alzheimer-s-detection-sequential

March 28, 2024

[1]:
```python
import os
import cv2
import itertools
import numpy as np
import pandas as pd

test_dir = "/kaggle/input/alzheimers-dataset-4-class-of-images/Alzheimer_s␣
↪Dataset/test/"
train_dir = "/kaggle/input/alzheimers-dataset-4-class-of-images/Alzheimer_s␣
↪Dataset/train/"

data = []
```

[2]:
```python
for dirtrain in os.listdir(train_dir):
    print(dirtrain)
    for tr in os.listdir(train_dir + dirtrain):
        img = cv2.imread(train_dir + dirtrain + "/" + tr)
        img = cv2.resize(img, (32, 32))
        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
        img = img.reshape(32, 32, 1)

        data.append([img, dirtrain])
```

```
ModerateDemented
NonDemented
VeryMildDemented
MildDemented
```

[3]:
```python
for dirtest in  os.listdir(test_dir):
    print(dirtest)
    for ts in os.listdir(test_dir + dirtest):
        img = cv2.imread(test_dir + dirtest + "/" + ts)
        img = cv2.resize(img, (32, 32))
        img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
        img = img.reshape(32, 32, 1)

        data.append([img, dirtest])
```

```
ModerateDemented
NonDemented
VeryMildDemented
MildDemented
```

[4]:
```
import random
random.seed(20)
```

[5]:
```
random.shuffle(data)
```

[6]:
```
x, y = [], []
for e in data:
    x.append(e[0])
    y.append(e[1])
```

[7]:
```
from sklearn.preprocessing import OneHotEncoder

x = np.array(x)
y = np.array(y)
y = y.reshape(y.shape[0],1)
enc = OneHotEncoder(handle_unknown='ignore').fit(y)
print(enc.categories_)
y = enc.transform(y).toarray()
print(f'Data   :   {str(x.shape)}')
print(f'Labels :   {str(y.shape)}')
```

```
[array(['MildDemented', 'ModerateDemented', 'NonDemented',
       'VeryMildDemented'], dtype='<U16')]
Data   :   (6400, 32, 32, 1)
Labels :   (6400, 4)
```

[8]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=1,␣
 ↪test_size=0.2)
```

[9]:
```
import tensorflow as tf
```

```
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/__init__.py:98:
UserWarning: unable to load libtensorflow_io_plugins.so: unable to open file:
libtensorflow_io_plugins.so, from paths: ['/opt/conda/lib/python3.10/site-
packages/tensorflow_io/python/ops/libtensorflow_io_plugins.so']
caused by: ['/opt/conda/lib/python3.10/site-
packages/tensorflow_io/python/ops/libtensorflow_io_plugins.so: undefined symbol:
_ZN3tsl6StatusC1EN10tensorflow5error4CodeESt17basic_string_viewIcSt11char_traits
IcEENS_14SourceLocationE']
  warnings.warn(f"unable to load libtensorflow_io_plugins.so: {e}")
/opt/conda/lib/python3.10/site-
```

```
packages/tensorflow_io/python/ops/__init__.py:104: UserWarning: file system
plugins are not loaded: unable to open file: libtensorflow_io.so, from paths:
['/opt/conda/lib/python3.10/site-
packages/tensorflow_io/python/ops/libtensorflow_io.so']
caused by: ['/opt/conda/lib/python3.10/site-
packages/tensorflow_io/python/ops/libtensorflow_io.so: undefined symbol:
_ZTVN10tensorflow13GcsFileSystemE']
  warnings.warn(f"file system plugins are not loaded: {e}")
```

[10]:
```
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
print(tf.config.list_physical_devices('GPU'))
```

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU'),
PhysicalDevice(name='/physical_device:GPU:1', device_type='GPU')]
```

[11]:
```
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense,Conv2D,MaxPooling2D,Flatten,Dropout,␣
 ↪BatchNormalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator


model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(64, (4, 4), padding='same', activation=tf.nn.relu,
    input_shape=(32, 32, 1)),
    tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2)), Dropout(0.25),

    tf.keras.layers.Conv2D(128, (3,3), padding='same', activation=tf.nn.relu),
    tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2)),
    Dropout(0.25),

    tf.keras.layers.Conv2D(128, (3,3), padding='same', activation=tf.nn.relu),
    tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2)),
    Dropout(0.3),

    tf.keras.layers.Conv2D(128, (2,2), padding='same', activation=tf.nn.relu),
    tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2)),
    Dropout(0.3),

    tf.keras.layers.Conv2D(256, (2,2), padding='same', activation=tf.nn.relu),
    tf.keras.layers.MaxPooling2D((2, 2), strides=(2,2)),
    Dropout(0.3),

    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation=tf.nn.relu),
```

```
    tf.keras.layers.Dense(4,  activation=tf.nn.softmax)
])
```

