Midterm

October 22, 2023

[1]:
```
print("""
Riker Wachtler
22 October 2023
Wine Classification Midterm Project
https://github.com/RikerW/midterm
""")
```

```
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22 October 2023
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```

[2]:
```
import os, shutil

import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns

import keras, keras_tuner as kt, tensorflow as tf
from keras import Sequential
from keras.layers import Dense
from keras.initializers import TruncatedNormal
from keras.utils import to_categorical
from keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from scikitplot.metrics import plot_confusion_matrix
from sklearn import datasets

import warnings

warnings.filterwarnings('ignore')
%matplotlib inline
sns.set_style("whitegrid")
```

```
Using TensorFlow backend
```

[3]:
```
print("""
This is a classification attempt on a very unoriginal dataset (for the midterm,␣
↪I mean), the wine dataset from UCI, used via the sklearn databases.

The data is composed of 13 features; Alcohol, Malic acid, Ash, Alcalinity of␣
↪ash, Magnesium, Total phenols, Flavanoids, Nonflavanoid phenols,␣
↪Proanthocyanins, Color intensity, Hue, OD280/OD315 of diluted wines, and␣
↪Proline. They are not measured on any uniform scale. The samples are in 3␣
↪classes, so this is a classification problem on those features. It has no␣
↪missing values and has been cleaned up already.

I used a very simple ANN with one hidden layer, and used hyperparameter tuning␣
↪to decide the number of nodes in that layer. The input layer was obviously␣
↪based on the input dimension & the output the number of classes, so they␣
↪were not tuned. I used a Hyperband tuner to do this, with the normal epoch/
↪factor of 100/3. After that search, I fit the model on the training data␣
↪(randomly selected as 75% of the dataset) over 300 epochs, validated with␣
↪the remaining 25% test data from the dataset, and then plotted the accuracy/
↪loss & confusion matrix. """)
```

```
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Proanthocyanins, Color intensity, Hue, OD280/OD315 of diluted wines, and
Proline. They are not measured on any uniform scale. The samples are in 3
classes, so this is a classification problem on those features. It has no
missing values and has been cleaned up already.

I used a very simple ANN with one hidden layer, and used hyperparameter tuning
to decide the number of nodes in that layer. The input layer was obviously based
on the input dimension & the output the number of classes, so they were not
tuned. I used a Hyperband tuner to do this, with the normal epoch/factor of
100/3. After that search, I fit the model on the training data (randomly
selected as 75% of the dataset) over 300 epochs, validated with the remaining
25% test data from the dataset, and then plotted the accuracy/loss & confusion
matrix.
```

[4]:
```
# fetch dataset
wine = datasets.load_wine()

df = pd.DataFrame(wine.data, columns=wine.feature_names)
df['label'] = wine.target
```

[5]:
```python
# split dataset into train/test, proportioned at 25%
X, y = wine.data, wine.target
X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle = True, test_size = 0.25)

# convert y_train & y_test to categorical data
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```

[6]:
```python
df.head()
```

[6]:
```
   alcohol  malic_acid   ash  alcalinity_of_ash  magnesium  total_phenols  \
0    14.23        1.71  2.43               15.6      127.0           2.80
1    13.20        1.78  2.14               11.2      100.0           2.65
2    13.16        2.36  2.67               18.6      101.0           2.80
3    14.37        1.95  2.50               16.8      113.0           3.85
4    13.24        2.59  2.87               21.0      118.0           2.80

   flavanoids  nonflavanoid_phenols  proanthocyanins  color_intensity   hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   od280/od315_of_diluted_wines  proline  label
0                          3.92   1065.0      0
1                          3.40   1050.0      0
2                          3.17   1185.0      0
3                          3.45   1480.0      0
4                          2.93    735.0      0
```

