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- ## DSC 650 - Assignment 5.2 Tensorflow Keras Multi-Class Classifier Example

https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/chapter04_getting-started-with-neural-networks.ipynb (https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/chapter04_getting-started-with-neural-networks.ipynb)

There are three custom functions that are attempts at modularizing the books code:

- def build_model - Returns a Dense Sequential model based on input parameters
- def plot_model_history - Plots the loss and accuracy of a model by epoch. Loss should go down, Accuracy should go up
- def plot_model_validation = Plots the Training and Validation lass and accuracy on a model validation set

This topic-classification problem looks similar to the previous movie-review classifica-tion problem: in both cases, you're trying to classify short snippets of text. But there is a new constraint here: the number of output classes has gone from 2 to 46. The dimensionality of the output space is much larger. In a stack of Dense layers like that you've been using, each layer can only access information present in the output of the previous layer. If one layer drops some information relevant to the classification problem, this information can never be recovered by later layers: each layer can potentially become an information bottleneck. In the previous example, you used 16-dimensional intermediate layers, but a 16-dimensional space maybe too limited to learn to separate 46 different classes: such small layers may act as infor-mation bottlenecks, permanently dropping relevant information. For this reason you'll use larger layers. Let's go with 64 units.

There are two other things you should note about this architecture:

- You end the network with a Dense layer of size 46. This means for each inputsample, the network will output a 46-dimensional vector. Each entry in this vector (each dimension) will encode a different output class.
- The last layer uses a softmax activation. You saw this pattern in the MNISTexample. It means the network will output a probability distribution over the 46 different output classes for every input sample, the network will produce a 46-dimensional output vector, where output[i] is the probability that the sample belongs to class i. The 46 scores will sum to 1. The best loss function to use in this case is categorical_crossentropy. It measures the distance between two probability distributions: here, between the probability distribution output by the network and the true distribution of the labels. By minimizing the distance between these two distributions, you train the network to output something as close as possible to the true labels.

## Key Takeaways:

Here's what you should take away from this example:

- If you're trying to classify data points among N classes, your network should endwith a Dense layer of size N.
- In a single-label, multiclass classification problem, your network should endwith a softmax activation so that it will output a probability distribution over theN output classes.
- Categorical crossentropy is almost always the loss function you should use for such problems. It minimizes the distance between the probability distributionsoutput by the network and the true distribution of the targets.

- There are two ways to handle labels in multiclass classification:
  - Encoding the labels via categorical encoding (also known as one-hot encoding) and using **categorical_crossentropy** as a loss function. Keras.utils.to_categorical and to_one_hot() are examples to one hot encode labels.

    Example using keras.utils.to_categorical:

    ```
    from tensorflow.keras.utils import to_categorical
    y_train = to_categorical(train_labels)
    y_test = to_categorical(test_labels)
    ```

    Example: Using custom to_one_hot

    ```
    y_train = to_one_hot(train_labels)
    y_test = to_one_hot(test_labels)
    ```

  - Encoding the labels as integers and using the **sparse_categorical_crossentropy** loss function.

    ```
    y_train = np.array(train_labels)
    y_test = np.array(test_labels)
    ```

- If you need to classify data into a large number of categories, you should avoid creating information bottlenecks in your network due to intermediate layers that are too small.

In [1]:

```
import os
import sys
# //*** Imports and Load Data
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd



from tensorflow import keras
from tensorflow.keras import layers

#//*** Use the whole window in the IPYNB editor
```

```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>
            
#//*** Maximize columns and rows displayed by pandas
pd.set_option('display.max_rows', 100)
```

In [2]:

```
#//*** Utilize Plaid-ml GPU acceleration. Uncomment if using home
from os import environ

#environ["KERAS_BACKEND"] = "plaidml.keras.backend"

```

In [3]:

```
#//*********************************************************
#//*** Attempt to modularize a Sequential Keras Module.
#//*********************************************************
def build_model(**kwargs):
    #//*** Define the Model
    from tensorflow.keras import models
    from tensorflow.keras import layers
    from tensorflow.keras import optimizers


    #//****************************
    #//*** Set Default values
    #//****************************
    total_layers = 2
    hidden_units = 16
    first_activation = "relu"
    final_activation='sigmoid'
    optimizer='rmsprop'
    loss = 'mse'
    metrics=['accuracy']
    shape = None
    do_compile = True
    output_layer = 1

    #//*** Apply Kwargs
    for key,value in kwargs.items():

        if key == 'layers':
            total_layers=value

        if key == 'hidden_units':
            hidden_units=value

        if key == 'loss':
            loss=value

        if key == 'first_activation':
            first_activation=value

        if key == 'final_activation':
            final_activation=value

        if key == 'optimizer':
            optimizer=value
```

```
        if key == 'metrics':
            metrics=value

        if key == 'shape':
            shape = value

        if key == 'compile':
            do_compile = value

        if key == 'output_layer':
            output_layer = value


    model = models.Sequential()

    #//*** Add the First Layer. Include an Input_Shape paramter if
    if shape == None:
        #//*** Add First Layer
        model.add(layers.Dense(hidden_units, activation=first_acti

    else:
        #//*** Add First Layer
        model.add(layers.Dense(hidden_units, activation=first_acti


    #//*** Add Additional Layers if total_layers greater than 2
    for x in range(total_layers-2):

        #//*** These are basic layers with same number of hidden u
        model.add(layers.Dense(hidden_units, activation=first_acti



    #//*** Add Final Layer
    model.add(layers.Dense(output_layer, activation=final_activati

    #//*** Compile Model
    if do_compile:

        model.compile(optimizer=optimizer,loss=loss,metrics=metric

    return model