[12]:
```
model.summary()
```

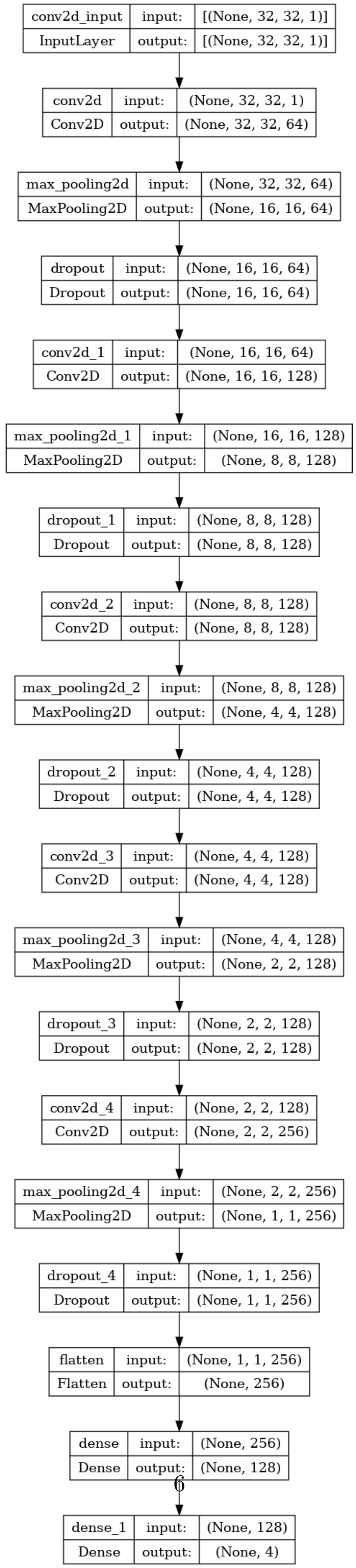
```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 64)        1088      
                                                                 
 max_pooling2d (MaxPooling2D  (None, 16, 16, 64)       0         
 )                                                               
                                                                 
 dropout (Dropout)           (None, 16, 16, 64)        0         
                                                                 
 conv2d_1 (Conv2D)           (None, 16, 16, 128)       73856     
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 8, 8, 128)        0         
 2D)                                                             
                                                                 
 dropout_1 (Dropout)         (None, 8, 8, 128)         0         
                                                                 
 conv2d_2 (Conv2D)           (None, 8, 8, 128)         147584    
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0         
 2D)                                                             
                                                                 
 dropout_2 (Dropout)         (None, 4, 4, 128)         0         
                                                                 
 conv2d_3 (Conv2D)           (None, 4, 4, 128)         65664     
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 2, 2, 128)        0         
 2D)                                                             
                                                                 
 dropout_3 (Dropout)         (None, 2, 2, 128)         0         
                                                                 
 conv2d_4 (Conv2D)           (None, 2, 2, 256)         131328    
                                                                 
 max_pooling2d_4 (MaxPooling  (None, 1, 1, 256)        0         
 2D)                                                             
                                                                 
 dropout_4 (Dropout)         (None, 1, 1, 256)         0         
                                                                 
 flatten (Flatten)           (None, 256)               0         
                                                                 
 dense (Dense)               (None, 128)               32896     
```

 dense_1 (Dense)   (None, 4)   516

```
=================================================================
Total params: 452,932
Trainable params: 452,932
Non-trainable params: 0
_________________________________________________________________
```

[13]:
```python
tf.keras.utils.plot_model(
    model,
    to_file="model.png",
    show_shapes=True,
    show_layer_names=True,
    rankdir="TB",
    expand_nested=True,
    dpi=96,
)
```

[13]:


conv2d_input | input: | [(None, 32, 32, 1)]
InputLayer | output: | [(None, 32, 32, 1)]
conv2d | input: | (None, 32, 32, 1)
Conv2D | output: | (None, 32, 32, 64)
max_pooling2d | input: | (None, 32, 32, 64)
MaxPooling2D | output: | (None, 16, 16, 64)
dropout | input: | (None, 16, 16, 64)
Dropout | output: | (None, 16, 16, 64)
conv2d_1 | input: | (None, 16, 16, 64)
Conv2D | output: | (None, 16, 16, 128)
max_pooling2d_1 | input: | (None, 16, 16, 128)
MaxPooling2D | output: | (None, 8, 8, 128)
dropout_1 | input: | (None, 8, 8, 128)
Dropout | output: | (None, 8, 8, 128)
conv2d_2 | input: | (None, 8, 8, 128)
Conv2D | output: | (None, 8, 8, 128)
max_pooling2d_2 | input: | (None, 8, 8, 128)
MaxPooling2D | output: | (None, 4, 4, 128)
dropout_2 | input: | (None, 4, 4, 128)
Dropout | output: | (None, 4, 4, 128)
conv2d_3 | input: | (None, 4, 4, 128)
Conv2D | output: | (None, 4, 4, 128)
max_pooling2d_3 | input: | (None, 4, 4, 128)
MaxPooling2D | output: | (None, 2, 2, 128)
dropout_3 | input: | (None, 2, 2, 128)
Dropout | output: | (None, 2, 2, 128)
conv2d_4 | input: | (None, 2, 2, 128)
Conv2D | output: | (None, 2, 2, 256)
max_pooling2d_4 | input: | (None, 2, 2, 256)
MaxPooling2D | output: | (None, 1, 1, 256)
dropout_4 | input: | (None, 1, 1, 256)
Dropout | output: | (None, 1, 1, 256)
flatten | input: | (None, 1, 1, 256)
Flatten | output: | (None, 256)
dense | input: | (None, 256)
Dense | output: | (None, 128)
dense_1 | input: | (None, 128)
Dense | output: | (None, 4)

