7 (Batc  (None, 4, 4, 64)         256       
 hNormalization)                                                 
                                                                 
 conv2d_7 (Conv2D)           (None, 4, 4, 128)         73856     
                                                                 
 max_pooling2d_7 (MaxPooling  (None, 2, 2, 128)        0         
 2D)                                                             
                                                                 
 batch_normalization_8 (Batc  (None, 2, 2, 128)        512       
 hNormalization)                                                 
                                                                 
 flatten_2 (Flatten)         (None, 512)               0         
                                                                 
 dense_3 (Dense)             (None, 50)                25650     
                                                                 
 batch_normalization_9 (Batc  (None, 50)               200       
 hNormalization)                                                 
                                                                 
 dense_4 (Dense)             (None, 10)                510       
                                                                 
=================================================================
Total params: 124,760
Trainable params: 124,180
```

```
Non-trainable params: 580
_________________________________________________________________
```

1.17 Part 14: Dropout regularization

Add dropout regularization between each intermediate dense layer, dropout probability 50%.

Question 18: How much did the test accuracy improve with dropout, compared to without dropout? **The test accuracy improved from 0.5860 to 0.6015**

Question 19: What other types of regularization can be applied? How can you add L2 regularization for the convolutional layers? **L1 regularization and L2 regularization can be applied. To add L2 regularization we can use kernel_regularizer in the convolutional layer created by conv2D**

1.18 4 convolutional layers, 1 intermediate dense layer (50 nodes), dropout

[24]:
```python
# Setup some training parameters
batch_size = 100
epochs = 20
input_shape = Xtrain.shape[1:]

# Build model
model4 = build_CNN(input_shape, n_conv_layers=4, n_filters=16,␣
 ↪n_dense_layers=1, n_nodes=50, use_dropout=True, learning_rate=0.01)

# Train the model  using training data and validation data
history4 = model4.fit(Xtrain, Ytrain, batch_size=batch_size, epochs=epochs,␣
 ↪validation_data=(Xval, Yval))
```

```
Epoch 1/20
75/75 [==============================] - 5s 13ms/step - loss: 1.9312 - accuracy:
0.3192 - val_loss: 2.0912 - val_accuracy: 0.2844
Epoch 2/20
75/75 [==============================] - 1s 9ms/step - loss: 1.5257 - accuracy:
0.4341 - val_loss: 2.0279 - val_accuracy: 0.2920
Epoch 3/20
75/75 [==============================] - 1s 9ms/step - loss: 1.3841 - accuracy:
0.4959 - val_loss: 1.5142 - val_accuracy: 0.4612
Epoch 4/20
75/75 [==============================] - 1s 9ms/step - loss: 1.2448 - accuracy:
0.5447 - val_loss: 1.3344 - val_accuracy: 0.5296
Epoch 5/20
75/75 [==============================] - 1s 8ms/step - loss: 1.1617 - accuracy:
0.5829 - val_loss: 1.2075 - val_accuracy: 0.5772
Epoch 6/20
75/75 [==============================] - 1s 8ms/step - loss: 1.0208 - accuracy:
0.6361 - val_loss: 1.2944 - val_accuracy: 0.5740
Epoch 7/20
```

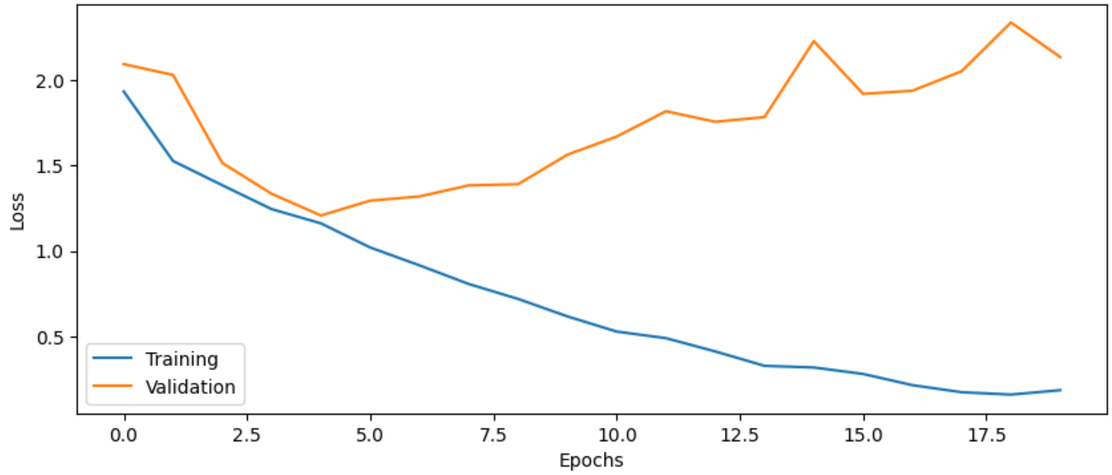
```
75/75 [==============================] - 1s 8ms/step - loss: 0.9166 - accuracy:
0.6721 - val_loss: 1.3187 - val_accuracy: 0.5636
Epoch 8/20
75/75 [==============================] - 1s 10ms/step - loss: 0.8077 - accuracy:
0.7143 - val_loss: 1.3836 - val_accuracy: 0.5808
Epoch 9/20
75/75 [==============================] - 1s 10ms/step - loss: 0.7206 - accuracy:
0.7487 - val_loss: 1.3900 - val_accuracy: 0.5968
Epoch 10/20
75/75 [==============================] - 1s 11ms/step - loss: 0.6188 - accuracy:
0.7797 - val_loss: 1.5626 - val_accuracy: 0.5600
Epoch 11/20
75/75 [==============================] - 1s 12ms/step - loss: 0.5302 - accuracy:
0.8171 - val_loss: 1.6681 - val_accuracy: 0.5828
Epoch 12/20
75/75 [==============================] - 1s 12ms/step - loss: 0.4916 - accuracy:
0.8288 - val_loss: 1.8160 - val_accuracy: 0.5768
Epoch 13/20
75/75 [==============================] - 1s 8ms/step - loss: 0.4142 - accuracy:
0.8581 - val_loss: 1.7546 - val_accuracy: 0.5848
Epoch 14/20
75/75 [==============================] - 1s 9ms/step - loss: 0.3301 - accuracy:
0.8900 - val_loss: 1.7820 - val_accuracy: 0.6000
Epoch 15/20
75/75 [==============================] - 1s 8ms/step - loss: 0.3205 - accuracy:
0.8887 - val_loss: 2.2253 - val_accuracy: 0.5544
Epoch 16/20
75/75 [==============================] - 1s 7ms/step - loss: 0.2828 - accuracy:
0.9024 - val_loss: 1.9174 - val_accuracy: 0.5944
Epoch 17/20
75/75 [==============================] - 1s 8ms/step - loss: 0.2174 - accuracy:
0.9281 - val_loss: 1.9356 - val_accuracy: 0.6056
Epoch 18/20
75/75 [==============================] - 1s 9ms/step - loss: 0.1761 - accuracy:
0.9419 - val_loss: 2.0496 - val_accuracy: 0.6148
Epoch 19/20
75/75 [==============================] - 1s 9ms/step - loss: 0.1623 - accuracy:
0.9421 - val_loss: 2.3339 - val_accuracy: 0.5844
Epoch 20/20
75/75 [==============================] - 1s 8ms/step - loss: 0.1881 - accuracy:
0.9356 - val_loss: 2.1323 - val_accuracy: 0.5880
```

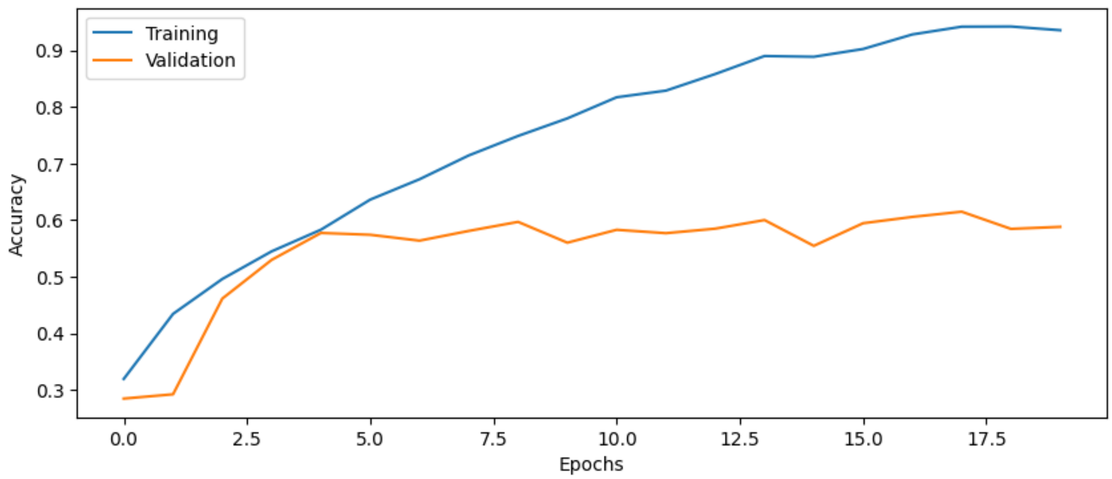
[25]:
```
# Evaluate the trained model on test set, not used in training or validation
score = model4.evaluate(Xtest, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 0s 3ms/step - loss: 2.1328 - accuracy:
```