```

In [4]:

```
#//*************************************************************
#//*** Plot a Fitted Models History of Loss and Accuracy
#//*************************************************************
def plot_model_history(input_history):
    loss = input_history.history['loss']
    acc = input_history.history['accuracy']


    epochs = range(1, len(loss) + 1)
    plt.plot(epochs, acc, "b", label="Training Accuracy")
    plt.title("Training Accuracy\nAccuracy should go up")
```

```
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()

    epochs = range(1, len(loss) + 1)
    plt.plot(epochs, loss, "bo", label="Training Loss")

    plt.title("Training Loss \nLoss should go down")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()

#//*************************************************************
#//*** Plot a Fitted Models History Training and Validation Loss
#//*************************************************************
def plot_model_validation(input_history):
    loss = input_history.history["loss"]
    val_loss = input_history.history["val_loss"]
    epochs = range(1, len(loss) + 1)
    plt.plot(epochs, loss, "bo", label="Training loss")
    plt.plot(epochs, val_loss, "b", label="Validation loss")
    plt.title("Training and validation loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()

    #//*** Plot the Validation Set Accuracy
    plt.clf()
    acc = input_history.history["accuracy"]
    val_acc = input_history.history["val_accuracy"]
    plt.plot(epochs, acc, "bo", label="Training accuracy")
    plt.plot(epochs, val_acc, "b", label="Validation accuracy")
    plt.title("Training and validation accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
```

# Classifying Newswires: A Multiclass classification example

Import the Reuters news wires data set from Keras. Data returns a Sparse Matrix of textual news wires that are categorizes by 46 categorizes.

In [42]:

```
#//*** Load this twice to remove deprecatation warnings
from tensorflow.keras.datasets import reuters
(train_data, train_labels), (test_data, test_labels) = reuters.loa
    num_words=10000)
```

In [6]:

```
#//*** Peek at the data
print(len(train_data))
print(len(test_data))
```

```
print(train_data[0])
print()
```

```
8982
2246
[1, 2, 2, 8, 43, 10, 447, 5, 25, 207, 270, 5, 3095, 111, 16, 369, 18
6, 90, 67, 7, 89, 5, 19, 102, 6, 19, 124, 15, 90, 67, 84, 22, 482, 2
6, 7, 48, 4, 49, 8, 864, 39, 209, 154, 6, 151, 6, 83, 11, 15, 22, 15
5, 11, 15, 7, 48, 9, 4579, 1005, 504, 6, 258, 6, 272, 11, 15, 22, 13
4, 44, 11, 15, 16, 8, 197, 1245, 90, 67, 52, 29, 209, 30, 32, 132, 6,
109, 15, 17, 12]

[ 3  4  3  4  4  4  4  3  3 16  3  3  4  4 19  8 16  3  3 21 11  4  4
3
  3  1  3  1  3 16  1  4 13 20  1  4  4 11  3  3  3 11 16  4  4 20 18
25
 19  3  4  3  4  3  4  3  3  4  4  3  4  4  3 19 35  8  4  4  3 16 25
3
 11  3  9 16 38 10  4  4  9  3  3 28 20  3  3  3  3  3  4  4  3  4  2
3
  1  3 19  4]
```

In [7]:

```
#//*** Decode News Wires Back From Text
#//*** Can convert the sparse matrix back to text if needed
word_index = reuters.get_word_index()
reverse_word_index = dict([(value, key) for (key, value) in word_i
decoded_newswire = " ".join([reverse_word_index.get(i - 3, "?") fo
```

In [8]:

```
#//*****************************************************************
#//*** Prepare the Data Using Vectorize sequences.
#//*** Each word is encoded into a 10,000 character string of zero
#//*** to 1 representing a specific word. Each element of the data
#//*** Strings.
#//*** This is essentially a manual conversion of a sparse one-hot
#//*** The dense matrix is a collection of tensors
#//*****************************************************************
#//*** Lists of integers must be converted into tensors.
def vectorize_sequences(sequences, dimension=10000):
    #//*** Builds zero filled matrix of shape dimension
    results = np.zeros((len(sequences), dimension))

    #//*** Assigns 1s to the specific integer for references.
    #//*** This is manual one-hot encoding
    for i, sequence in enumerate(sequences):

        for j in sequence:
            results[i, j] = 1.

    return results

#//*** Encode the Labels. Similar to vectorize_sequences except it

def to_one_hot(labels, dimension=46):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1.
```

```
    return results
```

In [43]:

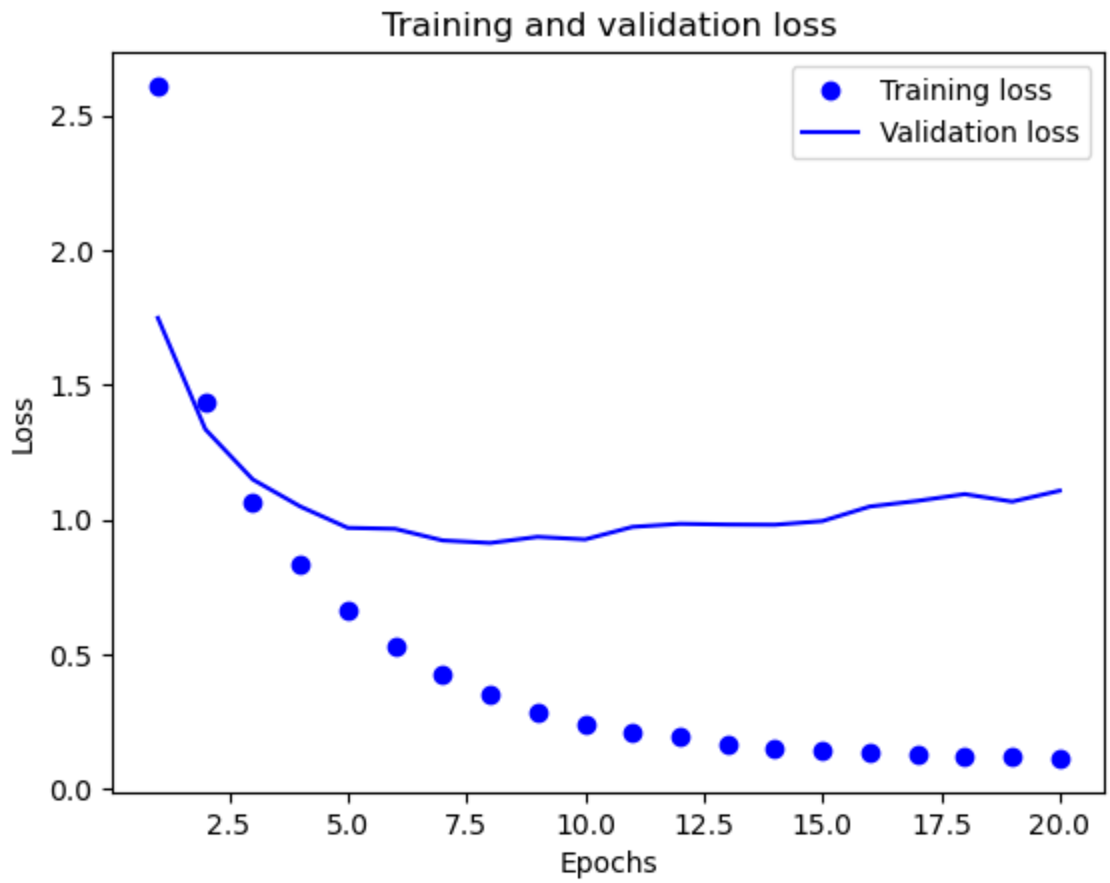
```

#//*** Encode the data to tensors (dense one-hot-encoded matrix)
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)

#//*** One hot encode the labels (could also use keras.utils.to_ca
y_train = to_one_hot(train_labels)
y_test = to_one_hot(test_labels)