[14]:
```
model.
↪compile(optimizer='Adam',loss='categorical_crossentropy',metrics=['accuracy'])
hist = model.fit(x_train, y_train, epochs=200, validation_split=0.2,␣
↪batch_size=64,verbose=1,shuffle=True)
```

```
Epoch 1/200

2024-03-27 20:26:53.181579: E
tensorflow/core/grappler/optimizers/meta_optimizer.cc:954] layout failed:
INVALID_ARGUMENT: Size of values 0 does not match size of permutation 4 @ fanin
shape insequential/dropout/dropout/SelectV2-2-TransposeNHWCToNCHW-
LayoutOptimizer

64/64 [==============================] - 9s 13ms/step - loss: 1.7947 - accuracy:
0.4568 - val_loss: 1.1257 - val_accuracy: 0.5088
Epoch 2/200
64/64 [==============================] - 0s 8ms/step - loss: 1.0439 - accuracy:
0.4895 - val_loss: 1.0339 - val_accuracy: 0.5088
Epoch 3/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9918 - accuracy:
0.5120 - val_loss: 0.9534 - val_accuracy: 0.5293
Epoch 4/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9784 - accuracy:
0.5173 - val_loss: 0.9280 - val_accuracy: 0.5547
Epoch 5/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9569 - accuracy:
0.5186 - val_loss: 0.9480 - val_accuracy: 0.5732
Epoch 6/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9540 - accuracy:
0.5347 - val_loss: 1.0205 - val_accuracy: 0.5400
Epoch 7/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9709 - accuracy:
0.5173 - val_loss: 0.9317 - val_accuracy: 0.5098
Epoch 8/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9466 - accuracy:
0.5303 - val_loss: 0.9320 - val_accuracy: 0.5840
Epoch 9/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9269 - accuracy:
0.5540 - val_loss: 0.9473 - val_accuracy: 0.5654
Epoch 10/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9211 - accuracy:
0.5562 - val_loss: 0.9019 - val_accuracy: 0.5898
Epoch 11/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9287 - accuracy:
0.5378 - val_loss: 0.8819 - val_accuracy: 0.5752
Epoch 12/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.9119 - accuracy:
0.5518 - val_loss: 0.9079 - val_accuracy: 0.5986
Epoch 13/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9135 - accuracy:
0.5562 - val_loss: 0.8569 - val_accuracy: 0.5967
Epoch 14/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9019 - accuracy:
0.5537 - val_loss: 0.8601 - val_accuracy: 0.6094
Epoch 15/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8920 - accuracy:
0.5610 - val_loss: 0.9281 - val_accuracy: 0.5664
Epoch 16/200
64/64 [==============================] - 0s 8ms/step - loss: 0.9079 - accuracy:
0.5510 - val_loss: 0.8979 - val_accuracy: 0.5977
Epoch 17/200
64/64 [==============================] - 0s 8ms/step - loss: 0.8824 - accuracy:
0.5723 - val_loss: 0.8333 - val_accuracy: 0.6191
Epoch 18/200
64/64 [==============================] - 0s 8ms/step - loss: 0.8714 - accuracy:
0.5793 - val_loss: 0.8260 - val_accuracy: 0.6025
Epoch 19/200
64/64 [==============================] - 0s 8ms/step - loss: 0.8823 - accuracy:
0.5654 - val_loss: 0.8211 - val_accuracy: 0.6201
Epoch 20/200
64/64 [==============================] - 0s 8ms/step - loss: 0.8503 - accuracy:
0.5876 - val_loss: 0.7976 - val_accuracy: 0.6260
Epoch 21/200
64/64 [==============================] - 0s 8ms/step - loss: 0.8491 - accuracy:
0.5916 - val_loss: 0.7859 - val_accuracy: 0.6201
Epoch 22/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8459 - accuracy:
0.5918 - val_loss: 0.8449 - val_accuracy: 0.5869
Epoch 23/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8205 - accuracy:
0.5991 - val_loss: 0.7692 - val_accuracy: 0.6318
Epoch 24/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8220 - accuracy:
0.6074 - val_loss: 0.8119 - val_accuracy: 0.6318
Epoch 25/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8127 - accuracy:
0.6162 - val_loss: 0.7399 - val_accuracy: 0.6680
Epoch 26/200
64/64 [==============================] - 1s 8ms/step - loss: 0.8033 - accuracy:
0.6147 - val_loss: 0.7456 - val_accuracy: 0.6357
Epoch 27/200
64/64 [==============================] - 1s 8ms/step - loss: 0.7909 - accuracy:
0.6265 - val_loss: 0.8414 - val_accuracy: 0.6094
Epoch 28/200
```

```
64/64 [==============================] - 1s 9ms/step - loss: 0.7813 - accuracy:
0.6340 - val_loss: 0.7543 - val_accuracy: 0.6904
Epoch 29/200
64/64 [==============================] - 1s 8ms/step - loss: 0.7580 - accuracy:
0.6384 - val_loss: 0.7549 - val_accuracy: 0.6660
Epoch 30/200
64/64 [==============================] - 1s 10ms/step - loss: 0.7489 - accuracy:
0.6462 - val_loss: 0.7039 - val_accuracy: 0.6885
Epoch 31/200
64/64 [==============================] - 1s 9ms/step - loss: 0.7384 - accuracy:
0.6658 - val_loss: 0.7196 - val_accuracy: 0.6875
Epoch 32/200
64/64 [==============================] - 1s 8ms/step - loss: 0.7405 - accuracy:
0.6562 - val_loss: 0.7156 - val_accuracy: 0.6748
Epoch 33/200
64/64 [==============================] - 0s 8ms/step - loss: 0.7131 - accuracy:
0.6746 - val_loss: 0.6861 - val_accuracy: 0.6924
Epoch 34/200
64/64 [==============================] - 1s 8ms/step - loss: 0.7106 - accuracy:
0.6748 - val_loss: 0.6456 - val_accuracy: 0.7139
Epoch 35/200
64/64 [==============================] - 1s 8ms/step - loss: 0.7055 - accuracy:
0.6760 - val_loss: 0.6586 - val_accuracy: 0.7129
Epoch 36/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6716 - accuracy:
0.7000 - val_loss: 0.6534 - val_accuracy: 0.7305
Epoch 37/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6684 - accuracy:
0.7004 - val_loss: 0.7232 - val_accuracy: 0.6631
Epoch 38/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6365 - accuracy:
0.7200 - val_loss: 0.6939 - val_accuracy: 0.7021
Epoch 39/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6261 - accuracy:
0.7273 - val_loss: 0.5958 - val_accuracy: 0.7529
Epoch 40/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6173 - accuracy:
0.7295 - val_loss: 0.6335 - val_accuracy: 0.7217
Epoch 41/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6078 - accuracy:
0.7297 - val_loss: 0.5472 - val_accuracy: 0.7646
Epoch 42/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6202 - accuracy:
0.7253 - val_loss: 0.6055 - val_accuracy: 0.7441
Epoch 43/200
64/64 [==============================] - 0s 8ms/step - loss: 0.6065 - accuracy:
0.7251 - val_loss: 0.6526 - val_accuracy: 0.6875
Epoch 44/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.5910 - accuracy:
0.7393 - val_loss: 0.5168 - val_accuracy: 0.7852
Epoch 45/200
64/64 [==============================] - 0s 8ms/step - loss: 0.5549 - accuracy:
0.7695 - val_loss: 0.5588 - val_accuracy: 0.7471
Epoch 46/200
64/64 [==============================] - 0s 8ms/step - loss: 0.5352 - accuracy:
0.7742 - val_loss: 0.5542 - val_accuracy: 0.7617
Epoch 47/200
64/64 [==============================] - 0s 8ms/step - loss: 0.5234 - accuracy:
0.7788 - val_loss: 0.5271 - val_accuracy: 0.7920
Epoch 48/200
64/64 [==============================] - 0s 8ms/step - loss: 0.5078 - accuracy:
0.7881 - val_loss: 0.5388 - val_accuracy: 0.7852
Epoch 49/200