```
0.6035
Test loss: 2.1328
Test accuracy: 0.6035
```

[26]:
```
# Plot the history from the training run
plot_results(history4)
```





1.19 Part 15: Tweaking performance

You have now seen the basic building blocks of a 2D CNN. To further improve performance involves changing the number of convolutional layers, the number of filters per layer, the number of intermediate dense layers, the number of nodes in the intermediate dense layers, batch size, learning rate, number of epochs, etc. Spend some time (30 - 90 minutes) testing different settings.

Question 20: How high test accuracy can you obtain? What is your best configuration? **The**

highest test accuracy we could obtain was 0.6115. Our best configuration was 5 convolutional layers, 1 intermediate dense layer (50 nodes), dropout=False, and number of filters=64.

1.20 Your best config

[27]:
```
# Setup some training parameters
batch_size = 300
epochs = 20
input_shape = Xtrain.shape[1:]

# Build model
model5 = build_CNN(input_shape, n_conv_layers=5, n_filters=64,
 ↪n_dense_layers=1, n_nodes=50, use_dropout=False, learning_rate=0.01)

# Train the model  using training data and validation data
history5 = model5.fit(Xtrain, Ytrain, batch_size=batch_size, epochs=epochs,
 ↪validation_data=(Xval, Yval))
```

```
Epoch 1/20
25/25 [==============================] - 10s 80ms/step - loss: 2.0702 -
accuracy: 0.2596 - val_loss: 26.9517 - val_accuracy: 0.2052
Epoch 2/20
25/25 [==============================] - 1s 46ms/step - loss: 1.6882 - accuracy:
0.3665 - val_loss: 3.3960 - val_accuracy: 0.2804
Epoch 3/20
25/25 [==============================] - 1s 47ms/step - loss: 1.5235 - accuracy:
0.4292 - val_loss: 6.0865 - val_accuracy: 0.1404
Epoch 4/20
25/25 [==============================] - 1s 48ms/step - loss: 1.4028 - accuracy:
0.4776 - val_loss: 3.5593 - val_accuracy: 0.1640
Epoch 5/20
25/25 [==============================] - 1s 48ms/step - loss: 1.2732 - accuracy:
0.5269 - val_loss: 2.4185 - val_accuracy: 0.2664
Epoch 6/20
25/25 [==============================] - 1s 48ms/step - loss: 1.1532 - accuracy:
0.5760 - val_loss: 2.6051 - val_accuracy: 0.2764
Epoch 7/20
25/25 [==============================] - 1s 48ms/step - loss: 1.0318 - accuracy:
0.6255 - val_loss: 2.1414 - val_accuracy: 0.3320
Epoch 8/20
25/25 [==============================] - 1s 46ms/step - loss: 0.8669 - accuracy:
0.6879 - val_loss: 2.2963 - val_accuracy: 0.3444
Epoch 9/20
25/25 [==============================] - 1s 48ms/step - loss: 0.7207 - accuracy:
0.7437 - val_loss: 2.4738 - val_accuracy: 0.3184
Epoch 10/20
25/25 [==============================] - 1s 48ms/step - loss: 0.5994 - accuracy:
```

```
0.7911 - val_loss: 2.0173 - val_accuracy: 0.4448
Epoch 11/20
25/25 [==============================] - 1s 47ms/step - loss: 0.4557 - accuracy:
0.8445 - val_loss: 2.3375 - val_accuracy: 0.4068
Epoch 12/20
25/25 [==============================] - 1s 46ms/step - loss: 0.3310 - accuracy:
0.8880 - val_loss: 1.8677 - val_accuracy: 0.5236
Epoch 13/20
25/25 [==============================] - 1s 46ms/step - loss: 0.2527 - accuracy:
0.9161 - val_loss: 1.6099 - val_accuracy: 0.5756
Epoch 14/20
25/25 [==============================] - 1s 48ms/step - loss: 0.1644 - accuracy:
0.9453 - val_loss: 1.9336 - val_accuracy: 0.5592
Epoch 15/20
25/25 [==============================] - 1s 46ms/step - loss: 0.0931 - accuracy:
0.9679 - val_loss: 1.8138 - val_accuracy: 0.5956
Epoch 16/20
25/25 [==============================] - 1s 49ms/step - loss: 0.0696 - accuracy:
0.9771 - val_loss: 1.9482 - val_accuracy: 0.6048
Epoch 17/20
25/25 [==============================] - 1s 50ms/step - loss: 0.0476 - accuracy:
0.9857 - val_loss: 2.0768 - val_accuracy: 0.5832
Epoch 18/20
25/25 [==============================] - 1s 49ms/step - loss: 0.0389 - accuracy:
0.9877 - val_loss: 1.8591 - val_accuracy: 0.6356
Epoch 19/20
25/25 [==============================] - 1s 49ms/step - loss: 0.0278 - accuracy:
0.9923 - val_loss: 2.1377 - val_accuracy: 0.6012
Epoch 20/20
25/25 [==============================] - 1s 45ms/step - loss: 0.0170 - accuracy:
0.9955 - val_loss: 2.0183 - val_accuracy: 0.6204
```

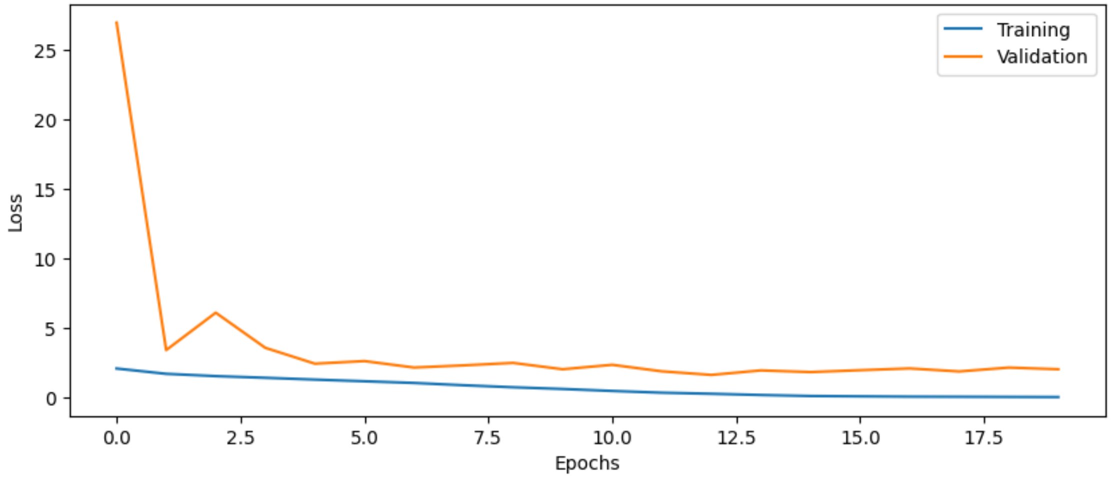
[28]:

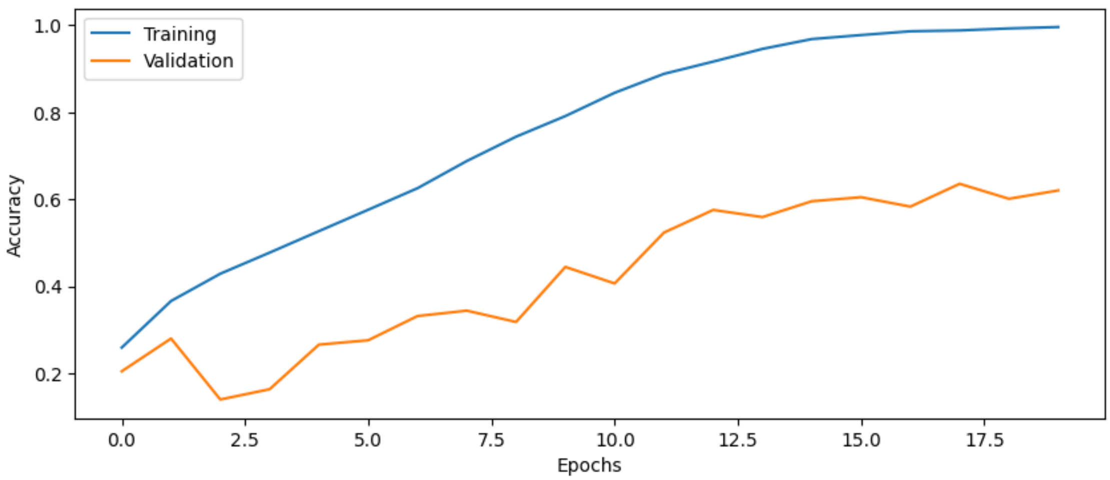
```python
# Evaluate the trained model on test set, not used in training or validation
score = model5.evaluate(Xtest, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 1s 8ms/step - loss: 2.0497 - accuracy:
0.6185
Test loss: 2.0497
Test accuracy: 0.6185
```

[29]:

```python
# Plot the history from the training run
plot_results(history5)
```





1.21 Part 16: Rotate the test images

How high is the test accuracy if we rotate the test images? In other words, how good is the CNN at generalizing to rotated images?

Rotate each test image 90 degrees, the cells are already finished.

Question 21: What is the test accuracy for rotated test images, compared to test images without rotation? Explain the difference in accuracy. **The test accuracy for rotated test images is 0.2260, which is far lower than the test accuracy for test images without rotation (0.6115). This is because the CNN is not trained on rotated images, so it does not know how to classify them.**

[30]:
```python
def myrotate(images):

    images_rot = np.rot90(images, axes=(1,2))

    return images_rot
```

[31]:
```python
# Rotate the test images 90 degrees
Xtest_rotated = myrotate(Xtest)

# Look at some rotated images
plt.figure(figsize=(16,4))
for i in range(10):
    idx = np.random.randint(500)

    plt.subplot(2,10,i+1)
    plt.imshow(Xtest[idx]/2+0.5)
    plt.title("Original")
    plt.axis('off')

    plt.subplot(2,10,i+11)
    plt.imshow(Xtest_rotated[idx]/2+0.5)
    plt.title("Rotated")
    plt.axis('off')
plt.show()
```

[32]:
```python
# Evaluate the trained model on rotated test set
score = model5.evaluate(Xtest_rotated, Ytest)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
63/63 [==============================] - 0s 5ms/step - loss: 6.3907 - accuracy:
0.1975
Test loss: 6.3907
Test accuracy: 0.1975
```

1.22 Part 17: Augmentation using Keras `ImageDataGenerator`

We can increase the number of training images through data augmentation (we now ignore that CIFAR10 actually has 60 000 training images). Image augmentation is about creating similar images, by performing operations such as rotation, scaling, elastic deformations and flipping of existing images. This will prevent overfitting, especially if all the training images are in a certain orientation.

We will perform the augmentation on the fly, using a built-in function in Keras, called `ImageDataGenerator`

See https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image/ImageDataGenerator , the .flow(x,y) functionality

Make sure to use different subsets for training and validation when you setup the flows, otherwise you will validate on the same data...

[33]:
```
# Get all 60 000 training images again. ImageDataGenerator manages validation␣
↪data on its own
(Xtrain, Ytrain), _ = cifar10.load_data()

# Reduce number of images to 10,000
Xtrain = Xtrain[0:10000]
Ytrain = Ytrain[0:10000]

# Change data type and rescale range
Xtrain = Xtrain.astype('float32')
Xtrain = Xtrain / 127.5 - 1

# Convert labels to hot encoding
Ytrain = to_categorical(Ytrain, 10)
```

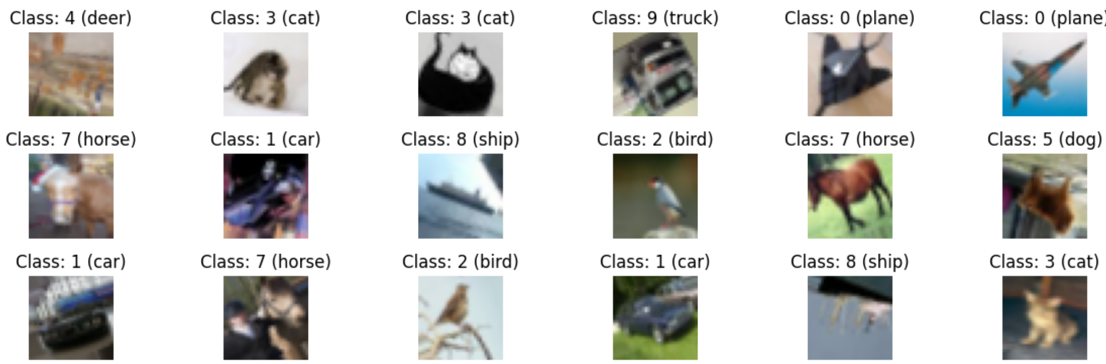
[34]:
```
# Set up a data generator with on-the-fly data augmentation, 20% validation␣
↪split
# Use a rotation range of 30 degrees, horizontal and vertical flipping
from keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=30,
    horizontal_flip=True,
    vertical_flip=True,
    validation_split=0.2
)


# Setup a flow for training data, assume that we can fit all images into CPU␣
↪memory
train_generator = datagen.flow(
    Xtrain, Ytrain,
```

```
    batch_size=32,
    subset='training'
)

# Setup a flow for validation data, assume that we can fit all images into CPU␣
↪memory
val_generator = datagen.flow(
    Xtrain, Ytrain,
    batch_size=32,
    subset='validation'
)
```

1.23 Part 18: What about big data?

Question 22: How would you change the code for the image generator if you cannot fit all training images in CPU memory? What is the disadvantage of doing that change? **If we cannot fit all training images in CPU memory, we would have to use the .flow_from_directory() function instead of the .flow() function. The disadvantage of this is that we would have to store the images in a directory, which would take much more time than just loading them into memory.**

[35]:
```
# Plot some augmented images
plot_datagen = datagen.flow(Xtrain, Ytrain, batch_size=1)

plt.figure(figsize=(12,4))
for i in range(18):
    (im, label) = plot_datagen.next()
    im = (im[0] + 1) * 127.5
    im = im.astype('int')
    label = np.flatnonzero(label)[0]

    plt.subplot(3,6,i+1)
    plt.tight_layout()
    plt.imshow(im)
    plt.title("Class: {} ({})".format(label, classes[label]))
    plt.axis('off')
plt.show()
```



1.24 Part 19: Train the CNN with images from the generator

See https://keras.io/api/models/model_training_apis/#fit-method for how to use model.fit with a generator instead of a fix dataset (numpy arrays)

To make the comparison fair to training without augmentation

`steps_per_epoch should be set to: len(Xtrain)*(1 - validation_split)/batch_size`

`validation_steps should be set to: len(Xtrain)*validation_split/batch_size`

This is required since with a generator, the fit function will not know how many examples your original dataset has.

Question 23: How quickly is the training accuracy increasing compared to without augmentation? Explain why there is a difference compared to without augmentation. We are here talking about the number of training epochs required to reach a certain accuracy, and not the training time in seconds. What parameter is necessary to change to perform more training?

The training accuracy is increasing slower with augmentation than without. This is because we are training on more images, and therefore the model is able to learn more. The parameter that is necessary to change to perform more training is the number of epochs.

Question 24: What other types of image augmentation can be applied, compared to what we use here? **Other types of image augmentation that can be applied are: zooming, shearing, shifting, brightness changes, and adding other types of noises**

[36]:
```python
# Setup some training parameters
batch_size = 100
epochs = 200
input_shape = Xtrain.shape[1:]