```

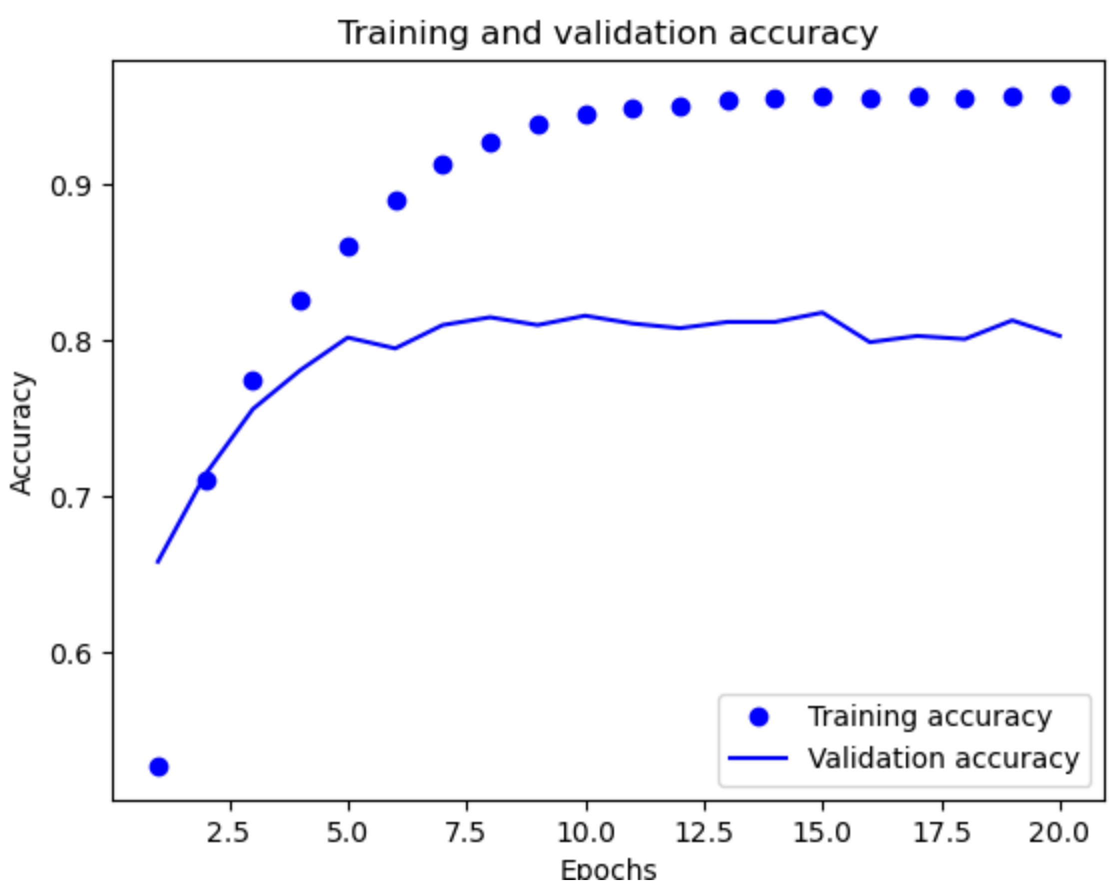
In [11]:

```
#//*** Test/Evaluate the model on a smaller subset to get a feel f
#//*** Allocate a validation subset
x_val = x_train[:1000]
partial_x_train = x_train[1000:]
y_val = y_train[:1000]
partial_y_train = y_train[1000:]

#//****************************
#//*** Book Supplied Settings
#//****************************
layers = 3
hidden_units = 64
first_activation = "relu"
final_activation = "softmax"
optimizer = "rmsprop"
loss = 'categorical_crossentropy'
model = build_model(
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,
    metrics=['accuracy'],
    #//*** Categorical Classifier, the Findal Layer should be equa
    output_layer = (np.max(train_labels) + 1)
)

#//*** Train Model on the validation set


history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))