64/64 [==============================] - 0s 8ms/step - loss: 0.5156 - accuracy:
0.7769 - val_loss: 0.4800 - val_accuracy: 0.8008
Epoch 50/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4898 - accuracy:
0.7969 - val_loss: 0.5443 - val_accuracy: 0.7686
Epoch 51/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4936 - accuracy:
0.7920 - val_loss: 0.4626 - val_accuracy: 0.8232
Epoch 52/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4775 - accuracy:
0.7996 - val_loss: 0.4480 - val_accuracy: 0.8096
Epoch 53/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4585 - accuracy:
0.8127 - val_loss: 0.4535 - val_accuracy: 0.8164
Epoch 54/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4608 - accuracy:
0.8064 - val_loss: 0.4783 - val_accuracy: 0.7998
Epoch 55/200
64/64 [==============================] - 1s 8ms/step - loss: 0.4412 - accuracy:
0.8130 - val_loss: 0.4223 - val_accuracy: 0.8408
Epoch 56/200
64/64 [==============================] - 0s 8ms/step - loss: 0.4240 - accuracy:
0.8240 - val_loss: 0.4023 - val_accuracy: 0.8350
Epoch 57/200
64/64 [==============================] - 1s 8ms/step - loss: 0.4375 - accuracy:
0.8203 - val_loss: 0.3821 - val_accuracy: 0.8389
Epoch 58/200
64/64 [==============================] - 1s 8ms/step - loss: 0.3975 - accuracy:
0.8452 - val_loss: 0.3763 - val_accuracy: 0.8691
Epoch 59/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3989 - accuracy:
0.8354 - val_loss: 0.4567 - val_accuracy: 0.8271
Epoch 60/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.3743 - accuracy:
0.8457 - val_loss: 0.4141 - val_accuracy: 0.8438
Epoch 61/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3808 - accuracy:
0.8479 - val_loss: 0.3514 - val_accuracy: 0.8740
Epoch 62/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3436 - accuracy:
0.8630 - val_loss: 0.3517 - val_accuracy: 0.8711
Epoch 63/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3524 - accuracy:
0.8665 - val_loss: 0.3847 - val_accuracy: 0.8643
Epoch 64/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3461 - accuracy:
0.8630 - val_loss: 0.3390 - val_accuracy: 0.8799
Epoch 65/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3453 - accuracy:
0.8645 - val_loss: 0.3171 - val_accuracy: 0.8838
Epoch 66/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3138 - accuracy:
0.8760 - val_loss: 0.3362 - val_accuracy: 0.8770
Epoch 67/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3069 - accuracy:
0.8772 - val_loss: 0.3038 - val_accuracy: 0.8965
Epoch 68/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3245 - accuracy:
0.8694 - val_loss: 0.3342 - val_accuracy: 0.8633
Epoch 69/200
64/64 [==============================] - 0s 8ms/step - loss: 0.3292 - accuracy:
0.8745 - val_loss: 0.2932 - val_accuracy: 0.9053
Epoch 70/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2889 - accuracy:
0.8875 - val_loss: 0.2885 - val_accuracy: 0.8955
Epoch 71/200
64/64 [==============================] - 1s 8ms/step - loss: 0.2750 - accuracy:
0.8950 - val_loss: 0.2883 - val_accuracy: 0.8936
Epoch 72/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2734 - accuracy:
0.8931 - val_loss: 0.2927 - val_accuracy: 0.8965
Epoch 73/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2722 - accuracy:
0.8921 - val_loss: 0.2855 - val_accuracy: 0.9082
Epoch 74/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2692 - accuracy:
0.8923 - val_loss: 0.2985 - val_accuracy: 0.9033
Epoch 75/200
64/64 [==============================] - 1s 8ms/step - loss: 0.2577 - accuracy:
0.8979 - val_loss: 0.2777 - val_accuracy: 0.9160
Epoch 76/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.2581 - accuracy:
0.9009 - val_loss: 0.2879 - val_accuracy: 0.8965
Epoch 77/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2432 - accuracy:
0.9099 - val_loss: 0.2618 - val_accuracy: 0.9033
Epoch 78/200
64/64 [==============================] - 1s 8ms/step - loss: 0.2433 - accuracy:
0.9099 - val_loss: 0.2767 - val_accuracy: 0.8975
Epoch 79/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2502 - accuracy:
0.9089 - val_loss: 0.2812 - val_accuracy: 0.9043
Epoch 80/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2229 - accuracy:
0.9138 - val_loss: 0.2717 - val_accuracy: 0.9072
Epoch 81/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2280 - accuracy:
0.9146 - val_loss: 0.2769 - val_accuracy: 0.9014
Epoch 82/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2265 - accuracy:
0.9124 - val_loss: 0.2511 - val_accuracy: 0.9150
Epoch 83/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2165 - accuracy:
0.9194 - val_loss: 0.2886 - val_accuracy: 0.9014
Epoch 84/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2172 - accuracy:
0.9243 - val_loss: 0.2552 - val_accuracy: 0.9141
Epoch 85/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2260 - accuracy:
0.9094 - val_loss: 0.2667 - val_accuracy: 0.9180
Epoch 86/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2021 - accuracy:
0.9229 - val_loss: 0.2478 - val_accuracy: 0.9209
Epoch 87/200
64/64 [==============================] - 1s 8ms/step - loss: 0.2250 - accuracy:
0.9165 - val_loss: 0.2572 - val_accuracy: 0.9180
Epoch 88/200
64/64 [==============================] - 0s 8ms/step - loss: 0.2100 - accuracy:
0.9189 - val_loss: 0.2225 - val_accuracy: 0.9316
Epoch 89/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1920 - accuracy:
0.9265 - val_loss: 0.2247 - val_accuracy: 0.9268
Epoch 90/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1978 - accuracy:
0.9282 - val_loss: 0.2306 - val_accuracy: 0.9248
Epoch 91/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1788 - accuracy:
0.9355 - val_loss: 0.2280 - val_accuracy: 0.9248
Epoch 92/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.1674 - accuracy:
0.9387 - val_loss: 0.2624 - val_accuracy: 0.9219
Epoch 93/200
64/64 [==============================] - 1s 9ms/step - loss: 0.2052 - accuracy:
0.9231 - val_loss: 0.2448 - val_accuracy: 0.9287
Epoch 94/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1866 - accuracy:
0.9341 - val_loss: 0.2756 - val_accuracy: 0.9111
Epoch 95/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1764 - accuracy:
0.9336 - val_loss: 0.2175 - val_accuracy: 0.9248
Epoch 96/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1794 - accuracy:
0.9312 - val_loss: 0.2322 - val_accuracy: 0.9219
Epoch 97/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1679 - accuracy:
0.9412 - val_loss: 0.2416 - val_accuracy: 0.9199
Epoch 98/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1664 - accuracy:
0.9397 - val_loss: 0.2241 - val_accuracy: 0.9287
Epoch 99/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1933 - accuracy:
0.9302 - val_loss: 0.2149 - val_accuracy: 0.9268
Epoch 100/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1656 - accuracy:
0.9399 - val_loss: 0.1997 - val_accuracy: 0.9395
Epoch 101/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1723 - accuracy:
0.9373 - val_loss: 0.2302 - val_accuracy: 0.9258