# Build model (your best config)
model6 = build_CNN(input_shape, n_conv_layers=5, n_filters=64, n_dense_layers=1, n_nodes=50, use_dropout=False, learning_rate=0.01)
```

```python
validation_split=0.2

# Train the model using on the fly augmentation
history6 = model6.fit(train_generator, batch_size=batch_size, epochs=epochs,␣
↪validation_data=val_generator, validation_split=validation_split, verbose=1)
```

```
Epoch 1/200
250/250 [==============================] - 13s 28ms/step - loss: 1.9662 -
accuracy: 0.2735 - val_loss: 1.9843 - val_accuracy: 0.2840
Epoch 2/200
250/250 [==============================] - 8s 32ms/step - loss: 1.7446 -
accuracy: 0.3545 - val_loss: 1.7260 - val_accuracy: 0.3840
Epoch 3/200
250/250 [==============================] - 6s 26ms/step - loss: 1.6206 -
accuracy: 0.4009 - val_loss: 1.7541 - val_accuracy: 0.3960
Epoch 4/200
250/250 [==============================] - 8s 30ms/step - loss: 1.5320 -
accuracy: 0.4425 - val_loss: 1.6617 - val_accuracy: 0.4305
Epoch 5/200
250/250 [==============================] - 8s 33ms/step - loss: 1.4552 -
accuracy: 0.4629 - val_loss: 1.3950 - val_accuracy: 0.5060
Epoch 6/200
250/250 [==============================] - 6s 26ms/step - loss: 1.3887 -
accuracy: 0.4969 - val_loss: 1.4071 - val_accuracy: 0.4990
Epoch 7/200
250/250 [==============================] - 8s 32ms/step - loss: 1.3256 -
accuracy: 0.5246 - val_loss: 1.3617 - val_accuracy: 0.5115
Epoch 8/200
250/250 [==============================] - 6s 26ms/step - loss: 1.2804 -
accuracy: 0.5399 - val_loss: 1.3171 - val_accuracy: 0.5375
Epoch 9/200
250/250 [==============================] - 8s 32ms/step - loss: 1.2332 -
accuracy: 0.5561 - val_loss: 1.2586 - val_accuracy: 0.5535
Epoch 10/200
250/250 [==============================] - 6s 26ms/step - loss: 1.1895 -
accuracy: 0.5698 - val_loss: 1.2591 - val_accuracy: 0.5590
Epoch 11/200
250/250 [==============================] - 8s 32ms/step - loss: 1.1487 -
accuracy: 0.5865 - val_loss: 1.3483 - val_accuracy: 0.5275
Epoch 12/200
250/250 [==============================] - 8s 31ms/step - loss: 1.0934 -
accuracy: 0.6130 - val_loss: 1.2481 - val_accuracy: 0.5650
Epoch 13/200
250/250 [==============================] - 6s 26ms/step - loss: 1.0585 -
accuracy: 0.6276 - val_loss: 1.2851 - val_accuracy: 0.5675
Epoch 14/200
250/250 [==============================] - 8s 32ms/step - loss: 1.0486 -
accuracy: 0.6306 - val_loss: 1.1619 - val_accuracy: 0.6015
```

```
Epoch 15/200
250/250 [==============================] - 8s 32ms/step - loss: 1.0001 -
accuracy: 0.6421 - val_loss: 1.2230 - val_accuracy: 0.5860
Epoch 16/200
250/250 [==============================] - 6s 26ms/step - loss: 0.9625 -
accuracy: 0.6612 - val_loss: 1.2512 - val_accuracy: 0.5730
Epoch 17/200
250/250 [==============================] - 8s 32ms/step - loss: 0.9419 -
accuracy: 0.6680 - val_loss: 1.1561 - val_accuracy: 0.6145
Epoch 18/200
250/250 [==============================] - 6s 25ms/step - loss: 0.9054 -
accuracy: 0.6808 - val_loss: 1.1628 - val_accuracy: 0.6110
Epoch 19/200
250/250 [==============================] - 8s 32ms/step - loss: 0.8771 -
accuracy: 0.6913 - val_loss: 1.1302 - val_accuracy: 0.6055
Epoch 20/200
250/250 [==============================] - 6s 26ms/step - loss: 0.8529 -
accuracy: 0.7050 - val_loss: 1.0808 - val_accuracy: 0.6250
Epoch 21/200
250/250 [==============================] - 6s 26ms/step - loss: 0.8203 -
accuracy: 0.7095 - val_loss: 1.0931 - val_accuracy: 0.6310
Epoch 22/200
250/250 [==============================] - 8s 32ms/step - loss: 0.8022 -
accuracy: 0.7221 - val_loss: 1.1061 - val_accuracy: 0.6305
Epoch 23/200
250/250 [==============================] - 6s 26ms/step - loss: 0.7885 -
accuracy: 0.7241 - val_loss: 1.1119 - val_accuracy: 0.6230
Epoch 24/200
250/250 [==============================] - 6s 25ms/step - loss: 0.7474 -
accuracy: 0.7414 - val_loss: 1.1160 - val_accuracy: 0.6145
Epoch 25/200
250/250 [==============================] - 7s 27ms/step - loss: 0.7291 -
accuracy: 0.7499 - val_loss: 1.1025 - val_accuracy: 0.6360
Epoch 26/200
250/250 [==============================] - 9s 34ms/step - loss: 0.7000 -
accuracy: 0.7542 - val_loss: 1.0689 - val_accuracy: 0.6625
Epoch 27/200
250/250 [==============================] - 6s 25ms/step - loss: 0.7057 -
accuracy: 0.7531 - val_loss: 1.1513 - val_accuracy: 0.6350
Epoch 28/200
250/250 [==============================] - 8s 32ms/step - loss: 0.6533 -
accuracy: 0.7711 - val_loss: 1.0561 - val_accuracy: 0.6505
Epoch 29/200
250/250 [==============================] - 6s 26ms/step - loss: 0.6456 -
accuracy: 0.7753 - val_loss: 1.0551 - val_accuracy: 0.6535
Epoch 30/200
250/250 [==============================] - 7s 29ms/step - loss: 0.6338 -
accuracy: 0.7754 - val_loss: 1.0848 - val_accuracy: 0.6325
```

```
Epoch 31/200
250/250 [==============================] - 8s 32ms/step - loss: 0.5996 -
accuracy: 0.7910 - val_loss: 1.0249 - val_accuracy: 0.6715
Epoch 32/200
250/250 [==============================] - 6s 25ms/step - loss: 0.5827 -
accuracy: 0.7980 - val_loss: 1.0943 - val_accuracy: 0.6525
Epoch 33/200
250/250 [==============================] - 8s 31ms/step - loss: 0.5708 -
accuracy: 0.8046 - val_loss: 1.0816 - val_accuracy: 0.6485
Epoch 34/200
250/250 [==============================] - 6s 26ms/step - loss: 0.5567 -
accuracy: 0.8026 - val_loss: 1.0918 - val_accuracy: 0.6600
Epoch 35/200
250/250 [==============================] - 8s 32ms/step - loss: 0.5278 -
accuracy: 0.8188 - val_loss: 1.1334 - val_accuracy: 0.6480
Epoch 36/200
250/250 [==============================] - 6s 25ms/step - loss: 0.5248 -
accuracy: 0.8171 - val_loss: 1.1065 - val_accuracy: 0.6595
Epoch 37/200
250/250 [==============================] - 8s 32ms/step - loss: 0.4897 -
accuracy: 0.8316 - val_loss: 1.0948 - val_accuracy: 0.6655
Epoch 38/200
250/250 [==============================] - 8s 33ms/step - loss: 0.4745 -
accuracy: 0.8399 - val_loss: 1.2317 - val_accuracy: 0.6370
Epoch 39/200
250/250 [==============================] - 6s 25ms/step - loss: 0.4717 -
accuracy: 0.8361 - val_loss: 1.2101 - val_accuracy: 0.6380
Epoch 40/200
250/250 [==============================] - 9s 36ms/step - loss: 0.4430 -
accuracy: 0.8491 - val_loss: 1.1272 - val_accuracy: 0.6535
Epoch 41/200
250/250 [==============================] - 6s 25ms/step - loss: 0.4294 -
accuracy: 0.8521 - val_loss: 1.1593 - val_accuracy: 0.6565
Epoch 42/200
250/250 [==============================] - 7s 28ms/step - loss: 0.4259 -
accuracy: 0.8519 - val_loss: 1.2252 - val_accuracy: 0.6580
Epoch 43/200
250/250 [==============================] - 9s 34ms/step - loss: 0.4179 -
accuracy: 0.8576 - val_loss: 1.2428 - val_accuracy: 0.6465
Epoch 44/200
250/250 [==============================] - 6s 25ms/step - loss: 0.4010 -
accuracy: 0.8633 - val_loss: 1.3126 - val_accuracy: 0.6500
Epoch 45/200
250/250 [==============================] - 7s 29ms/step - loss: 0.4017 -
accuracy: 0.8644 - val_loss: 1.1729 - val_accuracy: 0.6750
Epoch 46/200
250/250 [==============================] - 8s 31ms/step - loss: 0.3865 -
accuracy: 0.8666 - val_loss: 1.1813 - val_accuracy: 0.6450
```