[7]:
```python
df.describe()
```

[7]:
```
          alcohol  malic_acid         ash  alcalinity_of_ash   magnesium  \
count  178.000000  178.000000  178.000000         178.000000  178.000000
mean    13.000618    2.336348    2.366517          19.494944   99.741573
std      0.811827    1.117146    0.274344           3.339564   14.282484
min     11.030000    0.740000    1.360000          10.600000   70.000000
25%     12.362500    1.602500    2.210000          17.200000   88.000000
50%     13.050000    1.865000    2.360000          19.500000   98.000000
75%     13.677500    3.082500    2.557500          21.500000  107.000000
max     14.830000    5.800000    3.230000          30.000000  162.000000

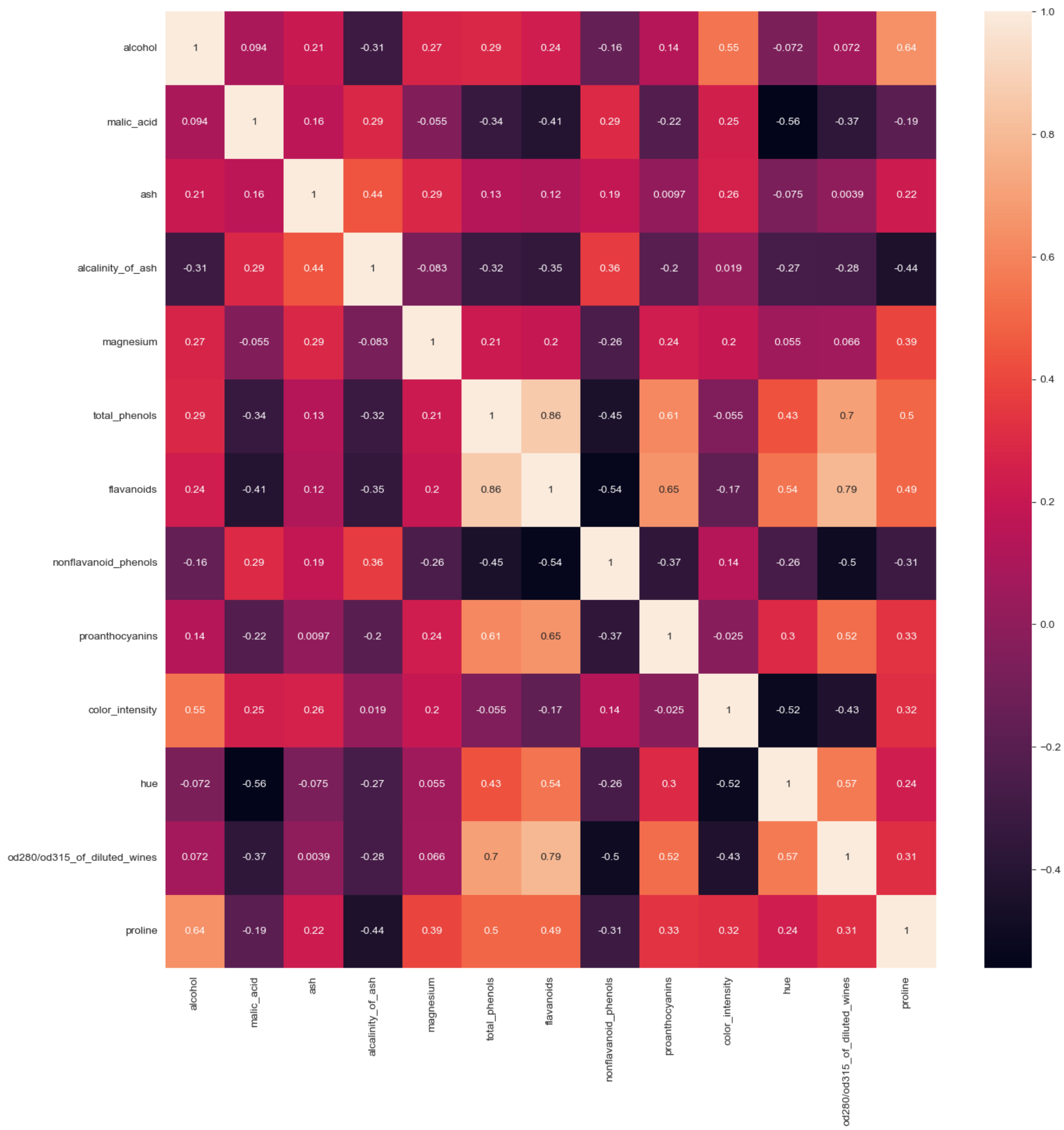
       total_phenols  flavanoids  nonflavanoid_phenols  proanthocyanins  \
count     178.000000  178.000000            178.000000       178.000000
mean        2.295112    2.029270              0.361854         1.590899
```

```
std        0.625851    0.998859              0.124453         0.572359
min        0.980000    0.340000              0.130000         0.410000
25%        1.742500    1.205000              0.270000         1.250000
50%        2.355000    2.135000              0.340000         1.555000
75%        2.800000    2.875000              0.437500         1.950000
max        3.880000    5.080000              0.660000         3.580000

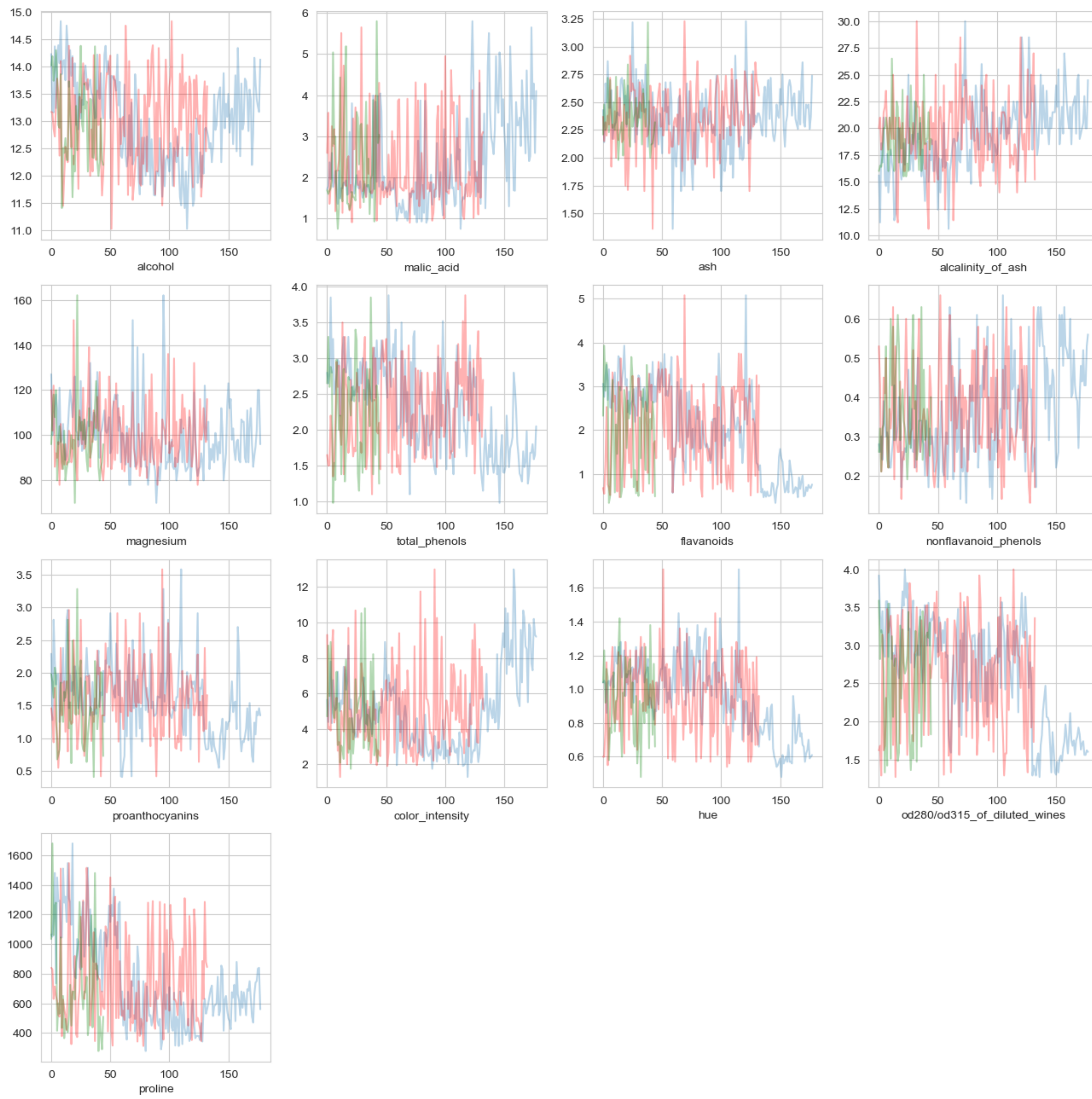
       color_intensity         hue  od280/od315_of_diluted_wines      proline  \
count       178.000000  178.000000                    178.000000   178.000000
mean          5.058090    0.957449                      2.611685   746.893258
std           2.318286    0.228572                      0.709990   314.907474
min           1.280000    0.480000                      1.270000   278.000000
25%           3.220000    0.782500                      1.937500   500.500000
50%           4.690000    0.965000                      2.780000   673.500000
75%           6.200000    1.120000                      3.170000   985.000000
max          13.000000    1.710000                      4.000000  1680.000000

            label
count  178.000000
mean     0.938202
std      0.775035
min      0.000000
25%      0.000000
50%      1.000000
75%      2.000000
max      2.000000
```

[8]:
```
plt.figure(figsize = (16,16))
sns.heatmap(df.iloc[:,:-1].corr(), annot=True)
plt.show()
```



[9]:
```
fig = plt.figure(figsize=(16, 16))
labels = wine.feature_names
for label in range(len(labels)):
    ax = fig.add_subplot(4,4,label+1)
    ax.plot(X[:, label], alpha = 0.3)
    ax.plot(X_train[:, label], color="red", alpha = 0.3)
    ax.plot(X_test[:, label], color="green", alpha = 0.3)
    ax.set_xlabel(labels[label])
```



[10]:
```
fig = plt.figure(figsize=(24,12))
ax1 = fig.add_subplot(3,1,1)
ax1.plot(y)
ax2 = fig.add_subplot(3,1,2)
ax2.plot(y_train)
ax3 = fig.add_subplot(3,1,3)
ax3.plot(y_test)
plt.show()
```

[11]:
```
folder_path = "logs/midterm"

# Check if the folder exists before attempting to delete it
if os.path.exists(folder_path):
    # Remove the folder and its contents recursively
    shutil.rmtree(folder_path)
    print(f"The folder '{folder_path}' has been deleted.")
else:
    print(f"The folder '{folder_path}' does not exist.")
```

```
The folder 'logs/midterm' has been deleted.
```

[12]:
```
# define model builder for tuning
input_dim = len(X_train[0, :])
class_num = len(y_train[0, :])



# Only the hidden layer is tuned, and just its nodes
# We use rect. linear unified function for the hidden layer
# and then softmax for output because this is classification and we want that␣
 ↪probability distribution
def model_builder(hp):
    # create model
    init = TruncatedNormal(stddev=0.01)
    adam = Adam(learning_rate=0.005)
    model = Sequential()
    # hidden layer
    hp_units = hp.Int("units", min_value = 5, max_value = 60, step = 5)
```

```
    model.add(Dense(units = hp_units, input_dim = input_dim, activation =␣
↪"relu", kernel_initializer = init))
    ### add the final layer
    model.add(Dense(class_num, activation = "softmax", kernel_initializer =␣
↪init))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer=adam,␣
↪metrics=['accuracy'])
    return model
```

[13]:
```
# create a Hyperband tuner for accuracy, with 100 epochs
tuner = kt.Hyperband(model_builder, objective='val_accuracy', max_epochs=100,␣
↪factor=3,
                     directory="logs/", project_name='midterm')

# set the callback for loss
stop_early = tf.keras.callbacks.EarlyStopping(monitor="val_loss", patience=5)

# set up a search on the training set, 100 epochs, splitting at 20% for␣
↪validation
tuner.search(X_train, y_train, epochs=100, validation_split=0.2,␣
↪callbacks=[stop_early])

# Get the optimal hyperparameters
best_hps=tuner.get_best_hyperparameters(num_trials=5)[0]
print(f"""The hyperparameter search is complete. The optimal number of units in␣
↪the first densely-connected layer is {best_hps.get('units')}.""")
```

```
Trial 10 Complete [00h 00m 01s]
val_accuracy: 0.5555555820465088

Best val_accuracy So Far: 0.6296296119689941
Total elapsed time: 00h 00m 10s
The hyperparameter search is complete. The optimal number of units in the first
densely-connected layer is 40.
```