Epoch 102/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1433 - accuracy:
0.9487 - val_loss: 0.1971 - val_accuracy: 0.9414
Epoch 103/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1447 - accuracy:
0.9451 - val_loss: 0.2017 - val_accuracy: 0.9414
Epoch 104/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1714 - accuracy:
0.9402 - val_loss: 0.2652 - val_accuracy: 0.9150
Epoch 105/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1776 - accuracy:
0.9380 - val_loss: 0.2007 - val_accuracy: 0.9434
Epoch 106/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1615 - accuracy:
0.9402 - val_loss: 0.2176 - val_accuracy: 0.9316
Epoch 107/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1859 - accuracy:
0.9331 - val_loss: 0.2258 - val_accuracy: 0.9385
Epoch 108/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.1393 - accuracy:
0.9507 - val_loss: 0.2056 - val_accuracy: 0.9385
Epoch 109/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1447 - accuracy:
0.9539 - val_loss: 0.1788 - val_accuracy: 0.9463
Epoch 110/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1516 - accuracy:
0.9473 - val_loss: 0.2324 - val_accuracy: 0.9307
Epoch 111/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1483 - accuracy:
0.9509 - val_loss: 0.2075 - val_accuracy: 0.9404
Epoch 112/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1478 - accuracy:
0.9500 - val_loss: 0.2092 - val_accuracy: 0.9424
Epoch 113/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1320 - accuracy:
0.9536 - val_loss: 0.1965 - val_accuracy: 0.9443
Epoch 114/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1417 - accuracy:
0.9504 - val_loss: 0.1831 - val_accuracy: 0.9473
Epoch 115/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1536 - accuracy:
0.9475 - val_loss: 0.1987 - val_accuracy: 0.9434
Epoch 116/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1255 - accuracy:
0.9556 - val_loss: 0.2026 - val_accuracy: 0.9463
Epoch 117/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1442 - accuracy:
0.9465 - val_loss: 0.2255 - val_accuracy: 0.9268
Epoch 118/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1506 - accuracy:
0.9468 - val_loss: 0.2232 - val_accuracy: 0.9385
Epoch 119/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1459 - accuracy:
0.9458 - val_loss: 0.2061 - val_accuracy: 0.9482
Epoch 120/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1276 - accuracy:
0.9575 - val_loss: 0.1914 - val_accuracy: 0.9443
Epoch 121/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1367 - accuracy:
0.9556 - val_loss: 0.2077 - val_accuracy: 0.9414
Epoch 122/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1175 - accuracy:
0.9600 - val_loss: 0.1848 - val_accuracy: 0.9443
Epoch 123/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1540 - accuracy:
0.9500 - val_loss: 0.1975 - val_accuracy: 0.9443
Epoch 124/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.1380 - accuracy:
0.9548 - val_loss: 0.1960 - val_accuracy: 0.9375
Epoch 125/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1233 - accuracy:
0.9565 - val_loss: 0.1900 - val_accuracy: 0.9434
Epoch 126/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1276 - accuracy:
0.9590 - val_loss: 0.2547 - val_accuracy: 0.9248
Epoch 127/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1308 - accuracy:
0.9512 - val_loss: 0.1886 - val_accuracy: 0.9473
Epoch 128/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1397 - accuracy:
0.9556 - val_loss: 0.1853 - val_accuracy: 0.9404
Epoch 129/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1089 - accuracy:
0.9634 - val_loss: 0.1658 - val_accuracy: 0.9551
Epoch 130/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1120 - accuracy:
0.9602 - val_loss: 0.1938 - val_accuracy: 0.9443
Epoch 131/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1253 - accuracy:
0.9553 - val_loss: 0.1729 - val_accuracy: 0.9521
Epoch 132/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1053 - accuracy:
0.9624 - val_loss: 0.1921 - val_accuracy: 0.9453
Epoch 133/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1471 - accuracy:
0.9487 - val_loss: 0.2304 - val_accuracy: 0.9316
Epoch 134/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1199 - accuracy:
0.9580 - val_loss: 0.1916 - val_accuracy: 0.9463
Epoch 135/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1158 - accuracy:
0.9614 - val_loss: 0.2188 - val_accuracy: 0.9307
Epoch 136/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1225 - accuracy:
0.9614 - val_loss: 0.1973 - val_accuracy: 0.9375
Epoch 137/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1001 - accuracy:
0.9661 - val_loss: 0.2009 - val_accuracy: 0.9346
Epoch 138/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1340 - accuracy:
0.9543 - val_loss: 0.1926 - val_accuracy: 0.9424
Epoch 139/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1066 - accuracy:
0.9641 - val_loss: 0.1569 - val_accuracy: 0.9561
Epoch 140/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.1016 - accuracy:
0.9624 - val_loss: 0.1589 - val_accuracy: 0.9531
Epoch 141/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1103 - accuracy:
0.9587 - val_loss: 0.1799 - val_accuracy: 0.9521
Epoch 142/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1152 - accuracy:
0.9666 - val_loss: 0.2165 - val_accuracy: 0.9277
Epoch 143/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1085 - accuracy:
0.9600 - val_loss: 0.1606 - val_accuracy: 0.9404
Epoch 144/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1098 - accuracy:
0.9629 - val_loss: 0.1618 - val_accuracy: 0.9551
Epoch 145/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0935 - accuracy:
0.9688 - val_loss: 0.1548 - val_accuracy: 0.9570
Epoch 146/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1067 - accuracy:
0.9639 - val_loss: 0.1906 - val_accuracy: 0.9482
Epoch 147/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0906 - accuracy:
0.9673 - val_loss: 0.1597 - val_accuracy: 0.9551
Epoch 148/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1243 - accuracy:
0.9575 - val_loss: 0.1973 - val_accuracy: 0.9443
Epoch 149/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1073 - accuracy:
0.9653 - val_loss: 0.1901 - val_accuracy: 0.9482
Epoch 150/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1053 - accuracy:
0.9653 - val_loss: 0.2039 - val_accuracy: 0.9404
Epoch 151/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1105 - accuracy:
0.9639 - val_loss: 0.1654 - val_accuracy: 0.9463
Epoch 152/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1082 - accuracy:
0.9656 - val_loss: 0.1768 - val_accuracy: 0.9453
Epoch 153/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0979 - accuracy:
0.9688 - val_loss: 0.1561 - val_accuracy: 0.9512
Epoch 154/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1223 - accuracy:
0.9624 - val_loss: 0.1916 - val_accuracy: 0.9482
Epoch 155/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1002 - accuracy:
0.9653 - val_loss: 0.1696 - val_accuracy: 0.9482
Epoch 156/200
```