```
Epoch 47/200
250/250 [==============================] - 7s 26ms/step - loss: 0.3683 -
accuracy: 0.8714 - val_loss: 1.1927 - val_accuracy: 0.6510
Epoch 48/200
250/250 [==============================] - 6s 25ms/step - loss: 0.3681 -
accuracy: 0.8736 - val_loss: 1.2843 - val_accuracy: 0.6505
Epoch 49/200
250/250 [==============================] - 6s 25ms/step - loss: 0.3426 -
accuracy: 0.8798 - val_loss: 1.1160 - val_accuracy: 0.6765
Epoch 50/200
250/250 [==============================] - 8s 34ms/step - loss: 0.3329 -
accuracy: 0.8855 - val_loss: 1.2022 - val_accuracy: 0.6755
Epoch 51/200
250/250 [==============================] - 6s 25ms/step - loss: 0.3138 -
accuracy: 0.8931 - val_loss: 1.3201 - val_accuracy: 0.6490
Epoch 52/200
250/250 [==============================] - 8s 31ms/step - loss: 0.3323 -
accuracy: 0.8854 - val_loss: 1.1538 - val_accuracy: 0.6735
Epoch 53/200
250/250 [==============================] - 6s 25ms/step - loss: 0.3081 -
accuracy: 0.8953 - val_loss: 1.3795 - val_accuracy: 0.6455
Epoch 54/200
250/250 [==============================] - 6s 25ms/step - loss: 0.3228 -
accuracy: 0.8919 - val_loss: 1.2614 - val_accuracy: 0.6600
Epoch 55/200
250/250 [==============================] - 7s 29ms/step - loss: 0.3013 -
accuracy: 0.8963 - val_loss: 1.2602 - val_accuracy: 0.6635
Epoch 56/200
250/250 [==============================] - 8s 32ms/step - loss: 0.2783 -
accuracy: 0.9021 - val_loss: 1.2891 - val_accuracy: 0.6565
Epoch 57/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2734 -
accuracy: 0.9066 - val_loss: 1.2522 - val_accuracy: 0.6895
Epoch 58/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2742 -
accuracy: 0.9093 - val_loss: 1.2924 - val_accuracy: 0.6625
Epoch 59/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2809 -
accuracy: 0.9041 - val_loss: 1.3221 - val_accuracy: 0.6705
Epoch 60/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2643 -
accuracy: 0.9120 - val_loss: 1.3149 - val_accuracy: 0.6625
Epoch 61/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2698 -
accuracy: 0.9070 - val_loss: 1.2611 - val_accuracy: 0.6780
Epoch 62/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2709 -
accuracy: 0.9075 - val_loss: 1.2879 - val_accuracy: 0.6785
```

```
Epoch 63/200
250/250 [==============================] - 8s 30ms/step - loss: 0.2503 -
accuracy: 0.9120 - val_loss: 1.3843 - val_accuracy: 0.6600
Epoch 64/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2436 -
accuracy: 0.9145 - val_loss: 1.3259 - val_accuracy: 0.6620
Epoch 65/200
250/250 [==============================] - 8s 30ms/step - loss: 0.2503 -
accuracy: 0.9120 - val_loss: 1.3124 - val_accuracy: 0.6805
Epoch 66/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2412 -
accuracy: 0.9179 - val_loss: 1.3079 - val_accuracy: 0.6720
Epoch 67/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2285 -
accuracy: 0.9216 - val_loss: 1.3548 - val_accuracy: 0.6780
Epoch 68/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2256 -
accuracy: 0.9178 - val_loss: 1.3229 - val_accuracy: 0.6830
Epoch 69/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2138 -
accuracy: 0.9284 - val_loss: 1.3362 - val_accuracy: 0.6815
Epoch 70/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2301 -
accuracy: 0.9191 - val_loss: 1.3695 - val_accuracy: 0.6880
Epoch 71/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2110 -
accuracy: 0.9260 - val_loss: 1.3349 - val_accuracy: 0.6765
Epoch 72/200
250/250 [==============================] - 8s 30ms/step - loss: 0.2009 -
accuracy: 0.9320 - val_loss: 1.4230 - val_accuracy: 0.6695
Epoch 73/200
250/250 [==============================] - 6s 25ms/step - loss: 0.2184 -
accuracy: 0.9264 - val_loss: 1.3432 - val_accuracy: 0.6720
Epoch 74/200
250/250 [==============================] - 8s 30ms/step - loss: 0.2079 -
accuracy: 0.9289 - val_loss: 1.3721 - val_accuracy: 0.6620
Epoch 75/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1825 -
accuracy: 0.9367 - val_loss: 1.3184 - val_accuracy: 0.6800
Epoch 76/200
250/250 [==============================] - 8s 31ms/step - loss: 0.2178 -
accuracy: 0.9240 - val_loss: 1.3982 - val_accuracy: 0.6790
Epoch 77/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1954 -
accuracy: 0.9331 - val_loss: 1.2627 - val_accuracy: 0.6880
Epoch 78/200
250/250 [==============================] - 8s 33ms/step - loss: 0.2060 -
accuracy: 0.9314 - val_loss: 1.3160 - val_accuracy: 0.6745
```

```
Epoch 79/200
250/250 [==============================] - 7s 29ms/step - loss: 0.1984 -
accuracy: 0.9330 - val_loss: 1.4538 - val_accuracy: 0.6500
Epoch 80/200
250/250 [==============================] - 6s 24ms/step - loss: 0.1883 -
accuracy: 0.9352 - val_loss: 1.4330 - val_accuracy: 0.6610
Epoch 81/200
250/250 [==============================] - 8s 32ms/step - loss: 0.1844 -
accuracy: 0.9361 - val_loss: 1.4697 - val_accuracy: 0.6720
Epoch 82/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1753 -
accuracy: 0.9402 - val_loss: 1.3816 - val_accuracy: 0.6815
Epoch 83/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1796 -
accuracy: 0.9373 - val_loss: 1.4426 - val_accuracy: 0.6655
Epoch 84/200
250/250 [==============================] - 8s 32ms/step - loss: 0.1731 -
accuracy: 0.9438 - val_loss: 1.4031 - val_accuracy: 0.6830
Epoch 85/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1735 -
accuracy: 0.9415 - val_loss: 1.3797 - val_accuracy: 0.6720
Epoch 86/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1707 -
accuracy: 0.9427 - val_loss: 1.4301 - val_accuracy: 0.6735
Epoch 87/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1643 -
accuracy: 0.9457 - val_loss: 1.3447 - val_accuracy: 0.6980
Epoch 88/200
250/250 [==============================] - 7s 26ms/step - loss: 0.1578 -
accuracy: 0.9479 - val_loss: 1.3500 - val_accuracy: 0.6935
Epoch 89/200
250/250 [==============================] - 8s 34ms/step - loss: 0.1678 -
accuracy: 0.9448 - val_loss: 1.3677 - val_accuracy: 0.6865
Epoch 90/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1437 -
accuracy: 0.9488 - val_loss: 1.4759 - val_accuracy: 0.6840
Epoch 91/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1652 -
accuracy: 0.9423 - val_loss: 1.3913 - val_accuracy: 0.6890
Epoch 92/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1599 -
accuracy: 0.9446 - val_loss: 1.5371 - val_accuracy: 0.6795
Epoch 93/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1483 -
accuracy: 0.9513 - val_loss: 1.3979 - val_accuracy: 0.6885
Epoch 94/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1439 -
accuracy: 0.9510 - val_loss: 1.5539 - val_accuracy: 0.6570
```