[14]:
```
# Build the model with the optimal hyperparameters and train it on the data for␣
↪300 epochs
model = tuner.hypermodel.build(best_hps)
history = model.fit(X_train, y_train, epochs=300, validation_data=(X_test,␣
↪y_test), shuffle=False)
val_acc_per_epoch = history.history['val_accuracy']
best_epoch = val_acc_per_epoch.index(max(val_acc_per_epoch)) + 1
print('Best epoch: %d' % (best_epoch,))
```

```
Epoch 1/300
5/5 [==============================] - 1s 36ms/step - loss: 1.2292 - accuracy:
0.2707 - val_loss: 1.0373 - val_accuracy: 0.6444
```

```
Epoch 2/300
5/5 [==============================] - 0s 8ms/step - loss: 1.0084 - accuracy:
0.6617 - val_loss: 0.9675 - val_accuracy: 0.4889
Epoch 3/300
5/5 [==============================] - 0s 8ms/step - loss: 0.9383 - accuracy:
0.5113 - val_loss: 0.8977 - val_accuracy: 0.5778
Epoch 4/300
5/5 [==============================] - 0s 7ms/step - loss: 0.8821 - accuracy:
0.6391 - val_loss: 0.8345 - val_accuracy: 0.5778
Epoch 5/300
5/5 [==============================] - 0s 7ms/step - loss: 0.8048 - accuracy:
0.6466 - val_loss: 0.7485 - val_accuracy: 0.6444
Epoch 6/300
5/5 [==============================] - 0s 8ms/step - loss: 0.7366 - accuracy:
0.6767 - val_loss: 0.6854 - val_accuracy: 0.6444
Epoch 7/300
5/5 [==============================] - 0s 7ms/step - loss: 0.7117 - accuracy:
0.6767 - val_loss: 0.6521 - val_accuracy: 0.6444
Epoch 8/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6833 - accuracy:
0.6466 - val_loss: 0.6298 - val_accuracy: 0.6667
Epoch 9/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6642 - accuracy:
0.6767 - val_loss: 0.6202 - val_accuracy: 0.6667
Epoch 10/300
5/5 [==============================] - 0s 8ms/step - loss: 0.6612 - accuracy:
0.6767 - val_loss: 0.6126 - val_accuracy: 0.6667
Epoch 11/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6482 - accuracy:
0.6391 - val_loss: 0.6062 - val_accuracy: 0.6889
Epoch 12/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6454 - accuracy:
0.6541 - val_loss: 0.6042 - val_accuracy: 0.6667
Epoch 13/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6390 - accuracy:
0.6767 - val_loss: 0.6010 - val_accuracy: 0.6667
Epoch 14/300
5/5 [==============================] - 0s 8ms/step - loss: 0.6293 - accuracy:
0.6692 - val_loss: 0.5966 - val_accuracy: 0.6667
Epoch 15/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6279 - accuracy:
0.6692 - val_loss: 0.5934 - val_accuracy: 0.6667
Epoch 16/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6177 - accuracy:
0.6842 - val_loss: 0.5876 - val_accuracy: 0.6667
Epoch 17/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6131 - accuracy:
0.6917 - val_loss: 0.5816 - val_accuracy: 0.7111
```

```
Epoch 18/300
5/5 [==============================] - 0s 7ms/step - loss: 0.6031 - accuracy:
0.7143 - val_loss: 0.5751 - val_accuracy: 0.6667
Epoch 19/300
5/5 [==============================] - 0s 7ms/step - loss: 0.5907 - accuracy:
0.7293 - val_loss: 0.5640 - val_accuracy: 0.7333
Epoch 20/300
5/5 [==============================] - 0s 8ms/step - loss: 0.5859 - accuracy:
0.8120 - val_loss: 0.5545 - val_accuracy: 0.7111
Epoch 21/300
5/5 [==============================] - 0s 10ms/step - loss: 0.5646 - accuracy:
0.7895 - val_loss: 0.5414 - val_accuracy: 0.7333
Epoch 22/300
5/5 [==============================] - 0s 9ms/step - loss: 0.5568 - accuracy:
0.8271 - val_loss: 0.5235 - val_accuracy: 0.8667
Epoch 23/300
5/5 [==============================] - 0s 9ms/step - loss: 0.5345 - accuracy:
0.8120 - val_loss: 0.5098 - val_accuracy: 0.7556
Epoch 24/300
5/5 [==============================] - 0s 7ms/step - loss: 0.5111 - accuracy:
0.8722 - val_loss: 0.4848 - val_accuracy: 0.8889
Epoch 25/300
5/5 [==============================] - 0s 7ms/step - loss: 0.4909 - accuracy:
0.8722 - val_loss: 0.4623 - val_accuracy: 0.9111
Epoch 26/300
5/5 [==============================] - 0s 7ms/step - loss: 0.4672 - accuracy:
0.8647 - val_loss: 0.4357 - val_accuracy: 0.9556
Epoch 27/300
5/5 [==============================] - 0s 7ms/step - loss: 0.4319 - accuracy:
0.8797 - val_loss: 0.4054 - val_accuracy: 0.9778
Epoch 28/300
5/5 [==============================] - 0s 7ms/step - loss: 0.4076 - accuracy:
0.8872 - val_loss: 0.3777 - val_accuracy: 0.9556
Epoch 29/300
5/5 [==============================] - 0s 7ms/step - loss: 0.3716 - accuracy:
0.9023 - val_loss: 0.3470 - val_accuracy: 0.9778
Epoch 30/300
5/5 [==============================] - 0s 7ms/step - loss: 0.3494 - accuracy:
0.9023 - val_loss: 0.3248 - val_accuracy: 0.9778
Epoch 31/300
5/5 [==============================] - 0s 7ms/step - loss: 0.3182 - accuracy:
0.9098 - val_loss: 0.3042 - val_accuracy: 0.9778
Epoch 32/300
5/5 [==============================] - 0s 7ms/step - loss: 0.2915 - accuracy:
0.9173 - val_loss: 0.2892 - val_accuracy: 0.9778
Epoch 33/300
5/5 [==============================] - 0s 8ms/step - loss: 0.2709 - accuracy:
0.9323 - val_loss: 0.2700 - val_accuracy: 0.9778
```

```
Epoch 34/300
5/5 [==============================] - 0s 8ms/step - loss: 0.2516 - accuracy:
0.9248 - val_loss: 0.2528 - val_accuracy: 0.9778
Epoch 35/300
5/5 [==============================] - 0s 8ms/step - loss: 0.2401 - accuracy:
0.9248 - val_loss: 0.2396 - val_accuracy: 0.9778
Epoch 36/300
5/5 [==============================] - 0s 7ms/step - loss: 0.2255 - accuracy:
0.9323 - val_loss: 0.2310 - val_accuracy: 0.9778
Epoch 37/300
5/5 [==============================] - 0s 7ms/step - loss: 0.2152 - accuracy:
0.9398 - val_loss: 0.2259 - val_accuracy: 0.9778
Epoch 38/300
5/5 [==============================] - 0s 10ms/step - loss: 0.2027 - accuracy:
0.9474 - val_loss: 0.2213 - val_accuracy: 0.9778
Epoch 39/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1933 - accuracy:
0.9398 - val_loss: 0.2126 - val_accuracy: 0.9778
Epoch 40/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1863 - accuracy:
0.9398 - val_loss: 0.2068 - val_accuracy: 0.9778
Epoch 41/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1802 - accuracy:
0.9474 - val_loss: 0.1995 - val_accuracy: 0.9556
Epoch 42/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1745 - accuracy:
0.9549 - val_loss: 0.1977 - val_accuracy: 0.9556
Epoch 43/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1686 - accuracy:
0.9624 - val_loss: 0.1938 - val_accuracy: 0.9556
Epoch 44/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1629 - accuracy:
0.9624 - val_loss: 0.1939 - val_accuracy: 0.9556
Epoch 45/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1582 - accuracy:
0.9624 - val_loss: 0.1901 - val_accuracy: 0.9556
Epoch 46/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1535 - accuracy:
0.9624 - val_loss: 0.1874 - val_accuracy: 0.9556
Epoch 47/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1508 - accuracy:
0.9624 - val_loss: 0.1834 - val_accuracy: 0.9556
Epoch 48/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1475 - accuracy:
0.9624 - val_loss: 0.1827 - val_accuracy: 0.9556
Epoch 49/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1442 - accuracy:
0.9624 - val_loss: 0.1816 - val_accuracy: 0.9556
```

```
Epoch 50/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1403 - accuracy:
0.9699 - val_loss: 0.1806 - val_accuracy: 0.9556
Epoch 51/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1379 - accuracy:
0.9699 - val_loss: 0.1787 - val_accuracy: 0.9556
Epoch 52/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1351 - accuracy:
0.9699 - val_loss: 0.1771 - val_accuracy: 0.9556
Epoch 53/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1330 - accuracy:
0.9699 - val_loss: 0.1761 - val_accuracy: 0.9556
Epoch 54/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1304 - accuracy:
0.9699 - val_loss: 0.1760 - val_accuracy: 0.9556
Epoch 55/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1280 - accuracy:
0.9699 - val_loss: 0.1762 - val_accuracy: 0.9556
Epoch 56/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1254 - accuracy:
0.9699 - val_loss: 0.1742 - val_accuracy: 0.9556
Epoch 57/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1241 - accuracy:
0.9699 - val_loss: 0.1736 - val_accuracy: 0.9556
Epoch 58/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1220 - accuracy:
0.9699 - val_loss: 0.1727 - val_accuracy: 0.9556
Epoch 59/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1203 - accuracy:
0.9699 - val_loss: 0.1735 - val_accuracy: 0.9556
Epoch 60/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1181 - accuracy:
0.9699 - val_loss: 0.1723 - val_accuracy: 0.9556
Epoch 61/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1169 - accuracy:
0.9699 - val_loss: 0.1726 - val_accuracy: 0.9556
Epoch 62/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1150 - accuracy:
0.9699 - val_loss: 0.1708 - val_accuracy: 0.9556
Epoch 63/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1139 - accuracy:
0.9699 - val_loss: 0.1726 - val_accuracy: 0.9556
Epoch 64/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1118 - accuracy:
0.9699 - val_loss: 0.1714 - val_accuracy: 0.9556
Epoch 65/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1107 - accuracy:
0.9699 - val_loss: 0.1714 - val_accuracy: 0.9556
```

```
Epoch 66/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1095 - accuracy:
0.9699 - val_loss: 0.1704 - val_accuracy: 0.9556
Epoch 67/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1082 - accuracy:
0.9699 - val_loss: 0.1707 - val_accuracy: 0.9556
Epoch 68/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1069 - accuracy:
0.9699 - val_loss: 0.1709 - val_accuracy: 0.9556
Epoch 69/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1055 - accuracy:
0.9699 - val_loss: 0.1706 - val_accuracy: 0.9556
Epoch 70/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1047 - accuracy:
0.9699 - val_loss: 0.1704 - val_accuracy: 0.9556
Epoch 71/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1033 - accuracy:
0.9699 - val_loss: 0.1708 - val_accuracy: 0.9556
Epoch 72/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1021 - accuracy:
0.9699 - val_loss: 0.1704 - val_accuracy: 0.9556
Epoch 73/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1013 - accuracy:
0.9699 - val_loss: 0.1708 - val_accuracy: 0.9556
Epoch 74/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1001 - accuracy:
0.9699 - val_loss: 0.1705 - val_accuracy: 0.9556
Epoch 75/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0992 - accuracy:
0.9699 - val_loss: 0.1709 - val_accuracy: 0.9556
Epoch 76/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0982 - accuracy:
0.9699 - val_loss: 0.1706 - val_accuracy: 0.9556
Epoch 77/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0973 - accuracy:
0.9699 - val_loss: 0.1709 - val_accuracy: 0.9556
Epoch 78/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0962 - accuracy:
0.9699 - val_loss: 0.1706 - val_accuracy: 0.9556
Epoch 79/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0956 - accuracy:
0.9699 - val_loss: 0.1713 - val_accuracy: 0.9556
Epoch 80/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0945 - accuracy:
0.9699 - val_loss: 0.1712 - val_accuracy: 0.9556
Epoch 81/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0937 - accuracy:
0.9699 - val_loss: 0.1719 - val_accuracy: 0.9556
```