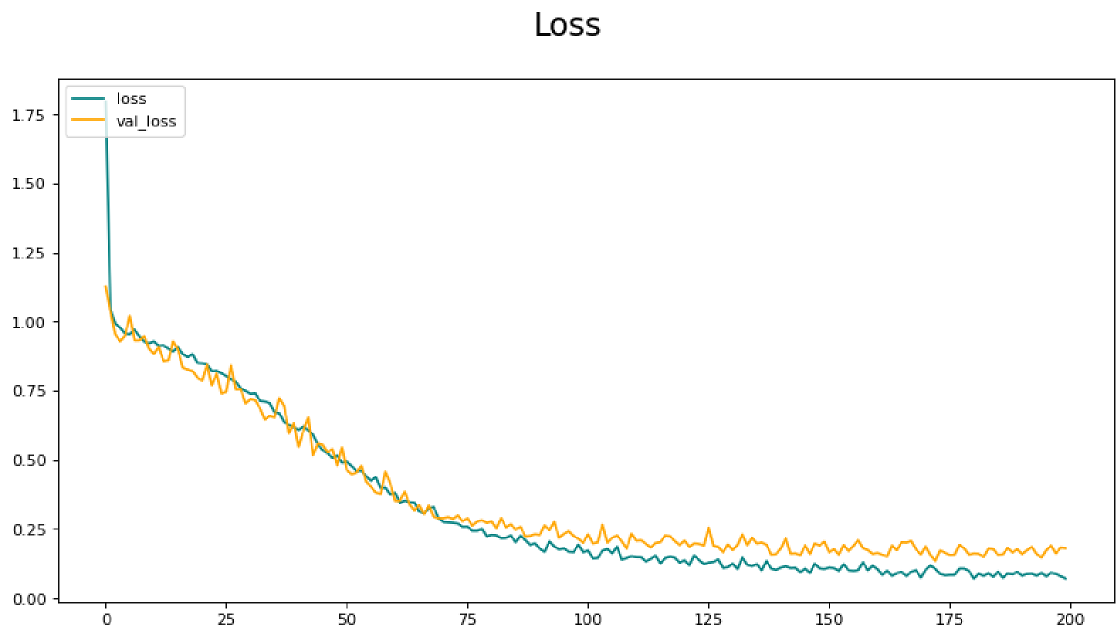
```
64/64 [==============================] - 1s 8ms/step - loss: 0.0981 - accuracy:
0.9692 - val_loss: 0.1887 - val_accuracy: 0.9443
Epoch 157/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1003 - accuracy:
0.9631 - val_loss: 0.2094 - val_accuracy: 0.9277
Epoch 158/200
64/64 [==============================] - 1s 8ms/step - loss: 0.1292 - accuracy:
0.9573 - val_loss: 0.1804 - val_accuracy: 0.9473
Epoch 159/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1003 - accuracy:
0.9680 - val_loss: 0.1742 - val_accuracy: 0.9434
Epoch 160/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1173 - accuracy:
0.9597 - val_loss: 0.1592 - val_accuracy: 0.9453
Epoch 161/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1050 - accuracy:
0.9619 - val_loss: 0.1632 - val_accuracy: 0.9463
Epoch 162/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0830 - accuracy:
0.9709 - val_loss: 0.1565 - val_accuracy: 0.9561
Epoch 163/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0989 - accuracy:
0.9690 - val_loss: 0.1505 - val_accuracy: 0.9551
Epoch 164/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0798 - accuracy:
0.9690 - val_loss: 0.1910 - val_accuracy: 0.9492
Epoch 165/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0898 - accuracy:
0.9697 - val_loss: 0.1731 - val_accuracy: 0.9561
Epoch 166/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0945 - accuracy:
0.9697 - val_loss: 0.2018 - val_accuracy: 0.9521
Epoch 167/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0796 - accuracy:
0.9734 - val_loss: 0.2009 - val_accuracy: 0.9492
Epoch 168/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0946 - accuracy:
0.9685 - val_loss: 0.2067 - val_accuracy: 0.9463
Epoch 169/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1008 - accuracy:
0.9641 - val_loss: 0.1765 - val_accuracy: 0.9570
Epoch 170/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0739 - accuracy:
0.9734 - val_loss: 0.1577 - val_accuracy: 0.9590
Epoch 171/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1023 - accuracy:
0.9692 - val_loss: 0.1876 - val_accuracy: 0.9473
Epoch 172/200
```

```
64/64 [==============================] - 0s 8ms/step - loss: 0.1173 - accuracy:
0.9644 - val_loss: 0.1552 - val_accuracy: 0.9570
Epoch 173/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1059 - accuracy:
0.9651 - val_loss: 0.1337 - val_accuracy: 0.9629
Epoch 174/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0875 - accuracy:
0.9695 - val_loss: 0.1724 - val_accuracy: 0.9473
Epoch 175/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0821 - accuracy:
0.9724 - val_loss: 0.1637 - val_accuracy: 0.9600
Epoch 176/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0838 - accuracy:
0.9685 - val_loss: 0.1555 - val_accuracy: 0.9600
Epoch 177/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0837 - accuracy:
0.9712 - val_loss: 0.1564 - val_accuracy: 0.9521
Epoch 178/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1069 - accuracy:
0.9634 - val_loss: 0.1925 - val_accuracy: 0.9512
Epoch 179/200
64/64 [==============================] - 0s 8ms/step - loss: 0.1068 - accuracy:
0.9634 - val_loss: 0.1799 - val_accuracy: 0.9424
Epoch 180/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0975 - accuracy:
0.9700 - val_loss: 0.1566 - val_accuracy: 0.9521
Epoch 181/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0704 - accuracy:
0.9778 - val_loss: 0.1613 - val_accuracy: 0.9551
Epoch 182/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0890 - accuracy:
0.9717 - val_loss: 0.1600 - val_accuracy: 0.9512
Epoch 183/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0800 - accuracy:
0.9736 - val_loss: 0.1492 - val_accuracy: 0.9541
Epoch 184/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0903 - accuracy:
0.9744 - val_loss: 0.1789 - val_accuracy: 0.9512
Epoch 185/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0772 - accuracy:
0.9709 - val_loss: 0.1773 - val_accuracy: 0.9541
Epoch 186/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0953 - accuracy:
0.9644 - val_loss: 0.1561 - val_accuracy: 0.9570
Epoch 187/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0732 - accuracy:
0.9751 - val_loss: 0.1580 - val_accuracy: 0.9541
Epoch 188/200
```

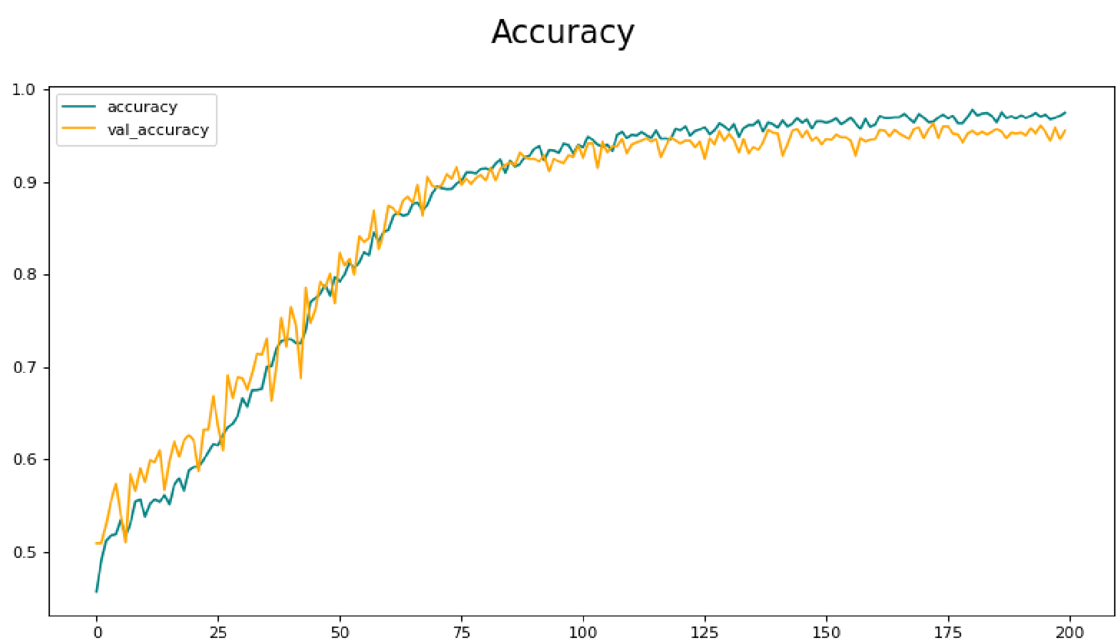
```
64/64 [==============================] - 0s 8ms/step - loss: 0.0893 - accuracy:
0.9690 - val_loss: 0.1813 - val_accuracy: 0.9473
Epoch 189/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0860 - accuracy:
0.9707 - val_loss: 0.1651 - val_accuracy: 0.9531
Epoch 190/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0941 - accuracy:
0.9685 - val_loss: 0.1765 - val_accuracy: 0.9521
Epoch 191/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0805 - accuracy:
0.9717 - val_loss: 0.1586 - val_accuracy: 0.9531
Epoch 192/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0875 - accuracy:
0.9690 - val_loss: 0.1730 - val_accuracy: 0.9502
Epoch 193/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0888 - accuracy:
0.9712 - val_loss: 0.1856 - val_accuracy: 0.9580
Epoch 194/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0806 - accuracy:
0.9744 - val_loss: 0.1595 - val_accuracy: 0.9521
Epoch 195/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0916 - accuracy:
0.9702 - val_loss: 0.1458 - val_accuracy: 0.9609
Epoch 196/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0785 - accuracy:
0.9727 - val_loss: 0.1732 - val_accuracy: 0.9541
Epoch 197/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0916 - accuracy:
0.9675 - val_loss: 0.1900 - val_accuracy: 0.9443
Epoch 198/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0875 - accuracy:
0.9692 - val_loss: 0.1612 - val_accuracy: 0.9590
Epoch 199/200
64/64 [==============================] - 1s 8ms/step - loss: 0.0787 - accuracy:
0.9712 - val_loss: 0.1828 - val_accuracy: 0.9463
Epoch 200/200
64/64 [==============================] - 0s 8ms/step - loss: 0.0705 - accuracy:
0.9746 - val_loss: 0.1803 - val_accuracy: 0.9551
```

[15]:
```python
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

fig = plt.figure(figsize=(12, 6), dpi=80)
plt.plot(hist.history['loss'], color='teal', label='loss')
plt.plot(hist.history['val_loss'], color='orange', label='val_loss')
fig.suptitle('Loss', fontsize=20)
plt.legend(loc="upper left")
```

```
plt.show()
```



[16]:
```
fig = plt.figure(figsize=(12, 6), dpi=80)
plt.plot(hist.history['accuracy'], color='teal', label='accuracy')
plt.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')
fig.suptitle('Accuracy', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```



[17]:
```
loss_and_metrics = model.evaluate(x_test, y_test, verbose=2)
y_pred = model.predict(x_test).argmax(axis=1)
print(f'Test Loss     : {loss_and_metrics[0]}')
print(f'Test Accuracy : {loss_and_metrics[1]}')
print(y_test.shape, y_pred.shape)
```

```
40/40 - 0s - loss: 0.1285 - accuracy: 0.9617 - 361ms/epoch - 9ms/step
40/40 [==============================] - 0s 2ms/step
Test Loss     : 0.12852796912193298
Test Accuracy : 0.961718738079071
(1280, 4) (1280,)
```

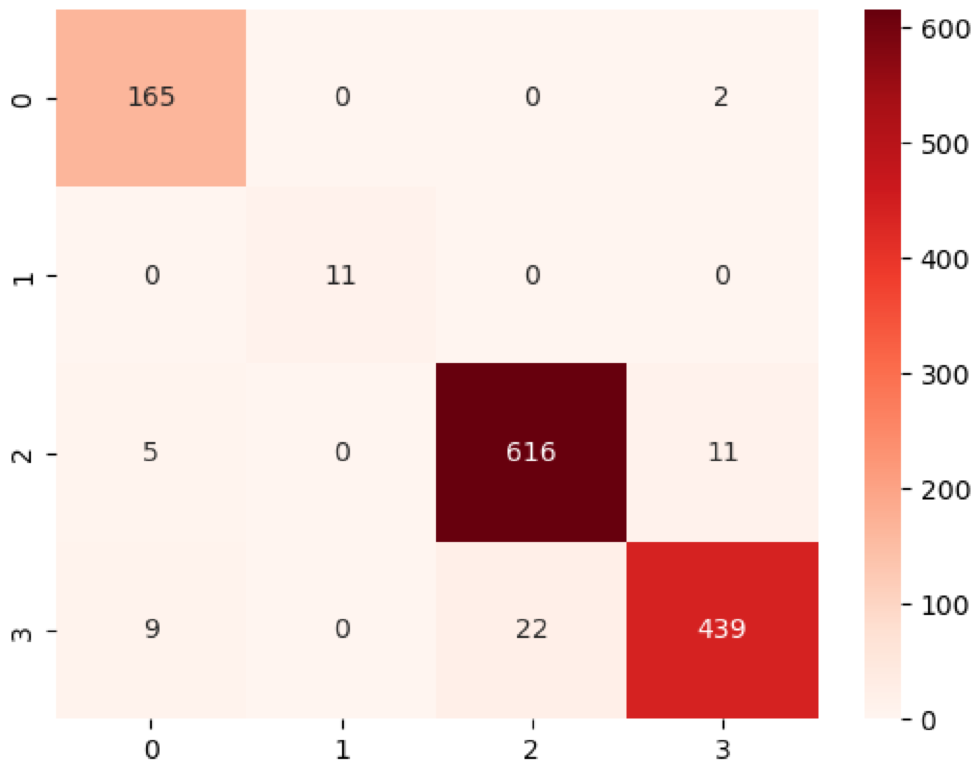
[18]:
```
from sklearn import metrics

df = pd.DataFrame(
  data = metrics.confusion_matrix(np.argmax(y_test, axis=1), y_pred),
  columns = ['0', '1', '2', '3'],
  index = ['0', '1', '2', '3']
)
df
```

[18]:

	0	1	2	3
0	165	0	0	2
1	0	11	0	0
2	5	0	616	11
3	9	0	22	439

[19]:
```
import seaborn as sns

sns.heatmap(df, cmap="Reds", annot=True, fmt='.0f')
```

[19]: <Axes: >


165
0
0
2
0
11
0
0
5
0
616
11
9
0
22
439
0
1
2
3
0
1
2
3
600
500
400
300
200
100
0