```
Epoch 95/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1571 -
accuracy: 0.9463 - val_loss: 1.4068 - val_accuracy: 0.6720
Epoch 96/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1501 -
accuracy: 0.9480 - val_loss: 1.3870 - val_accuracy: 0.6980
Epoch 97/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1422 -
accuracy: 0.9505 - val_loss: 1.4337 - val_accuracy: 0.6720
Epoch 98/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1435 -
accuracy: 0.9531 - val_loss: 1.2875 - val_accuracy: 0.7035
Epoch 99/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1465 -
accuracy: 0.9525 - val_loss: 1.5006 - val_accuracy: 0.6805
Epoch 100/200
250/250 [==============================] - 7s 27ms/step - loss: 0.1361 -
accuracy: 0.9524 - val_loss: 1.4890 - val_accuracy: 0.6750
Epoch 101/200
250/250 [==============================] - 8s 33ms/step - loss: 0.1530 -
accuracy: 0.9503 - val_loss: 1.4286 - val_accuracy: 0.6865
Epoch 102/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1377 -
accuracy: 0.9530 - val_loss: 1.4685 - val_accuracy: 0.6670
Epoch 103/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1453 -
accuracy: 0.9521 - val_loss: 1.3258 - val_accuracy: 0.6905
Epoch 104/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1313 -
accuracy: 0.9569 - val_loss: 1.5206 - val_accuracy: 0.6765
Epoch 105/200
250/250 [==============================] - 9s 35ms/step - loss: 0.1280 -
accuracy: 0.9566 - val_loss: 1.6879 - val_accuracy: 0.6565
Epoch 106/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1443 -
accuracy: 0.9511 - val_loss: 1.4417 - val_accuracy: 0.6810
Epoch 107/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1288 -
accuracy: 0.9576 - val_loss: 1.4352 - val_accuracy: 0.6745
Epoch 108/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1335 -
accuracy: 0.9534 - val_loss: 1.3659 - val_accuracy: 0.7025
Epoch 109/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1182 -
accuracy: 0.9597 - val_loss: 1.5181 - val_accuracy: 0.6790
Epoch 110/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1336 -
accuracy: 0.9506 - val_loss: 1.4993 - val_accuracy: 0.6725
```

```
Epoch 111/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1313 -
accuracy: 0.9546 - val_loss: 1.6057 - val_accuracy: 0.6785
Epoch 112/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1299 -
accuracy: 0.9549 - val_loss: 1.5854 - val_accuracy: 0.6775
Epoch 113/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1198 -
accuracy: 0.9582 - val_loss: 1.5321 - val_accuracy: 0.6795
Epoch 114/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1274 -
accuracy: 0.9545 - val_loss: 1.5809 - val_accuracy: 0.6750
Epoch 115/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1239 -
accuracy: 0.9588 - val_loss: 1.4539 - val_accuracy: 0.6935
Epoch 116/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1125 -
accuracy: 0.9639 - val_loss: 1.3430 - val_accuracy: 0.7045
Epoch 117/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1215 -
accuracy: 0.9567 - val_loss: 1.5814 - val_accuracy: 0.6605
Epoch 118/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1168 -
accuracy: 0.9582 - val_loss: 1.4392 - val_accuracy: 0.6930
Epoch 119/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1199 -
accuracy: 0.9604 - val_loss: 1.4063 - val_accuracy: 0.6865
Epoch 120/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1220 -
accuracy: 0.9544 - val_loss: 1.4826 - val_accuracy: 0.6960
Epoch 121/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1122 -
accuracy: 0.9589 - val_loss: 1.4918 - val_accuracy: 0.6995
Epoch 122/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1124 -
accuracy: 0.9600 - val_loss: 1.5170 - val_accuracy: 0.7000
Epoch 123/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0993 -
accuracy: 0.9646 - val_loss: 1.5441 - val_accuracy: 0.6805
Epoch 124/200
250/250 [==============================] - 9s 34ms/step - loss: 0.0921 -
accuracy: 0.9669 - val_loss: 1.6796 - val_accuracy: 0.6745
Epoch 125/200
250/250 [==============================] - 7s 26ms/step - loss: 0.1079 -
accuracy: 0.9615 - val_loss: 1.6273 - val_accuracy: 0.6855
Epoch 126/200
250/250 [==============================] - 8s 30ms/step - loss: 0.1164 -
accuracy: 0.9611 - val_loss: 1.4160 - val_accuracy: 0.6865
```

```
Epoch 127/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1064 -
accuracy: 0.9631 - val_loss: 1.4943 - val_accuracy: 0.6925
Epoch 128/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1112 -
accuracy: 0.9634 - val_loss: 1.5298 - val_accuracy: 0.6820
Epoch 129/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1112 -
accuracy: 0.9636 - val_loss: 1.5124 - val_accuracy: 0.6975
Epoch 130/200
250/250 [==============================] - 7s 29ms/step - loss: 0.0979 -
accuracy: 0.9661 - val_loss: 1.5886 - val_accuracy: 0.6885
Epoch 131/200
250/250 [==============================] - 7s 28ms/step - loss: 0.1035 -
accuracy: 0.9653 - val_loss: 1.4956 - val_accuracy: 0.6970
Epoch 132/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0977 -
accuracy: 0.9666 - val_loss: 1.5063 - val_accuracy: 0.6845
Epoch 133/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0941 -
accuracy: 0.9676 - val_loss: 1.6598 - val_accuracy: 0.6870
Epoch 134/200
250/250 [==============================] - 8s 32ms/step - loss: 0.1077 -
accuracy: 0.9650 - val_loss: 1.4834 - val_accuracy: 0.6925
Epoch 135/200
250/250 [==============================] - 8s 32ms/step - loss: 0.1106 -
accuracy: 0.9621 - val_loss: 1.4761 - val_accuracy: 0.6765
Epoch 136/200
250/250 [==============================] - 6s 25ms/step - loss: 0.1022 -
accuracy: 0.9640 - val_loss: 1.5534 - val_accuracy: 0.6865
Epoch 137/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0846 -
accuracy: 0.9696 - val_loss: 1.5102 - val_accuracy: 0.6920
Epoch 138/200
250/250 [==============================] - 8s 32ms/step - loss: 0.1186 -
accuracy: 0.9625 - val_loss: 1.5395 - val_accuracy: 0.6790
Epoch 139/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0909 -
accuracy: 0.9680 - val_loss: 1.4023 - val_accuracy: 0.6965
Epoch 140/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0938 -
accuracy: 0.9666 - val_loss: 1.7168 - val_accuracy: 0.6745
Epoch 141/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0969 -
accuracy: 0.9671 - val_loss: 1.5546 - val_accuracy: 0.6880
Epoch 142/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0963 -
accuracy: 0.9669 - val_loss: 1.5304 - val_accuracy: 0.6810
```