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Epoch 82/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0930 - accuracy:
0.9699 - val_loss: 0.1714 - val_accuracy: 0.9556
Epoch 83/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0922 - accuracy:
0.9699 - val_loss: 0.1717 - val_accuracy: 0.9556
Epoch 84/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0913 - accuracy:
0.9699 - val_loss: 0.1718 - val_accuracy: 0.9556
Epoch 85/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0905 - accuracy:
0.9699 - val_loss: 0.1725 - val_accuracy: 0.9556
Epoch 86/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0897 - accuracy:
0.9699 - val_loss: 0.1720 - val_accuracy: 0.9556
Epoch 87/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0893 - accuracy:
0.9699 - val_loss: 0.1719 - val_accuracy: 0.9556
Epoch 88/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0881 - accuracy:
0.9699 - val_loss: 0.1730 - val_accuracy: 0.9556
Epoch 89/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0877 - accuracy:
0.9699 - val_loss: 0.1733 - val_accuracy: 0.9556
Epoch 90/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0870 - accuracy:
0.9699 - val_loss: 0.1726 - val_accuracy: 0.9556
Epoch 91/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0863 - accuracy:
0.9699 - val_loss: 0.1728 - val_accuracy: 0.9556
Epoch 92/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0855 - accuracy:
0.9699 - val_loss: 0.1732 - val_accuracy: 0.9556
Epoch 93/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0850 - accuracy:
0.9699 - val_loss: 0.1744 - val_accuracy: 0.9556
Epoch 94/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0843 - accuracy:
0.9699 - val_loss: 0.1740 - val_accuracy: 0.9556
Epoch 95/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0838 - accuracy:
0.9699 - val_loss: 0.1736 - val_accuracy: 0.9556
Epoch 96/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0829 - accuracy:
0.9699 - val_loss: 0.1737 - val_accuracy: 0.9556
Epoch 97/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0825 - accuracy:
0.9699 - val_loss: 0.1748 - val_accuracy: 0.9556
```

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Epoch 98/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0819 - accuracy:
0.9699 - val_loss: 0.1755 - val_accuracy: 0.9556
Epoch 99/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0815 - accuracy:
0.9699 - val_loss: 0.1750 - val_accuracy: 0.9556
Epoch 100/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0807 - accuracy:
0.9699 - val_loss: 0.1742 - val_accuracy: 0.9556
Epoch 101/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0801 - accuracy:
0.9774 - val_loss: 0.1751 - val_accuracy: 0.9556
Epoch 102/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0795 - accuracy:
0.9699 - val_loss: 0.1765 - val_accuracy: 0.9556
Epoch 103/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0794 - accuracy:
0.9774 - val_loss: 0.1759 - val_accuracy: 0.9556
Epoch 104/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0785 - accuracy:
0.9699 - val_loss: 0.1754 - val_accuracy: 0.9556
Epoch 105/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0779 - accuracy:
0.9774 - val_loss: 0.1762 - val_accuracy: 0.9556
Epoch 106/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0775 - accuracy:
0.9699 - val_loss: 0.1772 - val_accuracy: 0.9556
Epoch 107/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0774 - accuracy:
0.9774 - val_loss: 0.1771 - val_accuracy: 0.9556
Epoch 108/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0766 - accuracy:
0.9699 - val_loss: 0.1782 - val_accuracy: 0.9556
Epoch 109/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0768 - accuracy:
0.9774 - val_loss: 0.1778 - val_accuracy: 0.9556
Epoch 110/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0759 - accuracy:
0.9699 - val_loss: 0.1809 - val_accuracy: 0.9556
Epoch 111/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0769 - accuracy:
0.9774 - val_loss: 0.1796 - val_accuracy: 0.9556
Epoch 112/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0757 - accuracy:
0.9699 - val_loss: 0.1846 - val_accuracy: 0.9556
Epoch 113/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0778 - accuracy:
0.9774 - val_loss: 0.1829 - val_accuracy: 0.9556
```