```

```
Epoch 1/20
16/16 [==============================] - 0s 21ms/step - loss: 2.7340
- accuracy: 0.5180 - val_loss: 1.8350 - val_accuracy: 0.6230
Epoch 2/20
16/16 [==============================] - 0s 12ms/step - loss: 1.4978
- accuracy: 0.6896 - val_loss: 1.3589 - val_accuracy: 0.6990
Epoch 3/20
16/16 [==============================] - 0s 12ms/step - loss: 1.1060
- accuracy: 0.7616 - val_loss: 1.1725 - val_accuracy: 0.7640
Epoch 4/20
16/16 [==============================] - 0s 12ms/step - loss: 0.8666
- accuracy: 0.8247 - val_loss: 1.0531 - val_accuracy: 0.7890
Epoch 5/20
16/16 [==============================] - 0s 12ms/step - loss: 0.6873
- accuracy: 0.8631 - val_loss: 0.9854 - val_accuracy: 0.8050
Epoch 6/20
16/16 [==============================] - 0s 12ms/step - loss: 0.5485
- accuracy: 0.8901 - val_loss: 0.9542 - val_accuracy: 0.8130
Epoch 7/20
16/16 [==============================] - 0s 13ms/step - loss: 0.4391
- accuracy: 0.9082 - val_loss: 0.8942 - val_accuracy: 0.8170
Epoch 8/20
16/16 [==============================] - 0s 13ms/step - loss: 0.3549
- accuracy: 0.9278 - val_loss: 0.8886 - val_accuracy: 0.8210
Epoch 9/20
16/16 [==============================] - 0s 14ms/step - loss: 0.2943
- accuracy: 0.9369 - val_loss: 0.8907 - val_accuracy: 0.8190
Epoch 10/20
16/16 [==============================] - 0s 13ms/step - loss: 0.2473
- accuracy: 0.9445 - val_loss: 0.8983 - val_accuracy: 0.8250
Epoch 11/20
16/16 [==============================] - 0s 13ms/step - loss: 0.2154
- accuracy: 0.9470 - val_loss: 0.9332 - val_accuracy: 0.8170
Epoch 12/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1881
- accuracy: 0.9504 - val_loss: 0.9167 - val_accuracy: 0.8270
Epoch 13/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1702
- accuracy: 0.9553 - val_loss: 0.9651 - val_accuracy: 0.8050
Epoch 14/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1528
- accuracy: 0.9529 - val_loss: 0.9722 - val_accuracy: 0.8170
Epoch 15/20
16/16 [==============================] - 0s 13ms/step - loss: 0.1435
- accuracy: 0.9551 - val_loss: 0.9966 - val_accuracy: 0.8100
Epoch 16/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1316
- accuracy: 0.9565 - val_loss: 1.0004 - val_accuracy: 0.8050
Epoch 17/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1252
- accuracy: 0.9568 - val_loss: 1.0278 - val_accuracy: 0.8100
Epoch 18/20
16/16 [==============================] - 0s 12ms/step - loss: 0.1253
- accuracy: 0.9580 - val_loss: 1.0228 - val_accuracy: 0.8170
Epoch 19/20
```

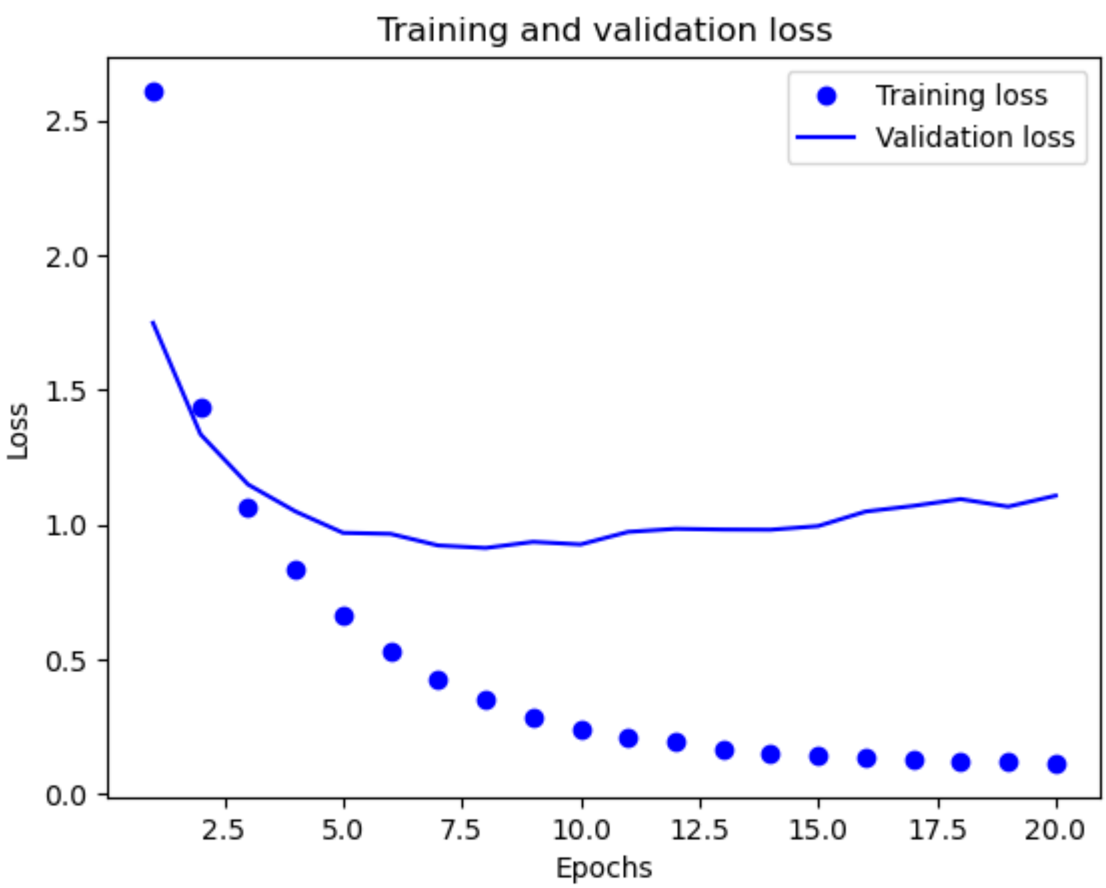
In [41]:

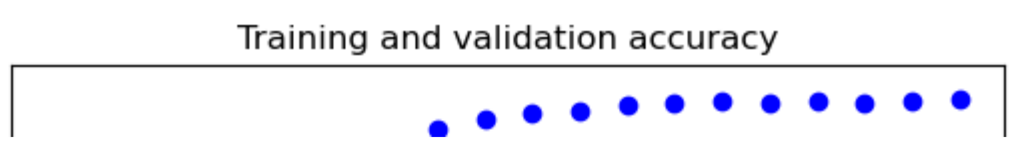

Training and validation loss
Training loss
Validation loss
Loss
Epochs
0.0
0.5
1.0
1.5
2.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