```
Epoch 143/200
250/250 [==============================] - 7s 30ms/step - loss: 0.1041 -
accuracy: 0.9661 - val_loss: 1.5001 - val_accuracy: 0.6780
Epoch 144/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0975 -
accuracy: 0.9684 - val_loss: 1.4173 - val_accuracy: 0.6890
Epoch 145/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0896 -
accuracy: 0.9690 - val_loss: 1.5743 - val_accuracy: 0.6930
Epoch 146/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0846 -
accuracy: 0.9705 - val_loss: 1.5820 - val_accuracy: 0.6875
Epoch 147/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0795 -
accuracy: 0.9721 - val_loss: 1.6071 - val_accuracy: 0.6990
Epoch 148/200
250/250 [==============================] - 8s 31ms/step - loss: 0.1062 -
accuracy: 0.9634 - val_loss: 1.6406 - val_accuracy: 0.6805
Epoch 149/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0976 -
accuracy: 0.9676 - val_loss: 1.5904 - val_accuracy: 0.6820
Epoch 150/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0852 -
accuracy: 0.9693 - val_loss: 1.6156 - val_accuracy: 0.6910
Epoch 151/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0949 -
accuracy: 0.9696 - val_loss: 1.6062 - val_accuracy: 0.6790
Epoch 152/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0920 -
accuracy: 0.9697 - val_loss: 1.5550 - val_accuracy: 0.6915
Epoch 153/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0763 -
accuracy: 0.9735 - val_loss: 1.7145 - val_accuracy: 0.6680
Epoch 154/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0927 -
accuracy: 0.9681 - val_loss: 1.5976 - val_accuracy: 0.6815
Epoch 155/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0832 -
accuracy: 0.9720 - val_loss: 1.6294 - val_accuracy: 0.6790
Epoch 156/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0865 -
accuracy: 0.9722 - val_loss: 1.6460 - val_accuracy: 0.6660
Epoch 157/200
250/250 [==============================] - 7s 29ms/step - loss: 0.0923 -
accuracy: 0.9682 - val_loss: 1.4661 - val_accuracy: 0.6900
Epoch 158/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0847 -
accuracy: 0.9705 - val_loss: 1.4814 - val_accuracy: 0.7105
```

```
Epoch 159/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0807 -
accuracy: 0.9720 - val_loss: 1.6523 - val_accuracy: 0.6945
Epoch 160/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0788 -
accuracy: 0.9719 - val_loss: 1.5483 - val_accuracy: 0.6960
Epoch 161/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0797 -
accuracy: 0.9734 - val_loss: 1.7702 - val_accuracy: 0.6795
Epoch 162/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0913 -
accuracy: 0.9696 - val_loss: 1.5399 - val_accuracy: 0.6990
Epoch 163/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0693 -
accuracy: 0.9765 - val_loss: 1.6820 - val_accuracy: 0.6900
Epoch 164/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0906 -
accuracy: 0.9675 - val_loss: 1.5094 - val_accuracy: 0.6860
Epoch 165/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0796 -
accuracy: 0.9750 - val_loss: 1.6429 - val_accuracy: 0.6855
Epoch 166/200
250/250 [==============================] - 8s 34ms/step - loss: 0.0793 -
accuracy: 0.9731 - val_loss: 1.8269 - val_accuracy: 0.6785
Epoch 167/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0756 -
accuracy: 0.9758 - val_loss: 1.6748 - val_accuracy: 0.6730
Epoch 168/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0831 -
accuracy: 0.9730 - val_loss: 1.7025 - val_accuracy: 0.6840
Epoch 169/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0907 -
accuracy: 0.9705 - val_loss: 1.6697 - val_accuracy: 0.6900
Epoch 170/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0772 -
accuracy: 0.9745 - val_loss: 1.5362 - val_accuracy: 0.6750
Epoch 171/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0781 -
accuracy: 0.9729 - val_loss: 1.5495 - val_accuracy: 0.6900
Epoch 172/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0719 -
accuracy: 0.9762 - val_loss: 1.7305 - val_accuracy: 0.6875
Epoch 173/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0693 -
accuracy: 0.9758 - val_loss: 1.8456 - val_accuracy: 0.6760
Epoch 174/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0850 -
accuracy: 0.9732 - val_loss: 1.6759 - val_accuracy: 0.6800
```

```
Epoch 175/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0691 -
accuracy: 0.9762 - val_loss: 1.6909 - val_accuracy: 0.6760
Epoch 176/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0754 -
accuracy: 0.9756 - val_loss: 1.5675 - val_accuracy: 0.6960
Epoch 177/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0660 -
accuracy: 0.9778 - val_loss: 1.8895 - val_accuracy: 0.6695
Epoch 178/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0695 -
accuracy: 0.9746 - val_loss: 1.5969 - val_accuracy: 0.7040
Epoch 179/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0829 -
accuracy: 0.9716 - val_loss: 1.5602 - val_accuracy: 0.6915
Epoch 180/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0666 -
accuracy: 0.9793 - val_loss: 1.5505 - val_accuracy: 0.7000
Epoch 181/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0734 -
accuracy: 0.9743 - val_loss: 1.6936 - val_accuracy: 0.6890
Epoch 182/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0731 -
accuracy: 0.9769 - val_loss: 2.1503 - val_accuracy: 0.6795
Epoch 183/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0693 -
accuracy: 0.9770 - val_loss: 2.2485 - val_accuracy: 0.6770
Epoch 184/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0596 -
accuracy: 0.9796 - val_loss: 1.8052 - val_accuracy: 0.6900
Epoch 185/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0789 -
accuracy: 0.9734 - val_loss: 1.6532 - val_accuracy: 0.6900
Epoch 186/200
250/250 [==============================] - 9s 34ms/step - loss: 0.0697 -
accuracy: 0.9771 - val_loss: 1.6921 - val_accuracy: 0.6925
Epoch 187/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0744 -
accuracy: 0.9756 - val_loss: 1.8383 - val_accuracy: 0.6690
Epoch 188/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0627 -
accuracy: 0.9789 - val_loss: 2.1704 - val_accuracy: 0.6880
Epoch 189/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0725 -
accuracy: 0.9774 - val_loss: 1.6552 - val_accuracy: 0.6985
Epoch 190/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0586 -
accuracy: 0.9805 - val_loss: 1.6979 - val_accuracy: 0.6905
```

```
Epoch 191/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0710 -
accuracy: 0.9771 - val_loss: 2.0778 - val_accuracy: 0.6825
Epoch 192/200
250/250 [==============================] - 8s 32ms/step - loss: 0.0786 -
accuracy: 0.9715 - val_loss: 1.6696 - val_accuracy: 0.6730
Epoch 193/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0692 -
accuracy: 0.9771 - val_loss: 1.6115 - val_accuracy: 0.6855
Epoch 194/200
250/250 [==============================] - 6s 26ms/step - loss: 0.0755 -
accuracy: 0.9745 - val_loss: 1.6868 - val_accuracy: 0.6870
Epoch 195/200
250/250 [==============================] - 7s 27ms/step - loss: 0.0575 -
accuracy: 0.9812 - val_loss: 1.7002 - val_accuracy: 0.6920
Epoch 196/200
250/250 [==============================] - 9s 35ms/step - loss: 0.0633 -
accuracy: 0.9793 - val_loss: 1.7681 - val_accuracy: 0.6905
Epoch 197/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0598 -
accuracy: 0.9812 - val_loss: 1.8148 - val_accuracy: 0.6765
Epoch 198/200
250/250 [==============================] - 8s 31ms/step - loss: 0.0682 -
accuracy: 0.9769 - val_loss: 1.6859 - val_accuracy: 0.6925
Epoch 199/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0670 -
accuracy: 0.9786 - val_loss: 1.8107 - val_accuracy: 0.6925
Epoch 200/200
250/250 [==============================] - 6s 25ms/step - loss: 0.0684 -
accuracy: 0.9755 - val_loss: 2.4986 - val_accuracy: 0.6640
```

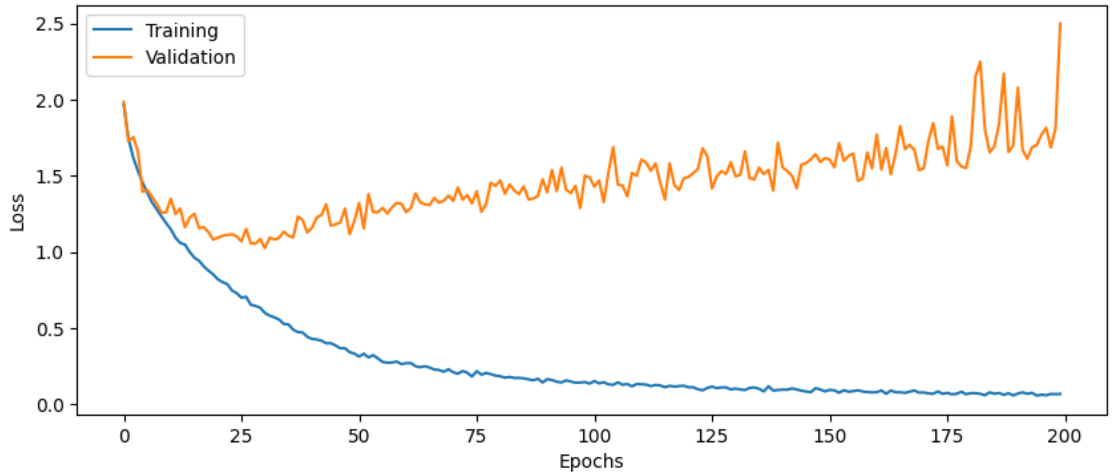
[37]:

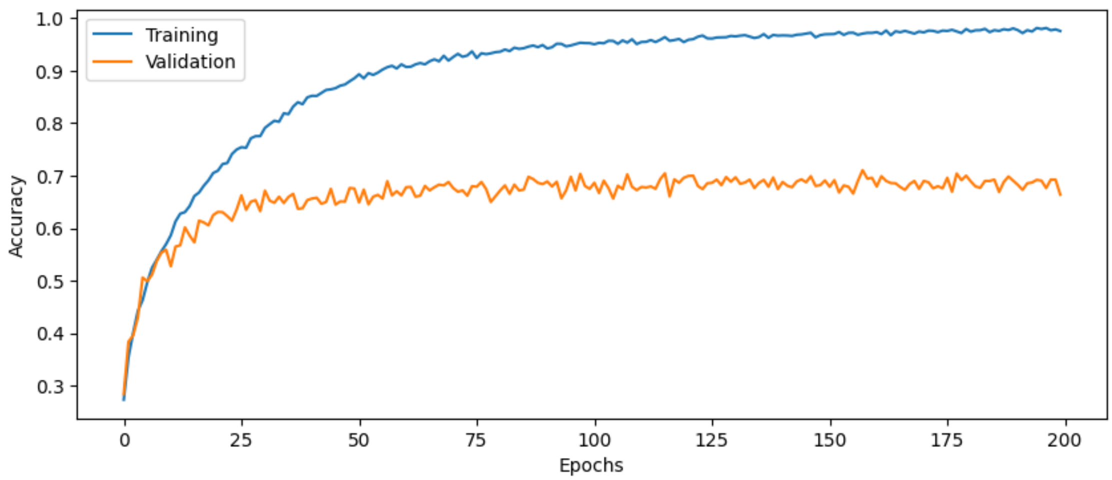
```
# Check if there is still a big difference in accuracy for original and rotated␣
↪test images