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Epoch 114/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0766 - accuracy:
0.9699 - val_loss: 0.1916 - val_accuracy: 0.9556
Epoch 115/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0809 - accuracy:
0.9774 - val_loss: 0.1912 - val_accuracy: 0.9556
Epoch 116/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0800 - accuracy:
0.9699 - val_loss: 0.2052 - val_accuracy: 0.9556
Epoch 117/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0891 - accuracy:
0.9699 - val_loss: 0.2093 - val_accuracy: 0.9778
Epoch 118/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0884 - accuracy:
0.9549 - val_loss: 0.2282 - val_accuracy: 0.9333
Epoch 119/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1053 - accuracy:
0.9549 - val_loss: 0.2393 - val_accuracy: 0.8889
Epoch 120/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1055 - accuracy:
0.9549 - val_loss: 0.2413 - val_accuracy: 0.9333
Epoch 121/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1139 - accuracy:
0.9474 - val_loss: 0.2445 - val_accuracy: 0.8889
Epoch 122/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1161 - accuracy:
0.9474 - val_loss: 0.2272 - val_accuracy: 0.9333
Epoch 123/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1019 - accuracy:
0.9624 - val_loss: 0.2471 - val_accuracy: 0.8889
Epoch 124/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1145 - accuracy:
0.9474 - val_loss: 0.2378 - val_accuracy: 0.9333
Epoch 125/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1052 - accuracy:
0.9624 - val_loss: 0.2537 - val_accuracy: 0.8889
Epoch 126/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1127 - accuracy:
0.9474 - val_loss: 0.2567 - val_accuracy: 0.9333
Epoch 127/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1184 - accuracy:
0.9474 - val_loss: 0.2785 - val_accuracy: 0.8889
Epoch 128/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1220 - accuracy:
0.9549 - val_loss: 0.2647 - val_accuracy: 0.9333
Epoch 129/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1193 - accuracy:
0.9474 - val_loss: 0.3059 - val_accuracy: 0.8889
```

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Epoch 130/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1295 - accuracy:
0.9549 - val_loss: 0.2720 - val_accuracy: 0.9333
Epoch 131/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1230 - accuracy:
0.9398 - val_loss: 0.3166 - val_accuracy: 0.8889
Epoch 132/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1294 - accuracy:
0.9624 - val_loss: 0.2904 - val_accuracy: 0.9333
Epoch 133/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1354 - accuracy:
0.9398 - val_loss: 0.3427 - val_accuracy: 0.8667
Epoch 134/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1358 - accuracy:
0.9549 - val_loss: 0.3070 - val_accuracy: 0.9333
Epoch 135/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1425 - accuracy:
0.9398 - val_loss: 0.3822 - val_accuracy: 0.8667
Epoch 136/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1443 - accuracy:
0.9549 - val_loss: 0.3191 - val_accuracy: 0.9333
Epoch 137/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1488 - accuracy:
0.9398 - val_loss: 0.4032 - val_accuracy: 0.8667
Epoch 138/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1464 - accuracy:
0.9624 - val_loss: 0.3447 - val_accuracy: 0.9333
Epoch 139/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1666 - accuracy:
0.9398 - val_loss: 0.4497 - val_accuracy: 0.8444
Epoch 140/300
5/5 [==============================] - 0s 11ms/step - loss: 0.1558 - accuracy:
0.9398 - val_loss: 0.3817 - val_accuracy: 0.9333
Epoch 141/300
5/5 [==============================] - 0s 10ms/step - loss: 0.1959 - accuracy:
0.9398 - val_loss: 0.5125 - val_accuracy: 0.8222
Epoch 142/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1710 - accuracy:
0.9323 - val_loss: 0.4164 - val_accuracy: 0.9111
Epoch 143/300
5/5 [==============================] - 0s 7ms/step - loss: 0.2245 - accuracy:
0.9098 - val_loss: 0.5744 - val_accuracy: 0.8000
Epoch 144/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1852 - accuracy:
0.9323 - val_loss: 0.3966 - val_accuracy: 0.9333
Epoch 145/300
5/5 [==============================] - 0s 7ms/step - loss: 0.2336 - accuracy:
0.9173 - val_loss: 0.6718 - val_accuracy: 0.8000
```

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Epoch 146/300
5/5 [==============================] - 0s 8ms/step - loss: 0.2050 - accuracy:
0.9323 - val_loss: 0.2605 - val_accuracy: 0.9333
Epoch 147/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1663 - accuracy:
0.9474 - val_loss: 0.1705 - val_accuracy: 0.9556
Epoch 148/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0927 - accuracy:
0.9549 - val_loss: 0.2776 - val_accuracy: 0.9333
Epoch 149/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1116 - accuracy:
0.9474 - val_loss: 0.2591 - val_accuracy: 0.9333
Epoch 150/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1380 - accuracy:
0.9549 - val_loss: 0.1887 - val_accuracy: 0.9111
Epoch 151/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0913 - accuracy:
0.9474 - val_loss: 0.2968 - val_accuracy: 0.9333
Epoch 152/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1340 - accuracy:
0.9474 - val_loss: 0.2341 - val_accuracy: 0.9556
Epoch 153/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1685 - accuracy:
0.9323 - val_loss: 0.2222 - val_accuracy: 0.9556
Epoch 154/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1261 - accuracy:
0.9474 - val_loss: 0.1808 - val_accuracy: 0.9111
Epoch 155/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0833 - accuracy:
0.9624 - val_loss: 0.2605 - val_accuracy: 0.9333
Epoch 156/300
5/5 [==============================] - 0s 7ms/step - loss: 0.1152 - accuracy:
0.9474 - val_loss: 0.2350 - val_accuracy: 0.9556
Epoch 157/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1230 - accuracy:
0.9624 - val_loss: 0.2222 - val_accuracy: 0.9333
Epoch 158/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0891 - accuracy:
0.9549 - val_loss: 0.2766 - val_accuracy: 0.9333
Epoch 159/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1230 - accuracy:
0.9323 - val_loss: 0.2170 - val_accuracy: 0.9556
Epoch 160/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1186 - accuracy:
0.9624 - val_loss: 0.2442 - val_accuracy: 0.9333
Epoch 161/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1048 - accuracy:
0.9549 - val_loss: 0.2709 - val_accuracy: 0.9333
```

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Epoch 162/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1275 - accuracy:
0.9398 - val_loss: 0.2058 - val_accuracy: 0.9556
Epoch 163/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1275 - accuracy:
0.9549 - val_loss: 0.2519 - val_accuracy: 0.9333
Epoch 164/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1140 - accuracy:
0.9549 - val_loss: 0.2803 - val_accuracy: 0.9333
Epoch 165/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1263 - accuracy:
0.9323 - val_loss: 0.1803 - val_accuracy: 0.9556
Epoch 166/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1194 - accuracy:
0.9624 - val_loss: 0.2214 - val_accuracy: 0.9111
Epoch 167/300
5/5 [==============================] - 0s 8ms/step - loss: 0.1210 - accuracy:
0.9549 - val_loss: 0.2755 - val_accuracy: 0.9333
Epoch 168/300
5/5 [==============================] - 0s 9ms/step - loss: 0.1159 - accuracy:
0.9624 - val_loss: 0.1755 - val_accuracy: 0.9556
Epoch 169/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0773 - accuracy:
0.9774 - val_loss: 0.2038 - val_accuracy: 0.9556
Epoch 170/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0832 - accuracy:
0.9624 - val_loss: 0.1844 - val_accuracy: 0.9556
Epoch 171/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0695 - accuracy:
0.9774 - val_loss: 0.1714 - val_accuracy: 0.9556
Epoch 172/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0556 - accuracy:
0.9774 - val_loss: 0.1963 - val_accuracy: 0.9556
Epoch 173/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0597 - accuracy:
0.9774 - val_loss: 0.1828 - val_accuracy: 0.9556
Epoch 174/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0546 - accuracy:
0.9850 - val_loss: 0.1779 - val_accuracy: 0.9556
Epoch 175/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0561 - accuracy:
0.9774 - val_loss: 0.1800 - val_accuracy: 0.9556
Epoch 176/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0533 - accuracy:
0.9774 - val_loss: 0.1846 - val_accuracy: 0.9556
Epoch 177/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0534 - accuracy:
0.9850 - val_loss: 0.1778 - val_accuracy: 0.9556
```