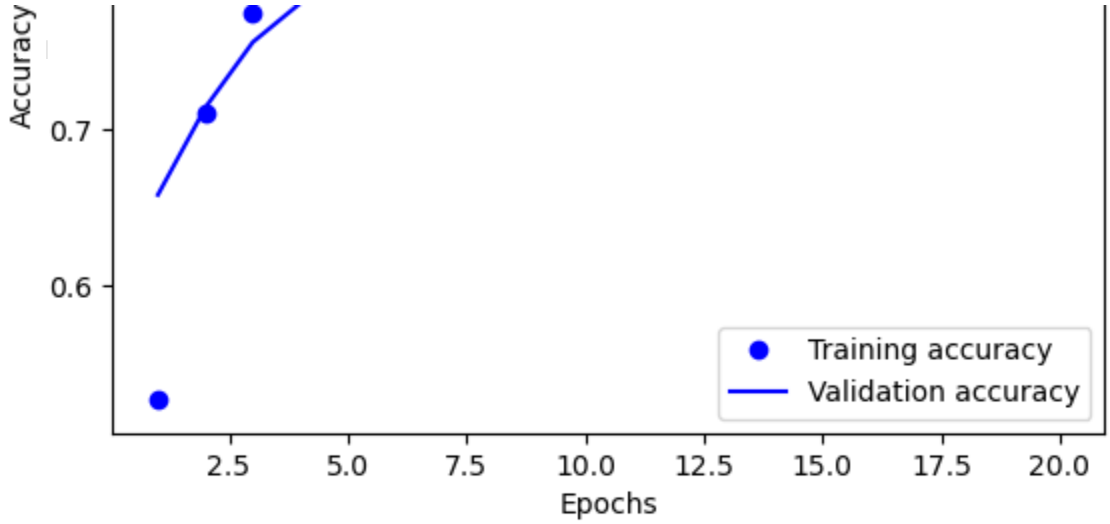

Training and validation accuracy
Training accuracy
Validation accuracy
Accuracy
Epochs
0.6
0.7
0.8
0.9
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

In [40]:

```
#//*** Plot the Validation Set Loss

loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

#//*** Plot the Validation Set Accuracy
plt.clf()
acc = history.history["accuracy"]
val_acc = history.history["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training accuracy")
plt.plot(epochs, val_acc, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```




Accuracy
0.7
0.6
Training accuracy
Validation accuracy
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs

In [39]:

```
Epoch 1/20
16/16 [==============================] - 0s 20ms/step - loss: 2.6100
- accuracy: 0.5268 - val_loss: 1.7485 - val_accuracy: 0.6580
Epoch 2/20
16/16 [==============================] - 0s 12ms/step - loss: 1.4363
- accuracy: 0.7106 - val_loss: 1.3349 - val_accuracy: 0.7140
Epoch 3/20
```

In [ ]:

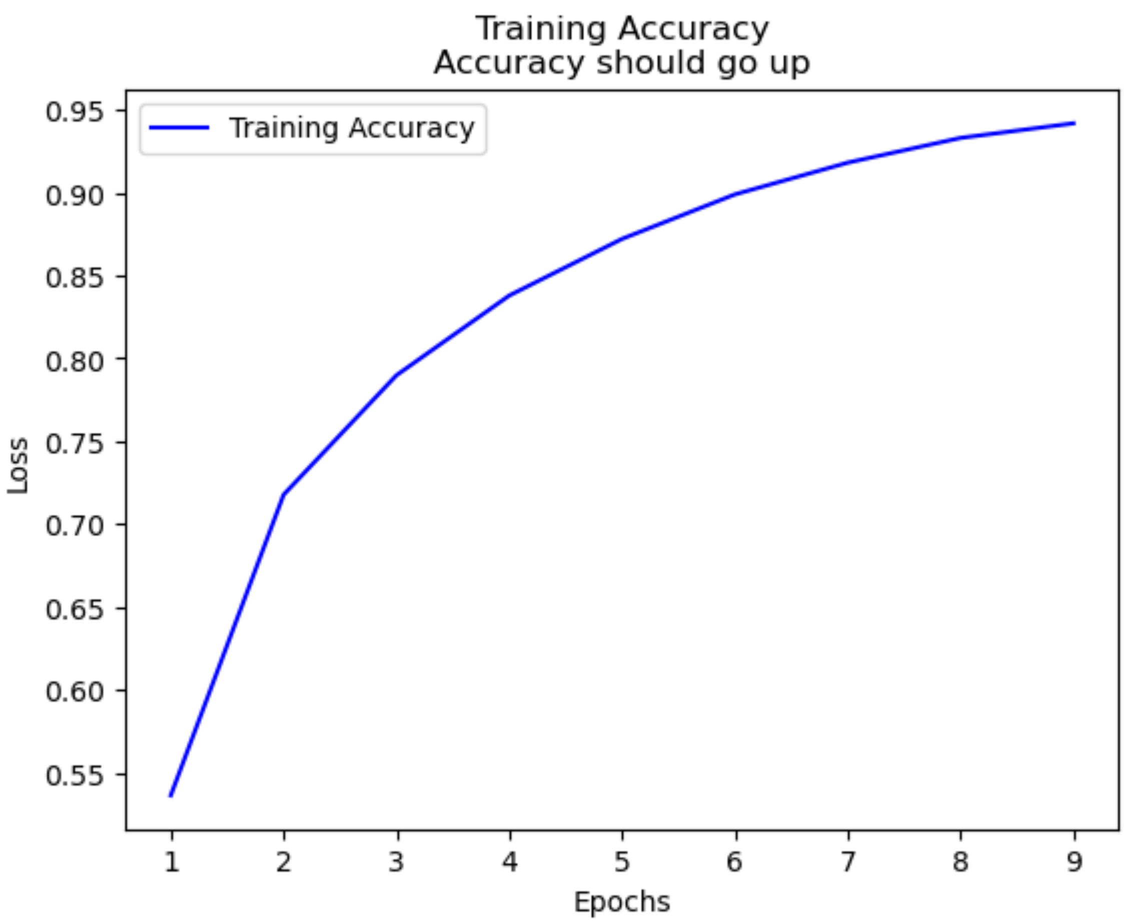
In [28]:

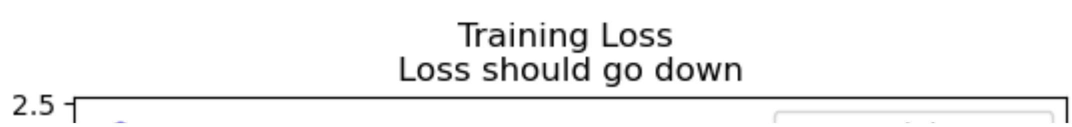
```
0.0
```

In [38]:

```python
#//*** Encode Labels using Keras to_categorical. Returns Sparse Ma
from tensorflow.keras.utils import to_categorical
y_train = to_categorical(train_labels)
y_test = to_categorical(test_labels)
#//*** Use Loss Functions 'categorical_crossentropy' for Sparse Ma
#//*** Displays labels
print(y_train[0])

#//***************************
#//*** Book Supplied Settings
#//***************************
layers = 3
hidden_units = 64
first_activation = "relu"
final_activation = "softmax"
optimizer = "rmsprop"
loss = 'categorical_crossentropy'
model = build_model(
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy'],
    #//*** Categorical Classifier, the Findal Layer should be equa
    output_layer = (np.max(train_labels) + 1)
)
history = model.fit(x_train,
          y_train,
          epochs=9,
          batch_size=512)

plot_model_history(history)

results = model.evaluate(x_test, y_test)
```

```
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Epoch 1/9
18/18 [==============================] - 0s 11ms/step - loss: 2.4112
- accuracy: 0.5364
Epoch 2/9
18/18 [==============================] - 0s 11ms/step - loss: 1.3060
- accuracy: 0.7178
Epoch 3/9
18/18 [==============================] - 0s 10ms/step - loss: 0.9742
- accuracy: 0.7898
Epoch 4/9
18/18 [==============================] - 0s 12ms/step - loss: 0.7572
- accuracy: 0.8379
Epoch 5/9
18/18 [==============================] - 0s 11ms/step - loss: 0.5966
- accuracy: 0.8721
Epoch 6/9
18/18 [==============================] - 0s 11ms/step - loss: 0.4706
- accuracy: 0.8989
Epoch 7/9
18/18 [==============================] - 0s 11ms/step - loss: 0.3837
- accuracy: 0.9181
```

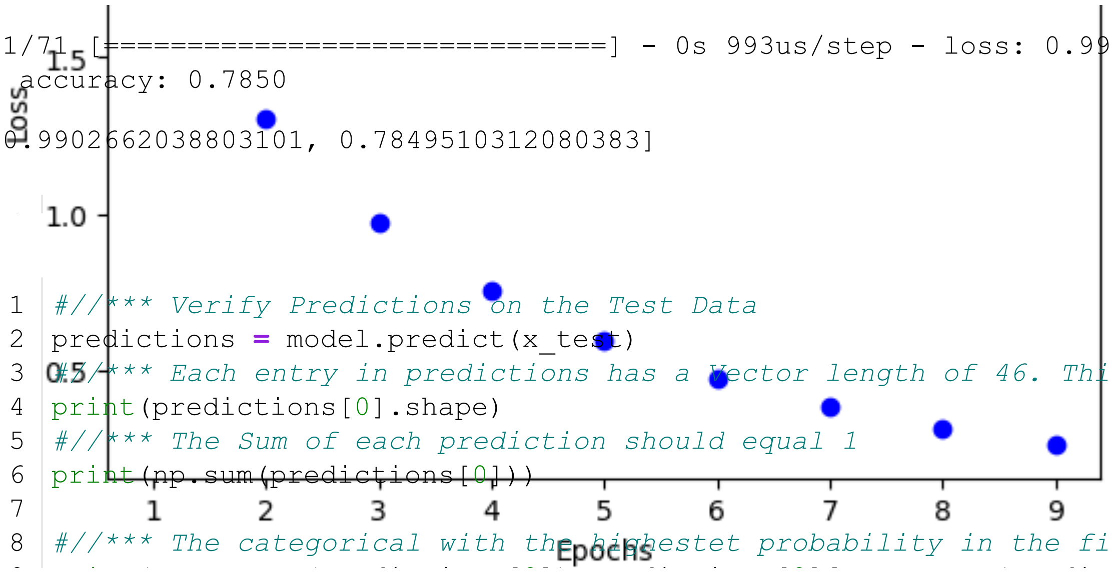