# Evaluate the trained model on original test set
score = model6.evaluate(Xtest, Ytest, batch_size = batch_size, verbose=0)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])

# Evaluate the trained model on rotated test set
score = model6.evaluate(Xtest_rotated, Ytest, batch_size = batch_size,␣
↪verbose=0)
print('Test loss: %.4f' % score[0])
print('Test accuracy: %.4f' % score[1])
```

```
Test loss: 2.0024
Test accuracy: 0.6975
Test loss: 5.1765
```

```
Test accuracy: 0.3180
```

[38]:
```
# Plot the history from the training run
plot_results(history6)
```





1.25 Part 20: Plot misclassified images

Lets plot some images where the CNN performed badly, these cells are already finished.

[39]:
```
# Find misclassified images
y_pred=model6.predict(Xtest)
y_pred=np.argmax(y_pred,axis=1)

y_correct = np.argmax(Ytest,axis=-1)
```

```
miss = np.flatnonzero(y_correct != y_pred)
```

```
63/63 [==============================] - 0s 3ms/step
```

[40]:
```
# Plot a few of them
plt.figure(figsize=(15,4))
perm = np.random.permutation(miss)
for i in range(18):
    im = (Xtest[perm[i]] + 1) * 127.5
    im = im.astype('int')
    label_correct = y_correct[perm[i]]
    label_pred = y_pred[perm[i]]

    plt.subplot(3,6,i+1)
    plt.tight_layout()
    plt.imshow(im)
    plt.axis('off')
    plt.title("{}, classified as {}".format(classes[label_correct],␣
 ↪classes[label_pred]))
plt.show()
```

1.26 Part 21: Testing on another size

Question 25: This CNN has been trained on 32 x 32 images, can it be applied to images of another size? If not, why is this the case? **No, it cannot be applied to images of another size. This is because the CNN has been trained on 32x32 images, and therefore it expects the input to be of that size.**

Question 26: Is it possible to design a CNN that can be trained on images of one size, and then applied to an image of any size? How? **Yes, it is possible to design a CNN that can be trained on images of one size, and then applied to an image of any size. This can be done by using a global average pooling layer(a pooling operation designed to replace fully connected layers in classical CNNs) instead of a fully connected layer. This will make the model independent of the input size.**

1.27 Part 22: Pre-trained 2D CNNs

There are many deep 2D CNNs that have been pre-trained using the large ImageNet database (several million images, 1000 classes). Import a pre-trained ResNet50 network from Keras applications. Show the network using `model.summary()`

Question 27: How many convolutional layers does ResNet50 have? **50 convolutional layers**

Question 28: How many trainable parameters does the ResNet50 network have? **approximately 23.5 million trainable parameters**

Question 29: What is the size of the images that ResNet50 expects as input? **input images of size 224x224 pixels**

Question 30: Using the answer to question 28, explain why the second derivative is seldom used when training deep networks. **computing the second-order derivative of the loss function with respect to all 23.5 million parameters in a deep network is computationally expensive. nevertheless it requires more memory.**

Apply the pre-trained CNN to 5 random color images that you download and copy to the cloud machine or your own computer. Are the predictions correct? How certain is the network of each image class?

These pre-trained networks can be fine tuned to your specific data, and normally only the last layers need to be re-trained, but it will still be too time consuming to do in this laboration.

See https://keras.io/api/applications/ and https://keras.io/api/applications/resnet/#resnet50-function

Useful functions

`image.load_img` in tensorflow.keras.preprocessing

`image.img_to_array` in tensorflow.keras.preprocessing

`ResNet50` in tensorflow.keras.applications.resnet50

`preprocess_input` in tensorflow.keras.applications.resnet50

`decode_predictions` in tensorflow.keras.applications.resnet50

`expand_dims` in numpy

[43]:
```
# Your code for using pre-trained ResNet 50 on 5 color images of your choice.
# The preprocessing should transform the image to a size that is expected by␣
↪the CNN.
import tensorflow.keras.preprocessing.image as image
from tensorflow.keras.applications.resnet50 import ResNet50, preprocess_input,␣
↪decode_predictions
from numpy import expand_dims


# define the code above as a function
def predict_image(image_path):
    img = image.load_img(image_path, target_size=(224, 224))
```

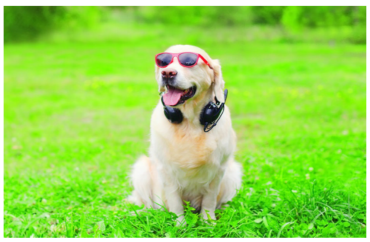
```python
    img = image.img_to_array(img)
    img = expand_dims(img, axis=0)
    img = preprocess_input(img)
    model = ResNet50()
    yhat = model.predict(img)
    label = decode_predictions(yhat)
    label = label[0][0]
    print('%s (%.2f%%)' % (label[1], label[2]*100))

predict_image("/data_DL_tasks/1.jpg")
predict_image("/data_DL_tasks/2.jpg")
predict_image("/data_DL_tasks/3.jpg")
predict_image("/data_DL_tasks/4.jpg")
predict_image("/data_DL_tasks/5.jpg")
```

```
1/1 [==============================] - 1s 1s/step
birdhouse (93.06%)
1/1 [==============================] - 1s 867ms/step
barn (34.20%)
1/1 [==============================] - 1s 914ms/step
borzoi (83.32%)
1/1 [==============================] - 1s 835ms/step
goose (64.14%)
1/1 [==============================] - 1s 854ms/step
hand_blower (23.56%)
```

[42]:

```python
# display the images in a 2x3 grid
plt.figure(figsize=(15,10))
for i in range(1,6):
    plt.subplot(2,3,i+1)
    plt.tight_layout()
    plt.imshow(plt.imread('/data_DL_tasks/{}.jpg'.format(i)))
    plt.axis('off')
```

```
<ipython-input-42-dfb445cefa38>:4: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.
  plt.subplot(2,3,i+1)
```

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