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Epoch 178/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0522 - accuracy:
0.9850 - val_loss: 0.1794 - val_accuracy: 0.9556
Epoch 179/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0523 - accuracy:
0.9850 - val_loss: 0.1817 - val_accuracy: 0.9556
Epoch 180/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0519 - accuracy:
0.9850 - val_loss: 0.1809 - val_accuracy: 0.9556
Epoch 181/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0518 - accuracy:
0.9850 - val_loss: 0.1794 - val_accuracy: 0.9556
Epoch 182/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0512 - accuracy:
0.9850 - val_loss: 0.1820 - val_accuracy: 0.9556
Epoch 183/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0514 - accuracy:
0.9850 - val_loss: 0.1818 - val_accuracy: 0.9556
Epoch 184/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0510 - accuracy:
0.9850 - val_loss: 0.1812 - val_accuracy: 0.9556
Epoch 185/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0508 - accuracy:
0.9850 - val_loss: 0.1818 - val_accuracy: 0.9556
Epoch 186/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0506 - accuracy:
0.9850 - val_loss: 0.1819 - val_accuracy: 0.9556
Epoch 187/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0503 - accuracy:
0.9850 - val_loss: 0.1821 - val_accuracy: 0.9556
Epoch 188/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0503 - accuracy:
0.9850 - val_loss: 0.1818 - val_accuracy: 0.9556
Epoch 189/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0497 - accuracy:
0.9850 - val_loss: 0.1828 - val_accuracy: 0.9556
Epoch 190/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0499 - accuracy:
0.9850 - val_loss: 0.1826 - val_accuracy: 0.9556
Epoch 191/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0495 - accuracy:
0.9850 - val_loss: 0.1826 - val_accuracy: 0.9556
Epoch 192/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0493 - accuracy:
0.9850 - val_loss: 0.1830 - val_accuracy: 0.9556
Epoch 193/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0492 - accuracy:
0.9850 - val_loss: 0.1828 - val_accuracy: 0.9556
```

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Epoch 194/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0489 - accuracy:
0.9850 - val_loss: 0.1833 - val_accuracy: 0.9556
Epoch 195/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0488 - accuracy:
0.9850 - val_loss: 0.1830 - val_accuracy: 0.9556
Epoch 196/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0485 - accuracy:
0.9850 - val_loss: 0.1834 - val_accuracy: 0.9556
Epoch 197/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0483 - accuracy:
0.9850 - val_loss: 0.1837 - val_accuracy: 0.9556
Epoch 198/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0482 - accuracy:
0.9850 - val_loss: 0.1837 - val_accuracy: 0.9556
Epoch 199/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0480 - accuracy:
0.9850 - val_loss: 0.1837 - val_accuracy: 0.9556
Epoch 200/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0477 - accuracy:
0.9850 - val_loss: 0.1840 - val_accuracy: 0.9556
Epoch 201/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0477 - accuracy:
0.9850 - val_loss: 0.1837 - val_accuracy: 0.9556
Epoch 202/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0474 - accuracy:
0.9850 - val_loss: 0.1842 - val_accuracy: 0.9556
Epoch 203/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0472 - accuracy:
0.9850 - val_loss: 0.1842 - val_accuracy: 0.9556
Epoch 204/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0471 - accuracy:
0.9850 - val_loss: 0.1843 - val_accuracy: 0.9556
Epoch 205/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0468 - accuracy:
0.9850 - val_loss: 0.1846 - val_accuracy: 0.9556
Epoch 206/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0467 - accuracy:
0.9850 - val_loss: 0.1847 - val_accuracy: 0.9556
Epoch 207/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0466 - accuracy:
0.9850 - val_loss: 0.1846 - val_accuracy: 0.9556
Epoch 208/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0462 - accuracy:
0.9850 - val_loss: 0.1849 - val_accuracy: 0.9556
Epoch 209/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0462 - accuracy:
0.9850 - val_loss: 0.1846 - val_accuracy: 0.9556
```

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Epoch 210/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0459 - accuracy:
0.9850 - val_loss: 0.1850 - val_accuracy: 0.9556
Epoch 211/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0458 - accuracy:
0.9850 - val_loss: 0.1850 - val_accuracy: 0.9556
Epoch 212/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0456 - accuracy:
0.9850 - val_loss: 0.1851 - val_accuracy: 0.9556
Epoch 213/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0454 - accuracy:
0.9850 - val_loss: 0.1856 - val_accuracy: 0.9556
Epoch 214/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0453 - accuracy:
0.9850 - val_loss: 0.1856 - val_accuracy: 0.9556
Epoch 215/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0452 - accuracy:
0.9850 - val_loss: 0.1853 - val_accuracy: 0.9556
Epoch 216/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0448 - accuracy:
0.9850 - val_loss: 0.1858 - val_accuracy: 0.9556
Epoch 217/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0448 - accuracy:
0.9850 - val_loss: 0.1853 - val_accuracy: 0.9556
Epoch 218/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0446 - accuracy:
0.9850 - val_loss: 0.1855 - val_accuracy: 0.9556
Epoch 219/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0444 - accuracy:
0.9850 - val_loss: 0.1858 - val_accuracy: 0.9556
Epoch 220/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0443 - accuracy:
0.9850 - val_loss: 0.1858 - val_accuracy: 0.9556
Epoch 221/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0441 - accuracy:
0.9850 - val_loss: 0.1862 - val_accuracy: 0.9556
Epoch 222/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0441 - accuracy:
0.9850 - val_loss: 0.1860 - val_accuracy: 0.9556
Epoch 223/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0437 - accuracy:
0.9850 - val_loss: 0.1862 - val_accuracy: 0.9556
Epoch 224/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0437 - accuracy:
0.9850 - val_loss: 0.1860 - val_accuracy: 0.9556
Epoch 225/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0435 - accuracy:
0.9850 - val_loss: 0.1862 - val_accuracy: 0.9556
```

```
Epoch 226/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0433 - accuracy:
0.9850 - val_loss: 0.1864 - val_accuracy: 0.9556
Epoch 227/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0432 - accuracy:
0.9850 - val_loss: 0.1862 - val_accuracy: 0.9556
Epoch 228/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0429 - accuracy:
0.9850 - val_loss: 0.1867 - val_accuracy: 0.9556
Epoch 229/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0430 - accuracy:
0.9850 - val_loss: 0.1864 - val_accuracy: 0.9556
Epoch 230/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0426 - accuracy:
0.9850 - val_loss: 0.1865 - val_accuracy: 0.9556
Epoch 231/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0425 - accuracy:
0.9850 - val_loss: 0.1864 - val_accuracy: 0.9556
Epoch 232/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0424 - accuracy:
0.9850 - val_loss: 0.1866 - val_accuracy: 0.9556
Epoch 233/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0422 - accuracy:
0.9850 - val_loss: 0.1866 - val_accuracy: 0.9556
Epoch 234/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0421 - accuracy:
0.9850 - val_loss: 0.1867 - val_accuracy: 0.9556
Epoch 235/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0420 - accuracy:
0.9850 - val_loss: 0.1868 - val_accuracy: 0.9556
Epoch 236/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0417 - accuracy:
0.9850 - val_loss: 0.1868 - val_accuracy: 0.9556
Epoch 237/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0417 - accuracy:
0.9850 - val_loss: 0.1871 - val_accuracy: 0.9556
Epoch 238/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0415 - accuracy:
0.9850 - val_loss: 0.1870 - val_accuracy: 0.9556
Epoch 239/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0413 - accuracy:
0.9850 - val_loss: 0.1871 - val_accuracy: 0.9556
Epoch 240/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0412 - accuracy:
0.9850 - val_loss: 0.1869 - val_accuracy: 0.9556
Epoch 241/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0410 - accuracy:
0.9850 - val_loss: 0.1873 - val_accuracy: 0.9556
```