```
71/71 [==============================] - 0s 993us/step - loss: 0.9903
- accuracy: 0.7850
```

Out[38]:
```
[0.9902662038803101, 0.7849510312080383]
```

In [ ]:

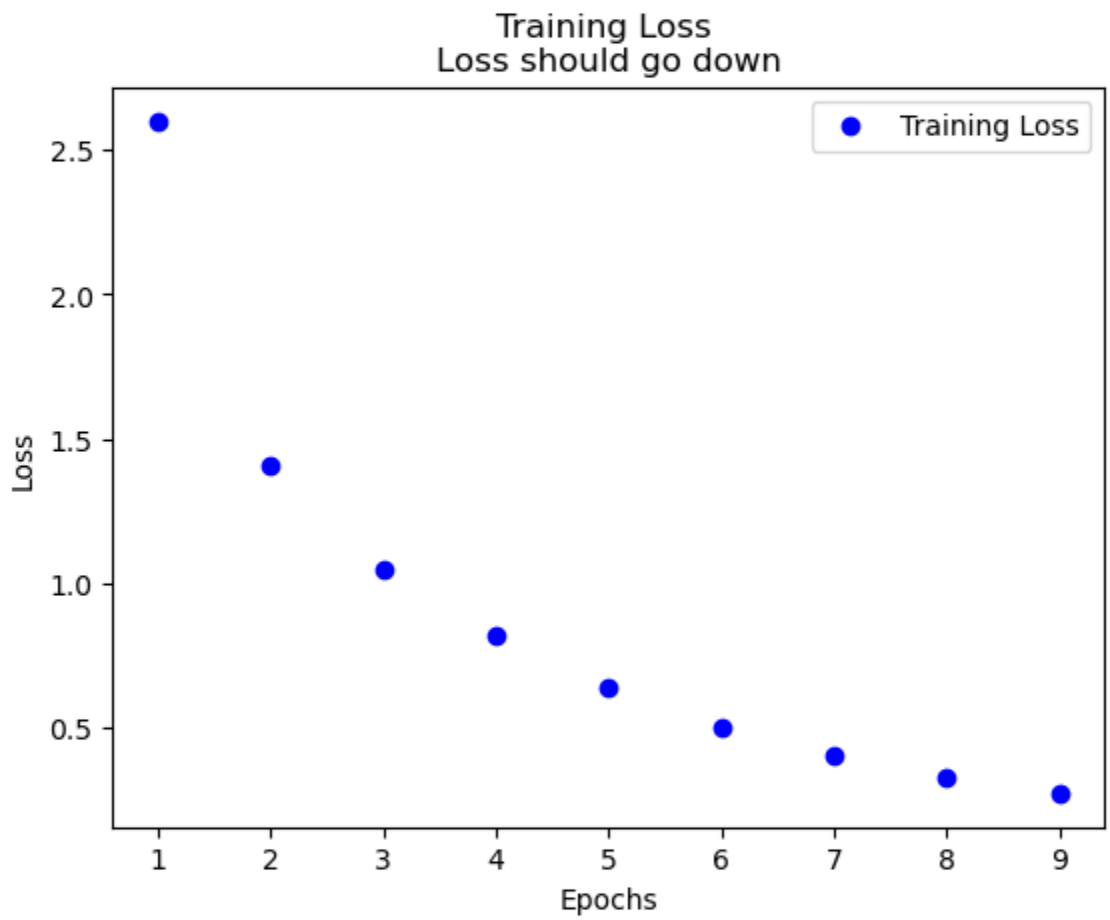



In [22]:
```
#//*** Verify Predictions on the Test Data
predictions = model.predict(x_test)
#//*** Each entry in predictions has a vector length of 46. This m
print(predictions[0].shape)
#//*** The Sum of each prediction should equal 1
print(np.sum(predictions[0]))

#//*** The categorical with the highestet probability in the first
```

```
(46,)
1.0000001
3 0.80857974
```

In [37]:
```
#//*** Alternate Label encoding
#//*** This method casts as an integer tensor (instead of a sparse
y_train = np.array(train_labels)
y_test = np.array(test_labels)
#//*** #For integer Labels - The loss function should be 'sparse_c

print(y_train[0])

#//****************************
#//*** Book Supplied Settings
#//****************************
layers = 3
hidden_units = 64
first_activation = "relu"
final_activation = "softmax"
optimizer = "rmsprop"
loss = 'sparse_categorical_crossentropy'
model = build_model(
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy'],
    #//*** Categorical Classifier, the Findal Layer should be equa
    output_layer = (np.max(train_labels) + 1)
)
history = model.fit(x_train,
          y_train,
          epochs=9,
          batch_size=512)

plot_model_history(history)

results = model.evaluate(x_test, y_test)
```

```
3
Epoch 1/9
18/18 [==============================] - 0s 11ms/step - loss: 2.5998
- accuracy: 0.5460
Epoch 2/9
18/18 [==============================] - 0s 11ms/step - loss: 1.4071
- accuracy: 0.7035
Epoch 3/9
18/18 [==============================] - 0s 11ms/step - loss: 1.0446
- accuracy: 0.7707
Epoch 4/9
18/18 [==============================] - 0s 11ms/step - loss: 0.8159
- accuracy: 0.8282
Epoch 5/9
18/18 [==============================] - 0s 10ms/step - loss: 0.6373
- accuracy: 0.8664
Epoch 6/9
18/18 [==============================] - 0s 11ms/step - loss: 0.5009
- accuracy: 0.8978
Epoch 7/9
18/18 [==============================] - 0s 11ms/step - loss: 0.4004
- accuracy: 0.9157
Epoch 8/9
18/18 [==============================] - 0s 10ms/step - loss: 0.3234
- accuracy: 0.9297
Epoch 9/9
18/18 [==============================] - 0s 9ms/step - loss: 0.2704 -
accuracy: 0.9380
```