```
Epoch 242/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0410 - accuracy:
0.9850 - val_loss: 0.1871 - val_accuracy: 0.9556
Epoch 243/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0407 - accuracy:
0.9850 - val_loss: 0.1875 - val_accuracy: 0.9556
Epoch 244/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0406 - accuracy:
0.9850 - val_loss: 0.1878 - val_accuracy: 0.9556
Epoch 245/300
5/5 [==============================] - 0s 11ms/step - loss: 0.0406 - accuracy:
0.9850 - val_loss: 0.1872 - val_accuracy: 0.9556
Epoch 246/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0403 - accuracy:
0.9850 - val_loss: 0.1873 - val_accuracy: 0.9556
Epoch 247/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0402 - accuracy:
0.9850 - val_loss: 0.1871 - val_accuracy: 0.9556
Epoch 248/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0400 - accuracy:
0.9850 - val_loss: 0.1878 - val_accuracy: 0.9556
Epoch 249/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0400 - accuracy:
0.9850 - val_loss: 0.1880 - val_accuracy: 0.9556
Epoch 250/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0399 - accuracy:
0.9850 - val_loss: 0.1873 - val_accuracy: 0.9556
Epoch 251/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0396 - accuracy:
0.9850 - val_loss: 0.1872 - val_accuracy: 0.9556
Epoch 252/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0395 - accuracy:
0.9850 - val_loss: 0.1882 - val_accuracy: 0.9556
Epoch 253/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0394 - accuracy:
0.9850 - val_loss: 0.1874 - val_accuracy: 0.9556
Epoch 254/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0392 - accuracy:
0.9850 - val_loss: 0.1879 - val_accuracy: 0.9556
Epoch 255/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0392 - accuracy:
0.9850 - val_loss: 0.1883 - val_accuracy: 0.9556
Epoch 256/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0390 - accuracy:
0.9850 - val_loss: 0.1874 - val_accuracy: 0.9556
Epoch 257/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0388 - accuracy:
0.9850 - val_loss: 0.1882 - val_accuracy: 0.9556
```

```
Epoch 258/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0388 - accuracy:
0.9850 - val_loss: 0.1883 - val_accuracy: 0.9556
Epoch 259/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0387 - accuracy:
0.9850 - val_loss: 0.1877 - val_accuracy: 0.9556
Epoch 260/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0385 - accuracy:
0.9850 - val_loss: 0.1877 - val_accuracy: 0.9556
Epoch 261/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0382 - accuracy:
0.9850 - val_loss: 0.1886 - val_accuracy: 0.9556
Epoch 262/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0384 - accuracy:
0.9850 - val_loss: 0.1881 - val_accuracy: 0.9556
Epoch 263/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0381 - accuracy:
0.9850 - val_loss: 0.1877 - val_accuracy: 0.9556
Epoch 264/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0379 - accuracy:
0.9850 - val_loss: 0.1881 - val_accuracy: 0.9556
Epoch 265/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0379 - accuracy:
0.9850 - val_loss: 0.1885 - val_accuracy: 0.9556
Epoch 266/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0378 - accuracy:
0.9850 - val_loss: 0.1879 - val_accuracy: 0.9556
Epoch 267/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0375 - accuracy:
0.9850 - val_loss: 0.1885 - val_accuracy: 0.9556
Epoch 268/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0375 - accuracy:
0.9850 - val_loss: 0.1886 - val_accuracy: 0.9556
Epoch 269/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0374 - accuracy:
0.9850 - val_loss: 0.1886 - val_accuracy: 0.9556
Epoch 270/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0372 - accuracy:
0.9850 - val_loss: 0.1880 - val_accuracy: 0.9556
Epoch 271/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0371 - accuracy:
0.9850 - val_loss: 0.1885 - val_accuracy: 0.9556
Epoch 272/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0370 - accuracy:
0.9850 - val_loss: 0.1887 - val_accuracy: 0.9556
Epoch 273/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0368 - accuracy:
0.9850 - val_loss: 0.1889 - val_accuracy: 0.9556
```

```
Epoch 274/300
5/5 [==============================] - 0s 16ms/step - loss: 0.0368 - accuracy:
0.9850 - val_loss: 0.1885 - val_accuracy: 0.9556
Epoch 275/300
5/5 [==============================] - 0s 13ms/step - loss: 0.0367 - accuracy:
0.9850 - val_loss: 0.1885 - val_accuracy: 0.9556
Epoch 276/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0364 - accuracy:
0.9850 - val_loss: 0.1884 - val_accuracy: 0.9556
Epoch 277/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0364 - accuracy:
0.9850 - val_loss: 0.1889 - val_accuracy: 0.9556
Epoch 278/300
5/5 [==============================] - 0s 11ms/step - loss: 0.0363 - accuracy:
0.9850 - val_loss: 0.1884 - val_accuracy: 0.9556
Epoch 279/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0361 - accuracy:
0.9850 - val_loss: 0.1887 - val_accuracy: 0.9556
Epoch 280/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0361 - accuracy:
0.9850 - val_loss: 0.1890 - val_accuracy: 0.9556
Epoch 281/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0360 - accuracy:
0.9850 - val_loss: 0.1888 - val_accuracy: 0.9556
Epoch 282/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0357 - accuracy:
0.9850 - val_loss: 0.1887 - val_accuracy: 0.9556
Epoch 283/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0357 - accuracy:
0.9850 - val_loss: 0.1891 - val_accuracy: 0.9556
Epoch 284/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0355 - accuracy:
0.9850 - val_loss: 0.1888 - val_accuracy: 0.9556
Epoch 285/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0355 - accuracy:
0.9850 - val_loss: 0.1886 - val_accuracy: 0.9556
Epoch 286/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0352 - accuracy:
0.9850 - val_loss: 0.1891 - val_accuracy: 0.9556
Epoch 287/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0353 - accuracy:
0.9850 - val_loss: 0.1890 - val_accuracy: 0.9556
Epoch 288/300
5/5 [==============================] - 0s 7ms/step - loss: 0.0351 - accuracy:
0.9850 - val_loss: 0.1889 - val_accuracy: 0.9556
Epoch 289/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0349 - accuracy:
0.9850 - val_loss: 0.1890 - val_accuracy: 0.9556
```

```
Epoch 290/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0348 - accuracy:
0.9850 - val_loss: 0.1891 - val_accuracy: 0.9556
Epoch 291/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0349 - accuracy:
0.9850 - val_loss: 0.1888 - val_accuracy: 0.9556
Epoch 292/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0346 - accuracy:
0.9850 - val_loss: 0.1890 - val_accuracy: 0.9556
Epoch 293/300
5/5 [==============================] - 0s 11ms/step - loss: 0.0346 - accuracy:
0.9850 - val_loss: 0.1894 - val_accuracy: 0.9556
Epoch 294/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0345 - accuracy:
0.9850 - val_loss: 0.1892 - val_accuracy: 0.9556
Epoch 295/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0343 - accuracy:
0.9850 - val_loss: 0.1888 - val_accuracy: 0.9556
Epoch 296/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0342 - accuracy:
0.9850 - val_loss: 0.1894 - val_accuracy: 0.9556
Epoch 297/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0341 - accuracy:
0.9850 - val_loss: 0.1891 - val_accuracy: 0.9556
Epoch 298/300
5/5 [==============================] - 0s 8ms/step - loss: 0.0340 - accuracy:
0.9850 - val_loss: 0.1886 - val_accuracy: 0.9556
Epoch 299/300
5/5 [==============================] - 0s 10ms/step - loss: 0.0338 - accuracy:
0.9850 - val_loss: 0.1892 - val_accuracy: 0.9556
Epoch 300/300
5/5 [==============================] - 0s 9ms/step - loss: 0.0338 - accuracy:
0.9850 - val_loss: 0.1894 - val_accuracy: 0.9556
Best epoch: 27
```

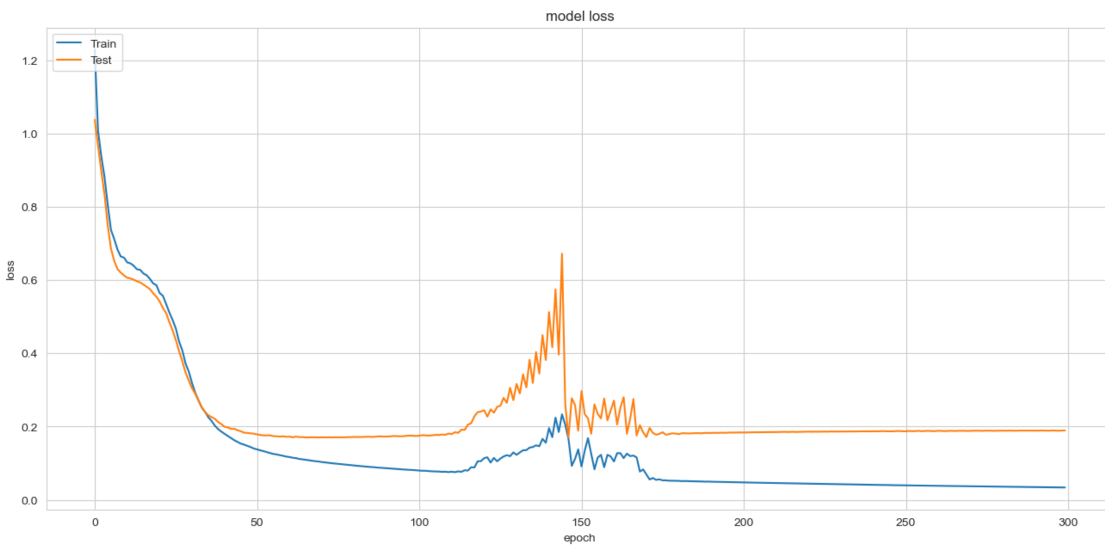
[15]:

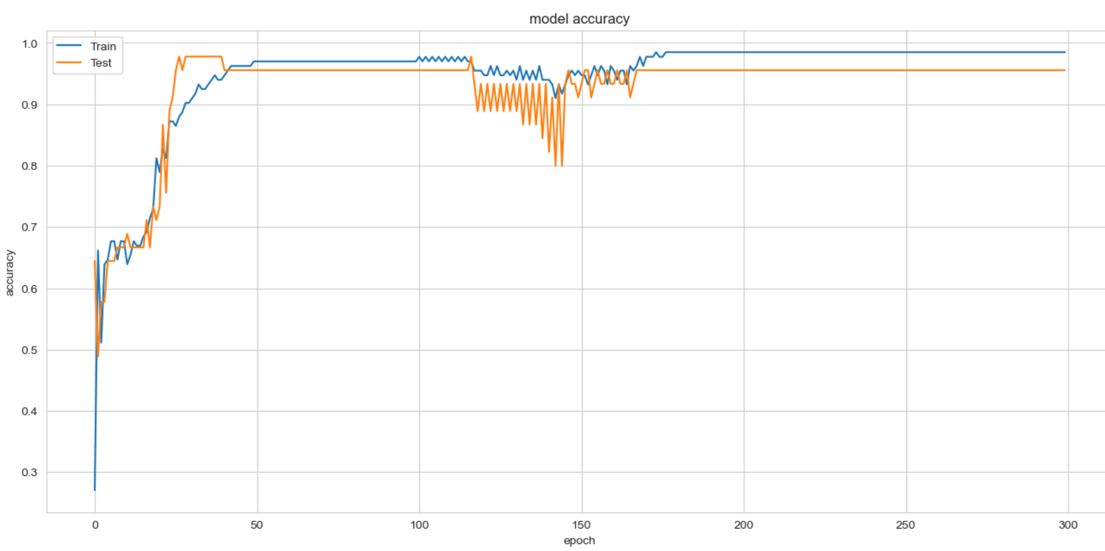
```
fig = plt.figure(figsize=(16, 16))

ax1 = fig.add_subplot(2,1,1)
ax1.plot(history.history['loss'])
ax1.plot(history.history['val_loss'])
ax1.set_title('model loss')
ax1.set_ylabel('loss')
ax1.set_xlabel('epoch')
ax1.legend(['Train', 'Test'], loc='upper left')

ax2 = fig.add_subplot(2,1,2)
ax2.plot(history.history['accuracy'])
```

```
ax2.plot(history.history['val_accuracy'])
ax2.set_title('model accuracy')
ax2.set_ylabel('accuracy')
ax2.set_xlabel('epoch')
ax2.legend(['Train', 'Test'], loc='upper left')
fig.show()
```





[16]:
```
y_pred = model.predict(X_test)
y_pred = np.argmax(y_pred, axis=1)
y_test_am = np.argmax(y_test, axis=1)

print(confusion_matrix(y_test_am, y_pred))
```

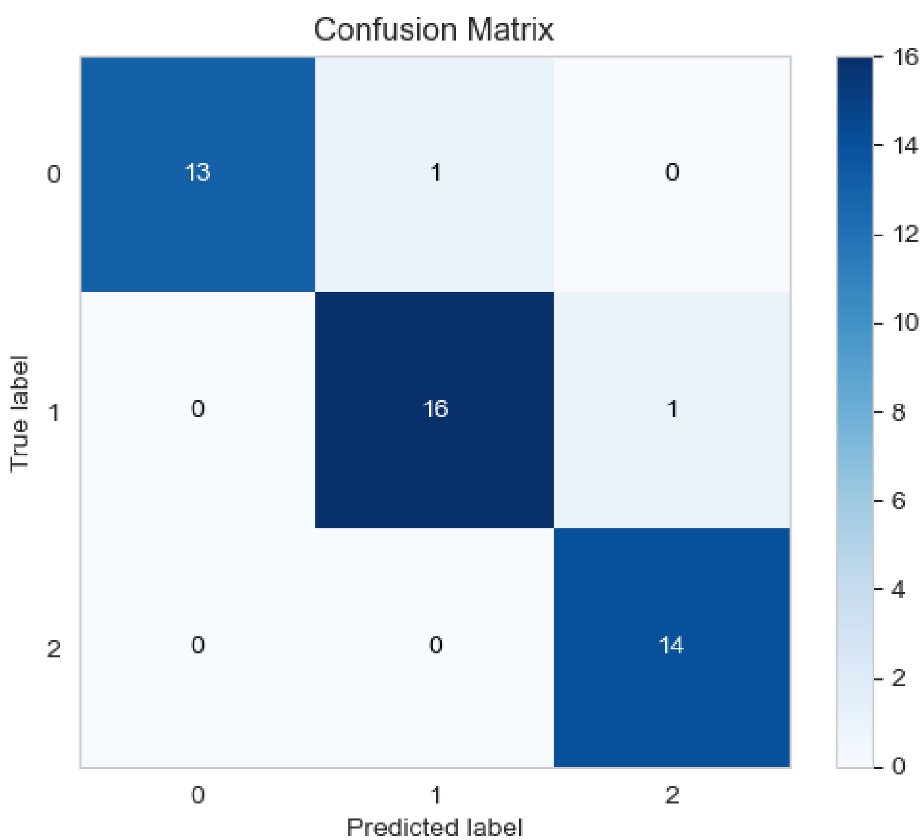
```python
print(classification_report(y_test_am, y_pred, labels=[0,1,2]))

plot_confusion_matrix(y_test_am, y_pred)
plt.show()
```

```
2/2 [==============================] - 0s 3ms/step
[[13  1  0]
 [ 0 16  1]
 [ 0  0 14]]
              precision    recall  f1-score   support

           0       1.00      0.93      0.96        14
           1       0.94      0.94      0.94        17
           2       0.93      1.00      0.97        14

    accuracy                           0.96        45
   macro avg       0.96      0.96      0.96        45
weighted avg       0.96      0.96      0.96        45
```



[17]:
```
print("""The precision of the model seems to be pretty great, the recall is␣
↪pretty solid, and the f1-score is quite solid overall. The accuracy is good␣
↪as well. Overall, very few issues in the predictions on the test set, so␣
↪this model is probably not overfit. The accuracy vs. val accuracy was around␣
↪99% vs. 97%, so that's better obviously but really not a huge difference.␣
↪All in all, I think the model is well fit.""")
```

```
The precision of the model seems to be pretty great, the recall is pretty solid,
and the f1-score is quite solid overall. The accuracy is good as well. Overall,
very few issues in the predictions on the test set, so this model is probably
not overfit. The accuracy vs. val accuracy was around 99% vs. 97%, so that's
better obviously but really not a huge difference. All in all, I think the model
is well fit.
```

[ ]:
```

```