```
71/71 [==============================] - 0s 985us/step - loss: 0.9178
- accuracy: 0.7956
```

Out[37]: [0.9177604913711548, 0.7956367135047913]

## Further experiments

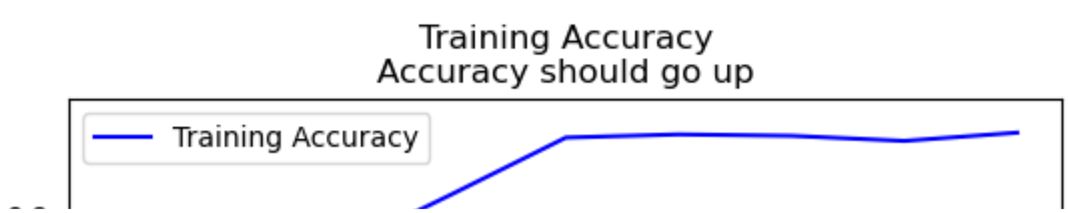
- Try using larger or smaller layers: 32 units, 128 units, and so on.
- You used two hidden layers. Now try using a single hidden layer, or three hidden layers.

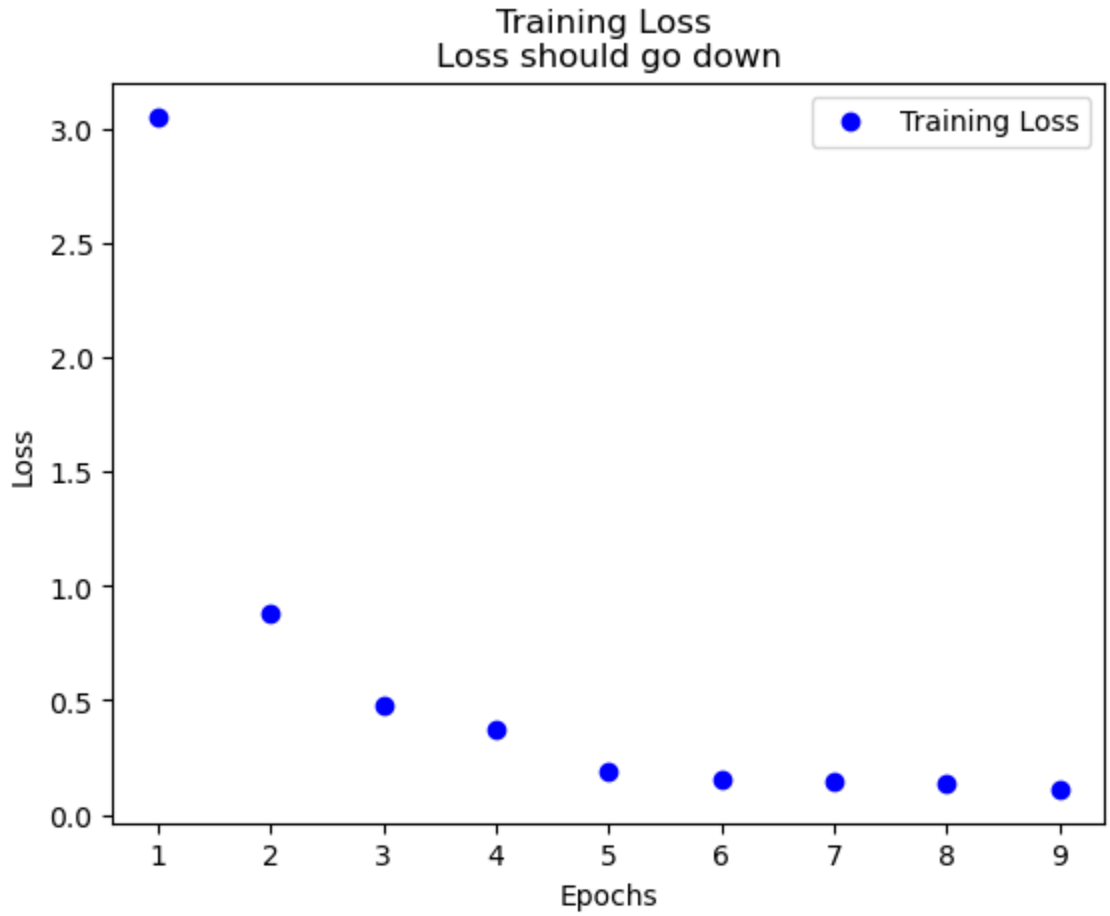
In [44]:

```
#//*** Try a larger layer

#//*** Encode Labels using Keras to_categorical. Returns Sparse Ma
from tensorflow.keras.utils import to_categorical
y_train = to_categorical(train_labels)
y_test = to_categorical(test_labels)
#//*** Use Loss Functions 'categorical_crossentropy' for Sparse Ma
#//*** Displays labels
print(y_train[0])

layers = 3
hidden_units = 5000
first_activation = "relu"
final_activation = "softmax"
```

```
optimizer = "rmsprop"
loss = 'categorical_crossentropy'
model = build_model(
    layers=layers,
    hidden_units = hidden_units,
    first_activation = first_activation,
    final_activation=final_activation,
    optimizer=optimizer,
    loss=loss,metrics=['accuracy'],
    #//*** Categorical Classifier, the Findal Layer should be equa
    output_layer = (np.max(train_labels) + 1)
)
history = model.fit(x_train,
            y_train,
            epochs=9,
            batch_size=512)

plot_model_history(history)

results = model.evaluate(x_test, y_test)
```

```
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Epoch 1/9
18/18 [==============================] - 11s 592ms/step - loss: 3.055
0 - accuracy: 0.5257
Epoch 2/9
18/18 [==============================] - 11s 598ms/step - loss: 0.878
6 - accuracy: 0.7915
Epoch 3/9
18/18 [==============================] - 11s 636ms/step - loss: 0.474
8 - accuracy: 0.8789
Epoch 4/9
18/18 [==============================] - 12s 651ms/step - loss: 0.371
0 - accuracy: 0.9137
Epoch 5/9
18/18 [==============================] - 12s 649ms/step - loss: 0.192
7 - accuracy: 0.9492
Epoch 6/9
18/18 [==============================] - 12s 654ms/step - loss: 0.156
3 - accuracy: 0.9512
Epoch 7/9
18/18 [==============================] - 12s 649ms/step - loss: 0.146
2 - accuracy: 0.9503
Epoch 8/9
18/18 [==============================] - 12s 652ms/step - loss: 0.136
8 - accuracy: 0.9471
Epoch 9/9
18/18 [==============================] - 12s 652ms/step - loss: 0.110
6 - accuracy: 0.9523
```






```
71/71 [==============================] - 2s 23ms/step - loss: 1.4691
- accuracy: 0.7845
```

Out[44]:
```
[1.4690574407577515, 0.7845057845115662]
```

In [45]:

Out[45]:
```
array([[2.3098184e-05, 1.1434501e-04, 3.0994298e-07, ..., 4.3895230e-
07,
         3.3933580e-09, 1.0391491e-08],
        [2.6360143e-02, 1.1021660e-01, 4.7626547e-03, ..., 1.3227408e-
03,
         4.1350038e-04, 1.9265359e-03],
        [7.3221745e-03, 7.4792886e-01, 1.0115582e-03, ..., 4.5362267e-
05,
         2.4255909e-05, 4.8168622e-05],
        ...,
        [1.7279215e-18, 7.5388534e-13, 7.4093282e-21, ..., 6.0184257e-
24,
         2.9832300e-29, 4.4508605e-26],
        [1.5984932e-02, 8.8159055e-02, 4.5590354e-03, ..., 2.4482547e-
03,
         5.4147886e-04, 1.2020848e-03],
        [3.0369174e-03, 5.2485794e-01, 3.6196187e-03, ..., 7.6811921e-
05,
         1.3787427e-05, 3.5026849e-05]], dtype=float32)
```

In [ ]:

In [ ]: