

# Midterm

October 22, 2023

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

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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

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, Flavonoids, 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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```
[4]: # fetch dataset
wine = pd.read_csv("data/wine.csv")

[5]: # split dataset into train/test, proportioned at 25%
X, y = wine, wine["label"]
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]: wine.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
1		3.40	1050.0
2		3.17	1185.0
3		3.45	1480.0
4		2.93	735.0

```
[7]: wine.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	

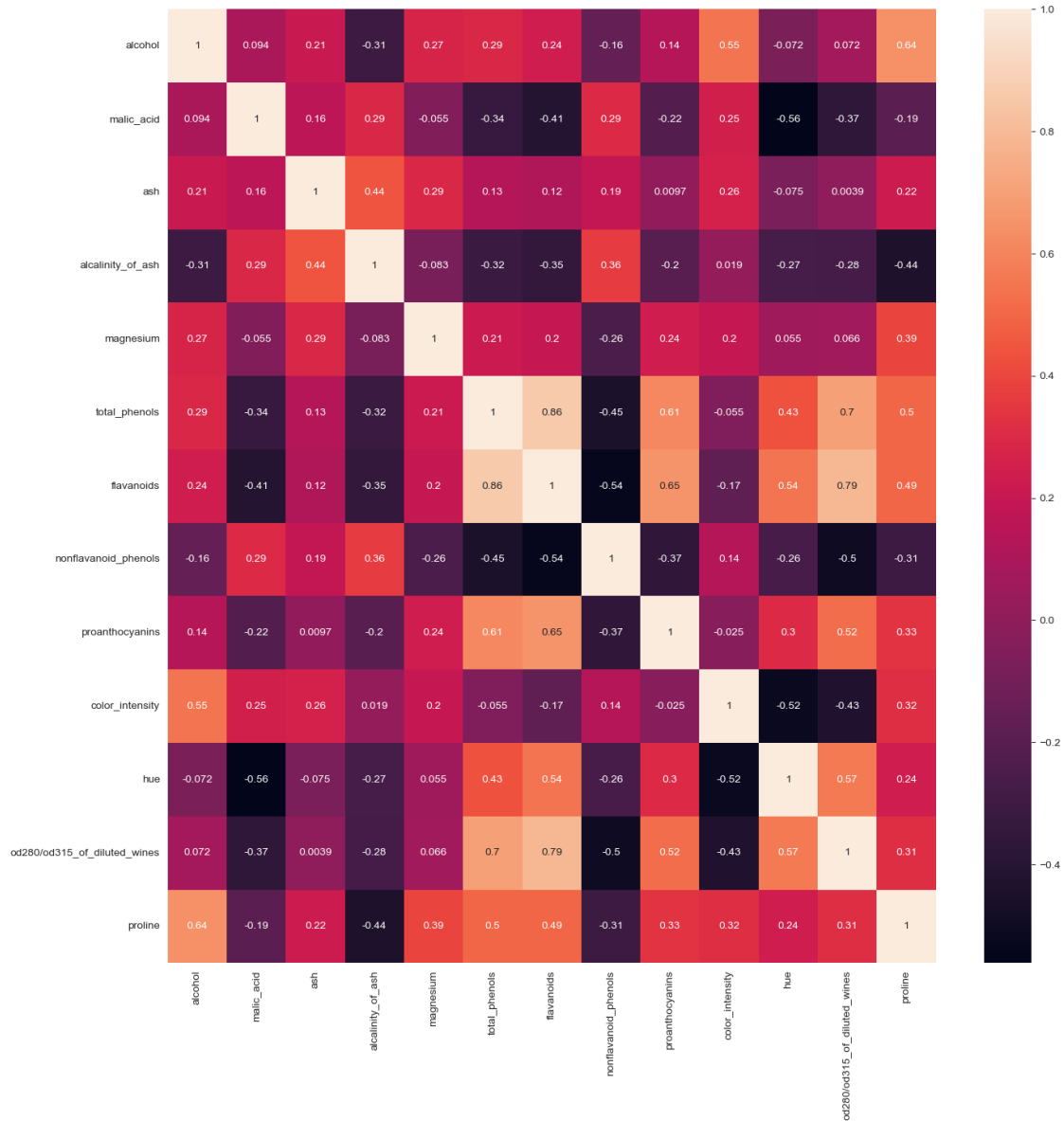
	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	\
count	178.000000	178.000000	178.000000	178.000000	
mean	2.295112	2.029270	0.361854	1.590899	
std	0.625851	0.998859	0.124453	0.572359	
min	0.980000	0.340000	0.130000	0.410000	
25%	1.742500	1.205000	0.270000	1.250000	
50%	2.355000	2.135000	0.340000	1.555000	

75%	2.800000	2.875000	0.437500	1.950000
max	3.880000	5.080000	0.660000	3.580000

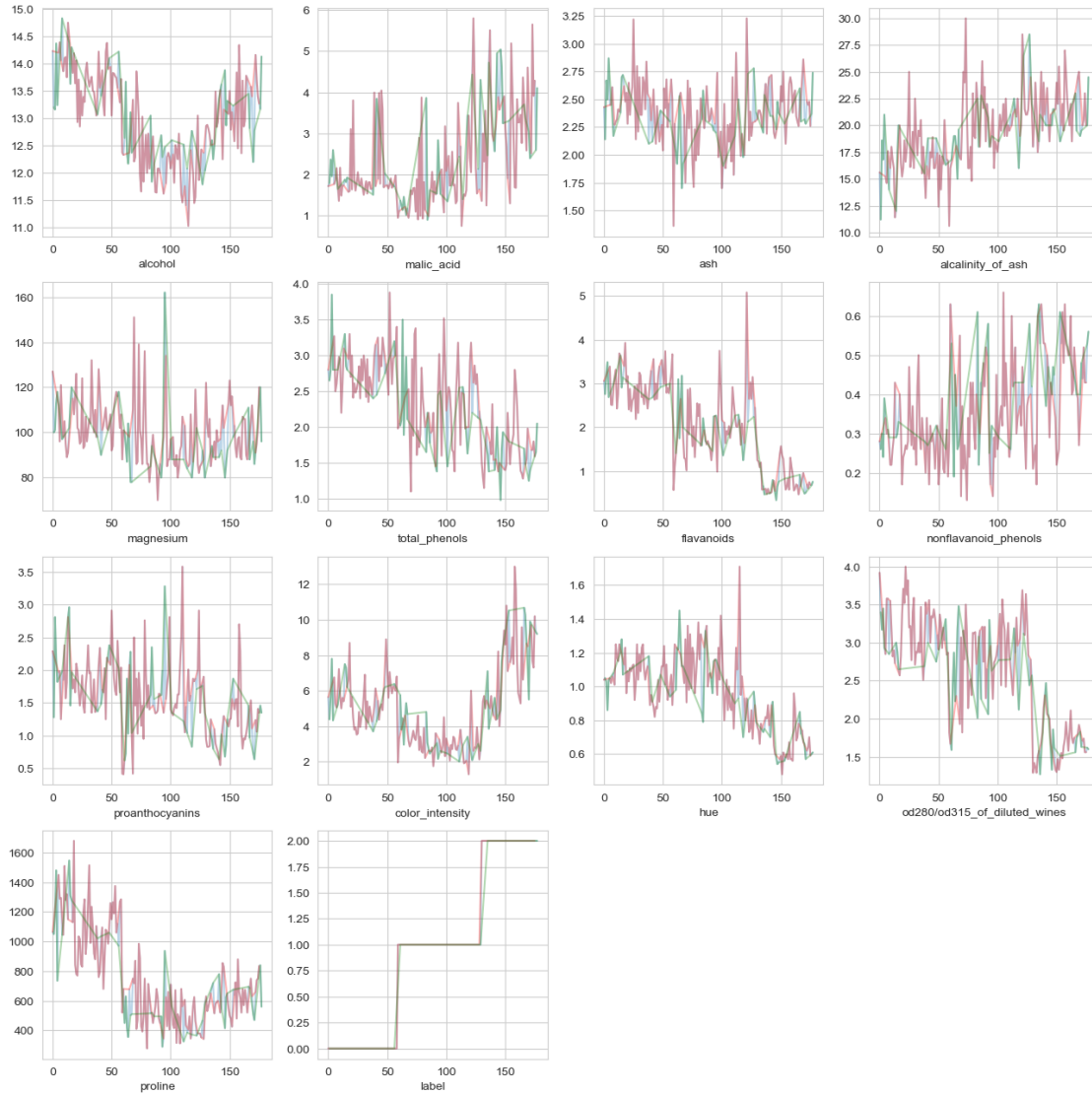
	color_intensity	hue	od280/od315_of_diluted_wines	proline \
count	178.000000	178.000000	178.000000	178.000000
mean	5.058090	0.957449	2.611685	746.893258
std	2.318286	0.228572	0.709990	314.907474
min	1.280000	0.480000	1.270000	278.000000
25%	3.220000	0.782500	1.937500	500.500000
50%	4.690000	0.965000	2.780000	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

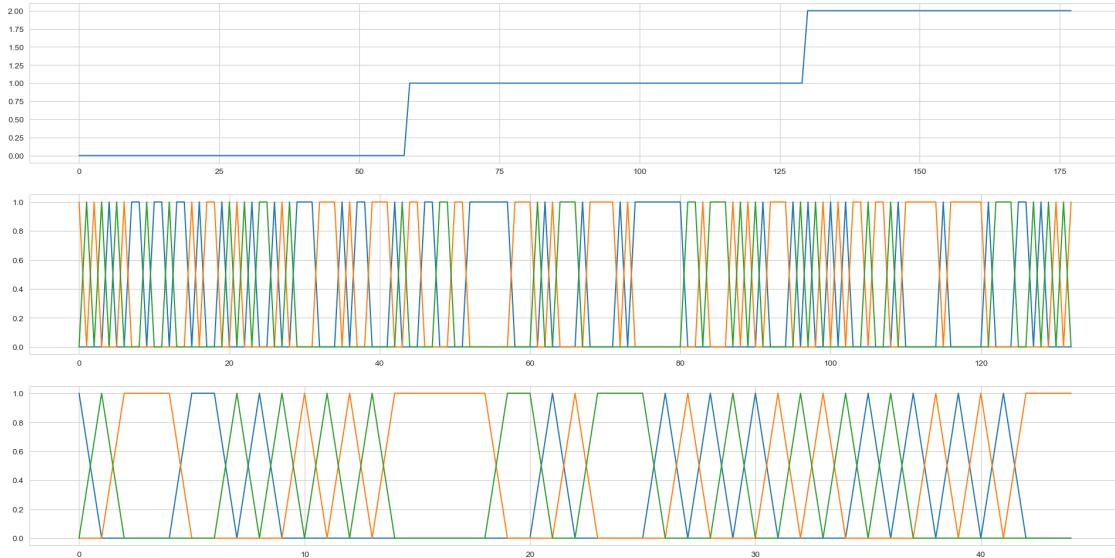
```
[8]: plt.figure(figsize = (16,16))
sns.heatmap(wine.iloc[:, :-1].corr(), annot=True)
plt.show()
```



```
[9]: fig = plt.figure(figsize=(16, 16))
labels = wine.columns
for label in range(len(labels)):
    ax = fig.add_subplot(4,4,label+1)
    ax.plot(X.iloc[:, label], alpha = 0.3)
    ax.plot(X_train.sort_index().iloc[:, label], color="red", alpha = 0.3)
    ax.plot(X_test.sort_index().iloc[:, 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.iloc[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 12 Complete [00h 00m 01s]  
val\_accuracy: 0.2222222238779068

Best val\_accuracy So Far: 0.6296296119689941  
Total elapsed time: 00h 00m 12s  
The hyperparameter search is complete. The optimal number of units in the first densely-connected layer is 55.

```

[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 40ms/step - loss: 1.1704 - accuracy:  
0.3308 - val\_loss: 1.1132 - val\_accuracy: 0.4222



Epoch 2/300  
5/5 [=====] - 0s 8ms/step - loss: 1.0984 - accuracy: 0.3985 - val\_loss: 1.0794 - val\_accuracy: 0.6444

Epoch 3/300  
5/5 [=====] - 0s 8ms/step - loss: 1.0695 - accuracy: 0.5865 - val\_loss: 1.0546 - val\_accuracy: 0.3556

Epoch 4/300  
5/5 [=====] - 0s 8ms/step - loss: 1.0247 - accuracy: 0.3835 - val\_loss: 1.0450 - val\_accuracy: 0.2667

Epoch 5/300  
5/5 [=====] - 0s 8ms/step - loss: 0.9810 - accuracy: 0.3534 - val\_loss: 1.0014 - val\_accuracy: 0.3778

Epoch 6/300  
5/5 [=====] - 0s 8ms/step - loss: 0.9358 - accuracy: 0.5338 - val\_loss: 0.9548 - val\_accuracy: 0.6444

Epoch 7/300  
5/5 [=====] - 0s 8ms/step - loss: 0.9125 - accuracy: 0.5865 - val\_loss: 0.9237 - val\_accuracy: 0.5556

Epoch 8/300  
5/5 [=====] - 0s 9ms/step - loss: 0.8549 - accuracy: 0.6090 - val\_loss: 0.8752 - val\_accuracy: 0.6444

Epoch 9/300  
5/5 [=====] - 0s 8ms/step - loss: 0.8355 - accuracy: 0.6165 - val\_loss: 0.8552 - val\_accuracy: 0.6444

Epoch 10/300  
5/5 [=====] - 0s 8ms/step - loss: 0.8030 - accuracy: 0.6241 - val\_loss: 0.8282 - val\_accuracy: 0.6667

Epoch 11/300  
5/5 [=====] - 0s 9ms/step - loss: 0.7845 - accuracy: 0.6165 - val\_loss: 0.8153 - val\_accuracy: 0.6444

Epoch 12/300  
5/5 [=====] - 0s 9ms/step - loss: 0.7694 - accuracy: 0.6241 - val\_loss: 0.7997 - val\_accuracy: 0.6667

Epoch 13/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7591 - accuracy: 0.6541 - val\_loss: 0.7879 - val\_accuracy: 0.6667

Epoch 14/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7486 - accuracy: 0.6767 - val\_loss: 0.7725 - val\_accuracy: 0.6667

Epoch 15/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7406 - accuracy: 0.6767 - val\_loss: 0.7681 - val\_accuracy: 0.6667

Epoch 16/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7330 - accuracy: 0.6842 - val\_loss: 0.7604 - val\_accuracy: 0.6667

Epoch 17/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7238 - accuracy: 0.6842 - val\_loss: 0.7571 - val\_accuracy: 0.6667

Epoch 18/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7198 - accuracy: 0.6842 - val\_loss: 0.7492 - val\_accuracy: 0.6667  
Epoch 19/300  
5/5 [=====] - 0s 9ms/step - loss: 0.7095 - accuracy: 0.6917 - val\_loss: 0.7387 - val\_accuracy: 0.6667  
Epoch 20/300  
5/5 [=====] - 0s 9ms/step - loss: 0.7056 - accuracy: 0.6842 - val\_loss: 0.7292 - val\_accuracy: 0.6667  
Epoch 21/300  
5/5 [=====] - 0s 8ms/step - loss: 0.7008 - accuracy: 0.6767 - val\_loss: 0.7434 - val\_accuracy: 0.6444  
Epoch 22/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6923 - accuracy: 0.6917 - val\_loss: 0.7240 - val\_accuracy: 0.6667  
Epoch 23/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6872 - accuracy: 0.6842 - val\_loss: 0.7176 - val\_accuracy: 0.6667  
Epoch 24/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6817 - accuracy: 0.6842 - val\_loss: 0.7176 - val\_accuracy: 0.6667  
Epoch 25/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6719 - accuracy: 0.6917 - val\_loss: 0.7111 - val\_accuracy: 0.6667  
Epoch 26/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6695 - accuracy: 0.6842 - val\_loss: 0.7062 - val\_accuracy: 0.6667  
Epoch 27/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6586 - accuracy: 0.6917 - val\_loss: 0.7011 - val\_accuracy: 0.6667  
Epoch 28/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6572 - accuracy: 0.6842 - val\_loss: 0.6984 - val\_accuracy: 0.6667  
Epoch 29/300  
5/5 [=====] - 0s 8ms/step - loss: 0.6478 - accuracy: 0.6842 - val\_loss: 0.6962 - val\_accuracy: 0.6667  
Epoch 30/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6430 - accuracy: 0.6917 - val\_loss: 0.6859 - val\_accuracy: 0.6667  
Epoch 31/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6379 - accuracy: 0.6992 - val\_loss: 0.6841 - val\_accuracy: 0.6667  
Epoch 32/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6316 - accuracy: 0.6917 - val\_loss: 0.6836 - val\_accuracy: 0.6444  
Epoch 33/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6280 - accuracy: 0.6917 - val\_loss: 0.6736 - val\_accuracy: 0.6667

Epoch 34/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6206 - accuracy: 0.6917 - val\_loss: 0.6722 - val\_accuracy: 0.6667  
Epoch 35/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6166 - accuracy: 0.6992 - val\_loss: 0.6652 - val\_accuracy: 0.6667  
Epoch 36/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6088 - accuracy: 0.6917 - val\_loss: 0.6682 - val\_accuracy: 0.6444  
Epoch 37/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6067 - accuracy: 0.6917 - val\_loss: 0.6555 - val\_accuracy: 0.6667  
Epoch 38/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6001 - accuracy: 0.6917 - val\_loss: 0.6474 - val\_accuracy: 0.6667  
Epoch 39/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5946 - accuracy: 0.6917 - val\_loss: 0.6769 - val\_accuracy: 0.6444  
Epoch 40/300  
5/5 [=====] - 0s 8ms/step - loss: 0.5961 - accuracy: 0.7068 - val\_loss: 0.6372 - val\_accuracy: 0.6667  
Epoch 41/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5842 - accuracy: 0.6917 - val\_loss: 0.6454 - val\_accuracy: 0.6667  
Epoch 42/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5843 - accuracy: 0.6842 - val\_loss: 0.6273 - val\_accuracy: 0.6667  
Epoch 43/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5705 - accuracy: 0.7068 - val\_loss: 0.6190 - val\_accuracy: 0.6667  
Epoch 44/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5802 - accuracy: 0.6917 - val\_loss: 0.6420 - val\_accuracy: 0.6444  
Epoch 45/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5555 - accuracy: 0.7143 - val\_loss: 0.6027 - val\_accuracy: 0.6667  
Epoch 46/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5401 - accuracy: 0.6917 - val\_loss: 0.5787 - val\_accuracy: 0.6667  
Epoch 47/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5320 - accuracy: 0.7143 - val\_loss: 0.5757 - val\_accuracy: 0.6667  
Epoch 48/300  
5/5 [=====] - 0s 8ms/step - loss: 0.5003 - accuracy: 0.6842 - val\_loss: 0.5181 - val\_accuracy: 0.6667  
Epoch 49/300  
5/5 [=====] - 0s 8ms/step - loss: 0.4634 - accuracy: 0.6992 - val\_loss: 0.4974 - val\_accuracy: 0.6667

Epoch 50/300  
5/5 [=====] - 0s 8ms/step - loss: 0.4553 - accuracy: 0.6917 - val\_loss: 0.4617 - val\_accuracy: 0.6667  
Epoch 51/300  
5/5 [=====] - 0s 7ms/step - loss: 0.4274 - accuracy: 0.6992 - val\_loss: 0.4485 - val\_accuracy: 0.6667  
Epoch 52/300  
5/5 [=====] - 0s 7ms/step - loss: 0.4204 - accuracy: 0.7669 - val\_loss: 0.4247 - val\_accuracy: 0.9778  
Epoch 53/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3941 - accuracy: 0.8872 - val\_loss: 0.4075 - val\_accuracy: 0.9778  
Epoch 54/300  
5/5 [=====] - 0s 8ms/step - loss: 0.3752 - accuracy: 0.9098 - val\_loss: 0.3762 - val\_accuracy: 0.9556  
Epoch 55/300  
5/5 [=====] - 0s 8ms/step - loss: 0.3685 - accuracy: 0.9098 - val\_loss: 0.3716 - val\_accuracy: 0.9778  
Epoch 56/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3598 - accuracy: 0.8872 - val\_loss: 0.3626 - val\_accuracy: 0.9778  
Epoch 57/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3408 - accuracy: 0.9098 - val\_loss: 0.3478 - val\_accuracy: 0.9778  
Epoch 58/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3296 - accuracy: 0.9173 - val\_loss: 0.3424 - val\_accuracy: 0.9778  
Epoch 59/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3221 - accuracy: 0.9173 - val\_loss: 0.3285 - val\_accuracy: 0.9778  
Epoch 60/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3085 - accuracy: 0.9248 - val\_loss: 0.3229 - val\_accuracy: 0.9778  
Epoch 61/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2992 - accuracy: 0.9398 - val\_loss: 0.3156 - val\_accuracy: 0.9778  
Epoch 62/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2891 - accuracy: 0.9549 - val\_loss: 0.3059 - val\_accuracy: 0.9778  
Epoch 63/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2789 - accuracy: 0.9624 - val\_loss: 0.3001 - val\_accuracy: 0.9778  
Epoch 64/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2703 - accuracy: 0.9624 - val\_loss: 0.2933 - val\_accuracy: 0.9778  
Epoch 65/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2606 - accuracy: 0.9624 - val\_loss: 0.2890 - val\_accuracy: 0.9778

Epoch 66/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2516 - accuracy: 0.9624 - val\_loss: 0.2757 - val\_accuracy: 0.9778  
Epoch 67/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2419 - accuracy: 0.9624 - val\_loss: 0.2644 - val\_accuracy: 0.9778  
Epoch 68/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2448 - accuracy: 0.9699 - val\_loss: 0.2726 - val\_accuracy: 0.9778  
Epoch 69/300  
5/5 [=====] - 0s 8ms/step - loss: 0.2372 - accuracy: 0.9624 - val\_loss: 0.2572 - val\_accuracy: 0.9556  
Epoch 70/300  
5/5 [=====] - 0s 8ms/step - loss: 0.2266 - accuracy: 0.9624 - val\_loss: 0.2595 - val\_accuracy: 0.9778  
Epoch 71/300  
5/5 [=====] - 0s 8ms/step - loss: 0.2157 - accuracy: 0.9699 - val\_loss: 0.2392 - val\_accuracy: 0.9556  
Epoch 72/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2112 - accuracy: 0.9624 - val\_loss: 0.2435 - val\_accuracy: 0.9778  
Epoch 73/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2063 - accuracy: 0.9774 - val\_loss: 0.2265 - val\_accuracy: 0.9556  
Epoch 74/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2039 - accuracy: 0.9624 - val\_loss: 0.2435 - val\_accuracy: 0.9778  
Epoch 75/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1961 - accuracy: 0.9774 - val\_loss: 0.2174 - val\_accuracy: 0.9556  
Epoch 76/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1929 - accuracy: 0.9699 - val\_loss: 0.2265 - val\_accuracy: 0.9778  
Epoch 77/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1850 - accuracy: 0.9774 - val\_loss: 0.2057 - val\_accuracy: 0.9556  
Epoch 78/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1865 - accuracy: 0.9699 - val\_loss: 0.2290 - val\_accuracy: 0.9778  
Epoch 79/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1779 - accuracy: 0.9774 - val\_loss: 0.1982 - val\_accuracy: 0.9556  
Epoch 80/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1813 - accuracy: 0.9699 - val\_loss: 0.2288 - val\_accuracy: 0.9778  
Epoch 81/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1735 - accuracy: 0.9850 - val\_loss: 0.1910 - val\_accuracy: 0.9556

Epoch 82/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1757 - accuracy: 0.9699 - val\_loss: 0.2219 - val\_accuracy: 0.9778  
Epoch 83/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1662 - accuracy: 0.9850 - val\_loss: 0.1829 - val\_accuracy: 0.9556  
Epoch 84/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1684 - accuracy: 0.9774 - val\_loss: 0.2197 - val\_accuracy: 0.9778  
Epoch 85/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1620 - accuracy: 0.9850 - val\_loss: 0.1754 - val\_accuracy: 0.9556  
Epoch 86/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1625 - accuracy: 0.9774 - val\_loss: 0.2283 - val\_accuracy: 0.9333  
Epoch 87/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1599 - accuracy: 0.9774 - val\_loss: 0.1791 - val\_accuracy: 0.9333  
Epoch 88/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1749 - accuracy: 0.9624 - val\_loss: 0.2622 - val\_accuracy: 0.9111  
Epoch 89/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1744 - accuracy: 0.9699 - val\_loss: 0.1975 - val\_accuracy: 0.9111  
Epoch 90/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1915 - accuracy: 0.9173 - val\_loss: 0.2551 - val\_accuracy: 0.9333  
Epoch 91/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1863 - accuracy: 0.9549 - val\_loss: 0.1669 - val\_accuracy: 0.9778  
Epoch 92/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1771 - accuracy: 0.9624 - val\_loss: 0.2753 - val\_accuracy: 0.9111  
Epoch 93/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1923 - accuracy: 0.9624 - val\_loss: 0.1568 - val\_accuracy: 0.9778  
Epoch 94/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1552 - accuracy: 0.9774 - val\_loss: 0.1976 - val\_accuracy: 0.9333  
Epoch 95/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1473 - accuracy: 0.9925 - val\_loss: 0.1727 - val\_accuracy: 0.9778  
Epoch 96/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1273 - accuracy: 0.9850 - val\_loss: 0.1449 - val\_accuracy: 0.9778  
Epoch 97/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1247 - accuracy: 0.9850 - val\_loss: 0.1742 - val\_accuracy: 0.9556

Epoch 98/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1223 - accuracy: 0.9925 - val\_loss: 0.1503 - val\_accuracy: 0.9556  
Epoch 99/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1194 - accuracy: 0.9850 - val\_loss: 0.1504 - val\_accuracy: 0.9778  
Epoch 100/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1153 - accuracy: 0.9925 - val\_loss: 0.1499 - val\_accuracy: 0.9778  
Epoch 101/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1117 - accuracy: 0.9850 - val\_loss: 0.1393 - val\_accuracy: 0.9778  
Epoch 102/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1110 - accuracy: 0.9850 - val\_loss: 0.1514 - val\_accuracy: 0.9778  
Epoch 103/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1091 - accuracy: 0.9925 - val\_loss: 0.1401 - val\_accuracy: 0.9778  
Epoch 104/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1069 - accuracy: 0.9850 - val\_loss: 0.1493 - val\_accuracy: 0.9778  
Epoch 105/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1056 - accuracy: 0.9925 - val\_loss: 0.1352 - val\_accuracy: 0.9778  
Epoch 106/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1029 - accuracy: 0.9850 - val\_loss: 0.1378 - val\_accuracy: 0.9778  
Epoch 107/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1013 - accuracy: 0.9925 - val\_loss: 0.1331 - val\_accuracy: 0.9778  
Epoch 108/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1002 - accuracy: 0.9925 - val\_loss: 0.1396 - val\_accuracy: 0.9778  
Epoch 109/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0985 - accuracy: 0.9925 - val\_loss: 0.1300 - val\_accuracy: 0.9778  
Epoch 110/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0964 - accuracy: 0.9850 - val\_loss: 0.1287 - val\_accuracy: 0.9778  
Epoch 111/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0954 - accuracy: 0.9925 - val\_loss: 0.1302 - val\_accuracy: 0.9778  
Epoch 112/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0942 - accuracy: 0.9925 - val\_loss: 0.1326 - val\_accuracy: 0.9778  
Epoch 113/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0925 - accuracy: 0.9925 - val\_loss: 0.1194 - val\_accuracy: 0.9778

Epoch 114/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0920 - accuracy: 0.9850 - val\_loss: 0.1298 - val\_accuracy: 0.9778  
Epoch 115/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0900 - accuracy: 0.9925 - val\_loss: 0.1227 - val\_accuracy: 1.0000  
Epoch 116/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0898 - accuracy: 0.9925 - val\_loss: 0.1259 - val\_accuracy: 0.9778  
Epoch 117/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0872 - accuracy: 0.9925 - val\_loss: 0.1186 - val\_accuracy: 0.9778  
Epoch 118/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0859 - accuracy: 0.9925 - val\_loss: 0.1219 - val\_accuracy: 0.9778  
Epoch 119/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0848 - accuracy: 0.9925 - val\_loss: 0.1166 - val\_accuracy: 0.9778  
Epoch 120/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0831 - accuracy: 0.9925 - val\_loss: 0.1152 - val\_accuracy: 0.9778  
Epoch 121/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0822 - accuracy: 0.9925 - val\_loss: 0.1143 - val\_accuracy: 1.0000  
Epoch 122/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0814 - accuracy: 0.9925 - val\_loss: 0.1215 - val\_accuracy: 0.9778  
Epoch 123/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0807 - accuracy: 0.9925 - val\_loss: 0.1091 - val\_accuracy: 0.9778  
Epoch 124/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0788 - accuracy: 0.9925 - val\_loss: 0.1142 - val\_accuracy: 1.0000  
Epoch 125/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0778 - accuracy: 0.9925 - val\_loss: 0.1081 - val\_accuracy: 1.0000  
Epoch 126/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0767 - accuracy: 0.9925 - val\_loss: 0.1146 - val\_accuracy: 0.9778  
Epoch 127/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0756 - accuracy: 0.9925 - val\_loss: 0.1086 - val\_accuracy: 1.0000  
Epoch 128/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0757 - accuracy: 0.9925 - val\_loss: 0.1122 - val\_accuracy: 0.9778  
Epoch 129/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0737 - accuracy: 0.9925 - val\_loss: 0.1022 - val\_accuracy: 1.0000



Epoch 130/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0727 - accuracy: 0.9925 - val\_loss: 0.1069 - val\_accuracy: 0.9778  
Epoch 131/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0717 - accuracy: 0.9925 - val\_loss: 0.1027 - val\_accuracy: 1.0000  
Epoch 132/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0707 - accuracy: 0.9925 - val\_loss: 0.1034 - val\_accuracy: 0.9778  
Epoch 133/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0696 - accuracy: 0.9925 - val\_loss: 0.1012 - val\_accuracy: 1.0000  
Epoch 134/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0690 - accuracy: 0.9925 - val\_loss: 0.1066 - val\_accuracy: 0.9778  
Epoch 135/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0681 - accuracy: 0.9925 - val\_loss: 0.0985 - val\_accuracy: 1.0000  
Epoch 136/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0671 - accuracy: 0.9925 - val\_loss: 0.1116 - val\_accuracy: 0.9778  
Epoch 137/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0674 - accuracy: 0.9925 - val\_loss: 0.1012 - val\_accuracy: 0.9778  
Epoch 138/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0652 - accuracy: 0.9925 - val\_loss: 0.1023 - val\_accuracy: 0.9778  
Epoch 139/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0649 - accuracy: 0.9925 - val\_loss: 0.0964 - val\_accuracy: 0.9778  
Epoch 140/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0632 - accuracy: 0.9925 - val\_loss: 0.0949 - val\_accuracy: 0.9778  
Epoch 141/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0630 - accuracy: 0.9925 - val\_loss: 0.1014 - val\_accuracy: 0.9778  
Epoch 142/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0618 - accuracy: 0.9925 - val\_loss: 0.0894 - val\_accuracy: 1.0000  
Epoch 143/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0614 - accuracy: 0.9925 - val\_loss: 0.1025 - val\_accuracy: 0.9778  
Epoch 144/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0609 - accuracy: 0.9925 - val\_loss: 0.0998 - val\_accuracy: 0.9778  
Epoch 145/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0603 - accuracy: 0.9925 - val\_loss: 0.0944 - val\_accuracy: 0.9778

Epoch 146/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0585 - accuracy: 0.9925 - val\_loss: 0.0914 - val\_accuracy: 0.9778  
Epoch 147/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0578 - accuracy: 0.9925 - val\_loss: 0.0964 - val\_accuracy: 0.9778  
Epoch 148/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0571 - accuracy: 0.9925 - val\_loss: 0.0958 - val\_accuracy: 0.9778  
Epoch 149/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0571 - accuracy: 0.9925 - val\_loss: 0.0940 - val\_accuracy: 0.9778  
Epoch 150/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0557 - accuracy: 0.9925 - val\_loss: 0.0870 - val\_accuracy: 0.9778  
Epoch 151/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0548 - accuracy: 0.9925 - val\_loss: 0.0907 - val\_accuracy: 0.9778  
Epoch 152/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0543 - accuracy: 0.9925 - val\_loss: 0.0987 - val\_accuracy: 0.9778  
Epoch 153/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0546 - accuracy: 0.9925 - val\_loss: 0.0868 - val\_accuracy: 0.9778  
Epoch 154/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0522 - accuracy: 0.9925 - val\_loss: 0.0832 - val\_accuracy: 0.9778  
Epoch 155/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0522 - accuracy: 0.9925 - val\_loss: 0.0942 - val\_accuracy: 0.9778  
Epoch 156/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0519 - accuracy: 0.9925 - val\_loss: 0.0902 - val\_accuracy: 0.9778  
Epoch 157/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0508 - accuracy: 0.9925 - val\_loss: 0.0894 - val\_accuracy: 0.9778  
Epoch 158/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0500 - accuracy: 0.9925 - val\_loss: 0.0794 - val\_accuracy: 0.9778  
Epoch 159/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0493 - accuracy: 0.9925 - val\_loss: 0.0904 - val\_accuracy: 0.9778  
Epoch 160/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0487 - accuracy: 0.9925 - val\_loss: 0.0903 - val\_accuracy: 0.9778  
Epoch 161/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0491 - accuracy: 0.9925 - val\_loss: 0.0830 - val\_accuracy: 0.9778

Epoch 162/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0473 - accuracy: 0.9925 - val\_loss: 0.0879 - val\_accuracy: 0.9778  
Epoch 163/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0473 - accuracy: 0.9925 - val\_loss: 0.0846 - val\_accuracy: 0.9778  
Epoch 164/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0463 - accuracy: 0.9925 - val\_loss: 0.0783 - val\_accuracy: 0.9778  
Epoch 165/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0453 - accuracy: 0.9925 - val\_loss: 0.0861 - val\_accuracy: 0.9778  
Epoch 166/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0453 - accuracy: 0.9925 - val\_loss: 0.0875 - val\_accuracy: 0.9778  
Epoch 167/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0447 - accuracy: 0.9925 - val\_loss: 0.0757 - val\_accuracy: 0.9778  
Epoch 168/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0436 - accuracy: 0.9925 - val\_loss: 0.0889 - val\_accuracy: 0.9778  
Epoch 169/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0435 - accuracy: 0.9925 - val\_loss: 0.0834 - val\_accuracy: 0.9778  
Epoch 170/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0429 - accuracy: 0.9925 - val\_loss: 0.0806 - val\_accuracy: 0.9778  
Epoch 171/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0418 - accuracy: 0.9925 - val\_loss: 0.0816 - val\_accuracy: 0.9778  
Epoch 172/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0418 - accuracy: 0.9925 - val\_loss: 0.0812 - val\_accuracy: 0.9778  
Epoch 173/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0410 - accuracy: 0.9925 - val\_loss: 0.0765 - val\_accuracy: 0.9778  
Epoch 174/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0398 - accuracy: 0.9925 - val\_loss: 0.0771 - val\_accuracy: 0.9778  
Epoch 175/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0399 - accuracy: 0.9925 - val\_loss: 0.0840 - val\_accuracy: 0.9778  
Epoch 176/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0394 - accuracy: 0.9925 - val\_loss: 0.0711 - val\_accuracy: 0.9778  
Epoch 177/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0385 - accuracy: 0.9925 - val\_loss: 0.0809 - val\_accuracy: 0.9778

Epoch 178/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0382 - accuracy: 0.9925 - val\_loss: 0.0743 - val\_accuracy: 0.9778  
Epoch 179/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0372 - accuracy: 0.9925 - val\_loss: 0.0830 - val\_accuracy: 0.9778  
Epoch 180/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0375 - accuracy: 0.9925 - val\_loss: 0.0688 - val\_accuracy: 0.9778  
Epoch 181/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0365 - accuracy: 0.9925 - val\_loss: 0.0817 - val\_accuracy: 0.9778  
Epoch 182/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0364 - accuracy: 0.9925 - val\_loss: 0.0818 - val\_accuracy: 0.9778  
Epoch 183/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0359 - accuracy: 0.9925 - val\_loss: 0.0725 - val\_accuracy: 0.9778  
Epoch 184/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0348 - accuracy: 0.9925 - val\_loss: 0.0744 - val\_accuracy: 0.9778  
Epoch 185/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0346 - accuracy: 0.9925 - val\_loss: 0.0808 - val\_accuracy: 0.9778  
Epoch 186/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0345 - accuracy: 0.9925 - val\_loss: 0.0655 - val\_accuracy: 0.9778  
Epoch 187/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0341 - accuracy: 1.0000 - val\_loss: 0.0847 - val\_accuracy: 0.9778  
Epoch 188/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0339 - accuracy: 0.9925 - val\_loss: 0.0728 - val\_accuracy: 0.9778  
Epoch 189/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0325 - accuracy: 1.0000 - val\_loss: 0.0667 - val\_accuracy: 0.9778  
Epoch 190/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0326 - accuracy: 1.0000 - val\_loss: 0.0830 - val\_accuracy: 0.9778  
Epoch 191/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0325 - accuracy: 0.9925 - val\_loss: 0.0701 - val\_accuracy: 0.9778  
Epoch 192/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0313 - accuracy: 1.0000 - val\_loss: 0.0677 - val\_accuracy: 0.9778  
Epoch 193/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0312 - accuracy: 1.0000 - val\_loss: 0.0760 - val\_accuracy: 0.9778

Epoch 194/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0312 - accuracy: 1.0000 - val\_loss: 0.0702 - val\_accuracy: 0.9778

Epoch 195/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0303 - accuracy: 1.0000 - val\_loss: 0.0748 - val\_accuracy: 0.9778

Epoch 196/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0299 - accuracy: 1.0000 - val\_loss: 0.0708 - val\_accuracy: 0.9778

Epoch 197/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0295 - accuracy: 1.0000 - val\_loss: 0.0664 - val\_accuracy: 0.9778

Epoch 198/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0291 - accuracy: 1.0000 - val\_loss: 0.0715 - val\_accuracy: 0.9778

Epoch 199/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0289 - accuracy: 1.0000 - val\_loss: 0.0710 - val\_accuracy: 0.9778

Epoch 200/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0285 - accuracy: 1.0000 - val\_loss: 0.0706 - val\_accuracy: 0.9778

Epoch 201/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0280 - accuracy: 1.0000 - val\_loss: 0.0702 - val\_accuracy: 0.9778

Epoch 202/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0277 - accuracy: 1.0000 - val\_loss: 0.0639 - val\_accuracy: 0.9778

Epoch 203/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0275 - accuracy: 1.0000 - val\_loss: 0.0744 - val\_accuracy: 0.9778

Epoch 204/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0275 - accuracy: 1.0000 - val\_loss: 0.0639 - val\_accuracy: 0.9778

Epoch 205/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0272 - accuracy: 1.0000 - val\_loss: 0.0789 - val\_accuracy: 0.9778

Epoch 206/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0270 - accuracy: 1.0000 - val\_loss: 0.0590 - val\_accuracy: 0.9778

Epoch 207/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0264 - accuracy: 1.0000 - val\_loss: 0.0798 - val\_accuracy: 0.9778

Epoch 208/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0261 - accuracy: 1.0000 - val\_loss: 0.0628 - val\_accuracy: 0.9778

Epoch 209/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0252 - accuracy: 1.0000 - val\_loss: 0.0617 - val\_accuracy: 0.9778

Epoch 210/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0255 - accuracy: 1.0000 - val\_loss: 0.0758 - val\_accuracy: 0.9778  
Epoch 211/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0254 - accuracy: 1.0000 - val\_loss: 0.0582 - val\_accuracy: 0.9778  
Epoch 212/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0253 - accuracy: 1.0000 - val\_loss: 0.0842 - val\_accuracy: 0.9778  
Epoch 213/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0257 - accuracy: 1.0000 - val\_loss: 0.0527 - val\_accuracy: 0.9778  
Epoch 214/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0255 - accuracy: 1.0000 - val\_loss: 0.0952 - val\_accuracy: 0.9556  
Epoch 215/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0261 - accuracy: 1.0000 - val\_loss: 0.0503 - val\_accuracy: 0.9778  
Epoch 216/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0250 - accuracy: 1.0000 - val\_loss: 0.0845 - val\_accuracy: 0.9778  
Epoch 217/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0242 - accuracy: 1.0000 - val\_loss: 0.0573 - val\_accuracy: 0.9778  
Epoch 218/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0230 - accuracy: 1.0000 - val\_loss: 0.0700 - val\_accuracy: 0.9778  
Epoch 219/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0234 - accuracy: 1.0000 - val\_loss: 0.0723 - val\_accuracy: 0.9778  
Epoch 220/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0227 - accuracy: 1.0000 - val\_loss: 0.0529 - val\_accuracy: 0.9778  
Epoch 221/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0234 - accuracy: 1.0000 - val\_loss: 0.0971 - val\_accuracy: 0.9556  
Epoch 222/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0248 - accuracy: 1.0000 - val\_loss: 0.0455 - val\_accuracy: 1.0000  
Epoch 223/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0252 - accuracy: 1.0000 - val\_loss: 0.1078 - val\_accuracy: 0.9556  
Epoch 224/300  
5/5 [=====] - 0s 10ms/step - loss: 0.0256 - accuracy: 1.0000 - val\_loss: 0.0429 - val\_accuracy: 1.0000  
Epoch 225/300  
5/5 [=====] - 0s 12ms/step - loss: 0.0254 - accuracy: 1.0000 - val\_loss: 0.1026 - val\_accuracy: 0.9556

Epoch 226/300  
5/5 [=====] - 0s 10ms/step - loss: 0.0246 - accuracy: 1.0000 - val\_loss: 0.0492 - val\_accuracy: 0.9778  
Epoch 227/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0227 - accuracy: 1.0000 - val\_loss: 0.0709 - val\_accuracy: 0.9778  
Epoch 228/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0225 - accuracy: 1.0000 - val\_loss: 0.0878 - val\_accuracy: 0.9778  
Epoch 229/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0232 - accuracy: 1.0000 - val\_loss: 0.0448 - val\_accuracy: 1.0000  
Epoch 230/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0259 - accuracy: 1.0000 - val\_loss: 0.1510 - val\_accuracy: 0.9111  
Epoch 231/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0423 - accuracy: 0.9850 - val\_loss: 0.0408 - val\_accuracy: 1.0000  
Epoch 232/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0252 - accuracy: 1.0000 - val\_loss: 0.1166 - val\_accuracy: 0.9333  
Epoch 233/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0266 - accuracy: 0.9925 - val\_loss: 0.0544 - val\_accuracy: 0.9778  
Epoch 234/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0277 - accuracy: 1.0000 - val\_loss: 0.0635 - val\_accuracy: 0.9778  
Epoch 235/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0315 - accuracy: 1.0000 - val\_loss: 0.1581 - val\_accuracy: 0.9111  
Epoch 236/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0723 - accuracy: 0.9774 - val\_loss: 0.0977 - val\_accuracy: 0.9556  
Epoch 237/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0368 - accuracy: 0.9925 - val\_loss: 0.0515 - val\_accuracy: 0.9778  
Epoch 238/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0462 - accuracy: 0.9850 - val\_loss: 0.1954 - val\_accuracy: 0.9333  
Epoch 239/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0738 - accuracy: 0.9774 - val\_loss: 0.1611 - val\_accuracy: 0.9778  
Epoch 240/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2791 - accuracy: 0.8872 - val\_loss: 0.8927 - val\_accuracy: 0.7111  
Epoch 241/300  
5/5 [=====] - 0s 7ms/step - loss: 0.4546 - accuracy: 0.8496 - val\_loss: 0.2584 - val\_accuracy: 0.8889

Epoch 242/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1742 - accuracy: 0.9098 - val\_loss: 0.3131 - val\_accuracy: 0.9111  
Epoch 243/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1711 - accuracy: 0.9323 - val\_loss: 0.1316 - val\_accuracy: 0.9778  
Epoch 244/300  
5/5 [=====] - 0s 7ms/step - loss: 0.3061 - accuracy: 0.8647 - val\_loss: 0.3509 - val\_accuracy: 0.9111  
Epoch 245/300  
5/5 [=====] - 0s 8ms/step - loss: 0.4427 - accuracy: 0.8421 - val\_loss: 0.1142 - val\_accuracy: 0.9556  
Epoch 246/300  
5/5 [=====] - 0s 7ms/step - loss: 0.2394 - accuracy: 0.9023 - val\_loss: 0.2512 - val\_accuracy: 0.9111  
Epoch 247/300  
5/5 [=====] - 0s 7ms/step - loss: 0.1829 - accuracy: 0.9173 - val\_loss: 0.2016 - val\_accuracy: 0.9333  
Epoch 248/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0804 - accuracy: 0.9774 - val\_loss: 0.0702 - val\_accuracy: 0.9556  
Epoch 249/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0435 - accuracy: 0.9850 - val\_loss: 0.0838 - val\_accuracy: 0.9778  
Epoch 250/300  
5/5 [=====] - 0s 11ms/step - loss: 0.0652 - accuracy: 0.9699 - val\_loss: 0.3470 - val\_accuracy: 0.8889  
Epoch 251/300  
5/5 [=====] - 0s 9ms/step - loss: 0.2436 - accuracy: 0.9098 - val\_loss: 0.1314 - val\_accuracy: 0.9778  
Epoch 252/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0990 - accuracy: 0.9699 - val\_loss: 0.0479 - val\_accuracy: 1.0000  
Epoch 253/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0326 - accuracy: 0.9850 - val\_loss: 0.0699 - val\_accuracy: 0.9778  
Epoch 254/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0481 - accuracy: 0.9925 - val\_loss: 0.1671 - val\_accuracy: 0.9333  
Epoch 255/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0654 - accuracy: 0.9925 - val\_loss: 0.0721 - val\_accuracy: 0.9778  
Epoch 256/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0776 - accuracy: 0.9699 - val\_loss: 0.0737 - val\_accuracy: 0.9778  
Epoch 257/300  
5/5 [=====] - 0s 7ms/step - loss: 0.0742 - accuracy: 0.9774 - val\_loss: 0.1401 - val\_accuracy: 0.9778



Epoch 258/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1396 - accuracy: 0.9624 - val\_loss: 0.3882 - val\_accuracy: 0.8889

Epoch 259/300  
5/5 [=====] - 0s 8ms/step - loss: 0.3641 - accuracy: 0.9248 - val\_loss: 0.8502 - val\_accuracy: 0.8000

Epoch 260/300  
5/5 [=====] - 0s 7ms/step - loss: 0.6919 - accuracy: 0.8496 - val\_loss: 0.1691 - val\_accuracy: 0.9111

Epoch 261/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0945 - accuracy: 0.9850 - val\_loss: 0.2105 - val\_accuracy: 0.9778

Epoch 262/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1558 - accuracy: 0.9474 - val\_loss: 0.3919 - val\_accuracy: 0.8889

Epoch 263/300  
5/5 [=====] - 0s 8ms/step - loss: 0.4159 - accuracy: 0.9098 - val\_loss: 0.2118 - val\_accuracy: 0.9778

Epoch 264/300  
5/5 [=====] - 0s 8ms/step - loss: 0.4318 - accuracy: 0.8947 - val\_loss: 0.3176 - val\_accuracy: 0.9111

Epoch 265/300  
5/5 [=====] - 0s 7ms/step - loss: 0.5518 - accuracy: 0.8722 - val\_loss: 0.1188 - val\_accuracy: 0.9333

Epoch 266/300  
5/5 [=====] - 0s 8ms/step - loss: 0.1597 - accuracy: 0.9474 - val\_loss: 0.0819 - val\_accuracy: 0.9778

Epoch 267/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0438 - accuracy: 0.9774 - val\_loss: 0.0899 - val\_accuracy: 0.9556

Epoch 268/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0716 - accuracy: 0.9774 - val\_loss: 0.0558 - val\_accuracy: 0.9778

Epoch 269/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0496 - accuracy: 0.9850 - val\_loss: 0.0635 - val\_accuracy: 0.9778

Epoch 270/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0379 - accuracy: 0.9925 - val\_loss: 0.0718 - val\_accuracy: 0.9778

Epoch 271/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0446 - accuracy: 0.9850 - val\_loss: 0.0506 - val\_accuracy: 1.0000

Epoch 272/300  
5/5 [=====] - 0s 10ms/step - loss: 0.0355 - accuracy: 0.9925 - val\_loss: 0.0490 - val\_accuracy: 1.0000

Epoch 273/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0328 - accuracy: 0.9925 - val\_loss: 0.0586 - val\_accuracy: 0.9778

Epoch 274/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0308 - accuracy: 1.0000 - val\_loss: 0.0582 - val\_accuracy: 0.9778

Epoch 275/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0283 - accuracy: 0.9925 - val\_loss: 0.0517 - val\_accuracy: 1.0000

Epoch 276/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0290 - accuracy: 0.9925 - val\_loss: 0.0526 - val\_accuracy: 1.0000

Epoch 277/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0277 - accuracy: 1.0000 - val\_loss: 0.0541 - val\_accuracy: 0.9778

Epoch 278/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0266 - accuracy: 1.0000 - val\_loss: 0.0534 - val\_accuracy: 1.0000

Epoch 279/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0268 - accuracy: 0.9925 - val\_loss: 0.0537 - val\_accuracy: 0.9778

Epoch 280/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0259 - accuracy: 1.0000 - val\_loss: 0.0539 - val\_accuracy: 0.9778

Epoch 281/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0254 - accuracy: 1.0000 - val\_loss: 0.0526 - val\_accuracy: 0.9778

Epoch 282/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0251 - accuracy: 1.0000 - val\_loss: 0.0524 - val\_accuracy: 0.9778

Epoch 283/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0247 - accuracy: 1.0000 - val\_loss: 0.0537 - val\_accuracy: 0.9778

Epoch 284/300  
5/5 [=====] - 0s 10ms/step - loss: 0.0243 - accuracy: 1.0000 - val\_loss: 0.0547 - val\_accuracy: 0.9778

Epoch 285/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0240 - accuracy: 1.0000 - val\_loss: 0.0548 - val\_accuracy: 0.9778

Epoch 286/300  
5/5 [=====] - 0s 9ms/step - loss: 0.0236 - accuracy: 1.0000 - val\_loss: 0.0543 - val\_accuracy: 0.9778

Epoch 287/300  
5/5 [=====] - 0s 8ms/step - loss: 0.0233 - accuracy: 1.0000 - val\_loss: 0.0539 - val\_accuracy: 0.9778

Epoch 288/300  
5/5 [=====] - 0s 10ms/step - loss: 0.0230 - accuracy: 1.0000 - val\_loss: 0.0541 - val\_accuracy: 0.9778

Epoch 289/300  
5/5 [=====] - 0s 11ms/step - loss: 0.0226 - accuracy: 1.0000 - val\_loss: 0.0546 - val\_accuracy: 0.9778

```

Epoch 290/300
5/5 [=====] - 0s 11ms/step - loss: 0.0223 - accuracy:
1.0000 - val_loss: 0.0548 - val_accuracy: 0.9778
Epoch 291/300
5/5 [=====] - 0s 10ms/step - loss: 0.0220 - accuracy:
1.0000 - val_loss: 0.0548 - val_accuracy: 0.9778
Epoch 292/300
5/5 [=====] - 0s 9ms/step - loss: 0.0217 - accuracy:
1.0000 - val_loss: 0.0548 - val_accuracy: 0.9778
Epoch 293/300
5/5 [=====] - 0s 8ms/step - loss: 0.0214 - accuracy:
1.0000 - val_loss: 0.0549 - val_accuracy: 0.9778
Epoch 294/300
5/5 [=====] - 0s 8ms/step - loss: 0.0211 - accuracy:
1.0000 - val_loss: 0.0551 - val_accuracy: 0.9778
Epoch 295/300
5/5 [=====] - 0s 7ms/step - loss: 0.0209 - accuracy:
1.0000 - val_loss: 0.0553 - val_accuracy: 0.9778
Epoch 296/300
5/5 [=====] - 0s 7ms/step - loss: 0.0206 - accuracy:
1.0000 - val_loss: 0.0555 - val_accuracy: 0.9778
Epoch 297/300
5/5 [=====] - 0s 7ms/step - loss: 0.0203 - accuracy:
1.0000 - val_loss: 0.0556 - val_accuracy: 0.9778
Epoch 298/300
5/5 [=====] - 0s 7ms/step - loss: 0.0201 - accuracy:
1.0000 - val_loss: 0.0558 - val_accuracy: 0.9778
Epoch 299/300
5/5 [=====] - 0s 8ms/step - loss: 0.0198 - accuracy:
1.0000 - val_loss: 0.0560 - val_accuracy: 0.9778
Epoch 300/300
5/5 [=====] - 0s 8ms/step - loss: 0.0196 - accuracy:
1.0000 - val_loss: 0.0562 - val_accuracy: 0.9778
Best epoch: 115

```

```

[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')

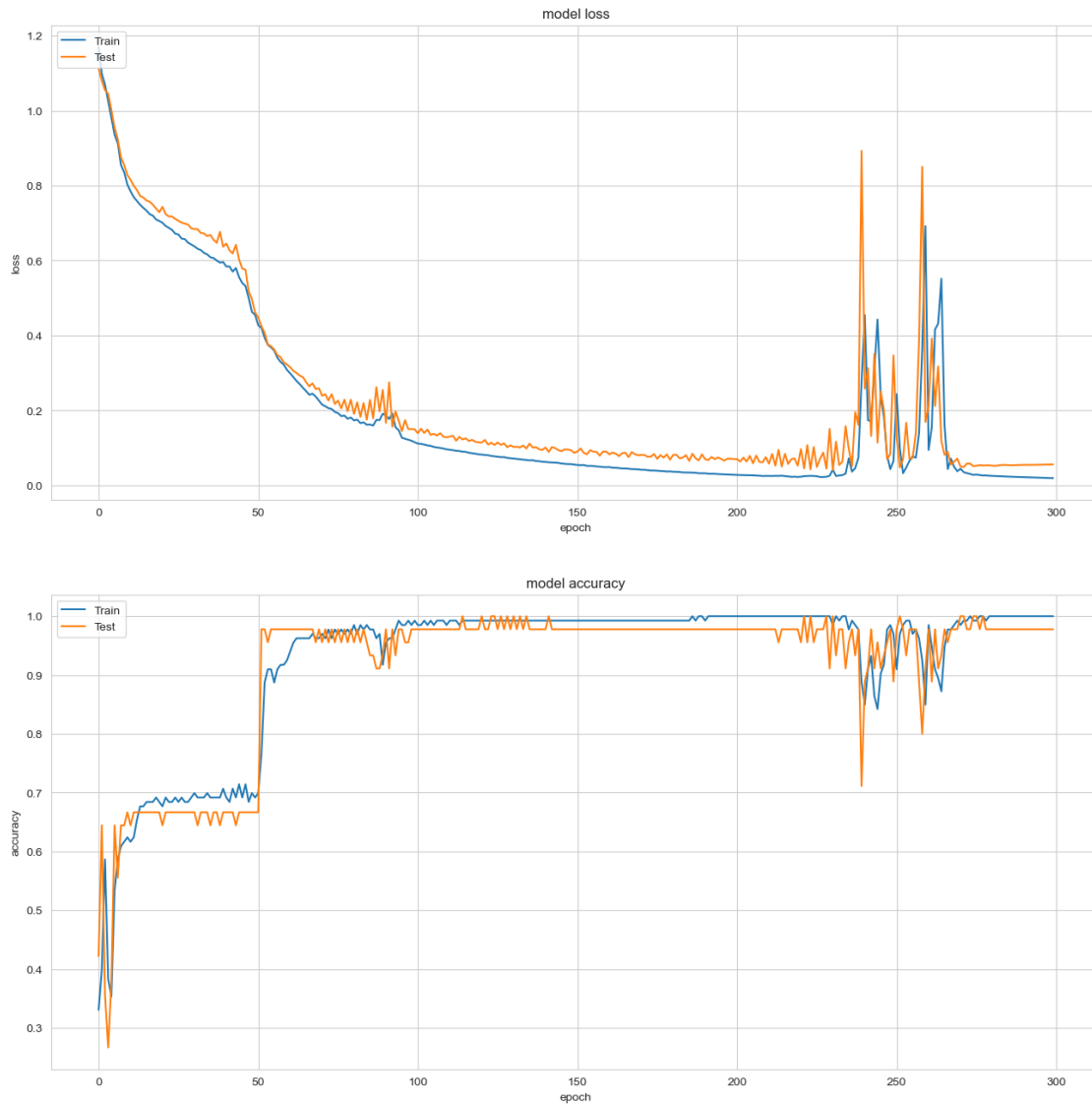
ax2 = fig.add_subplot(2,1,2)
ax2.plot(history.history['accuracy'])

```

```

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))

```

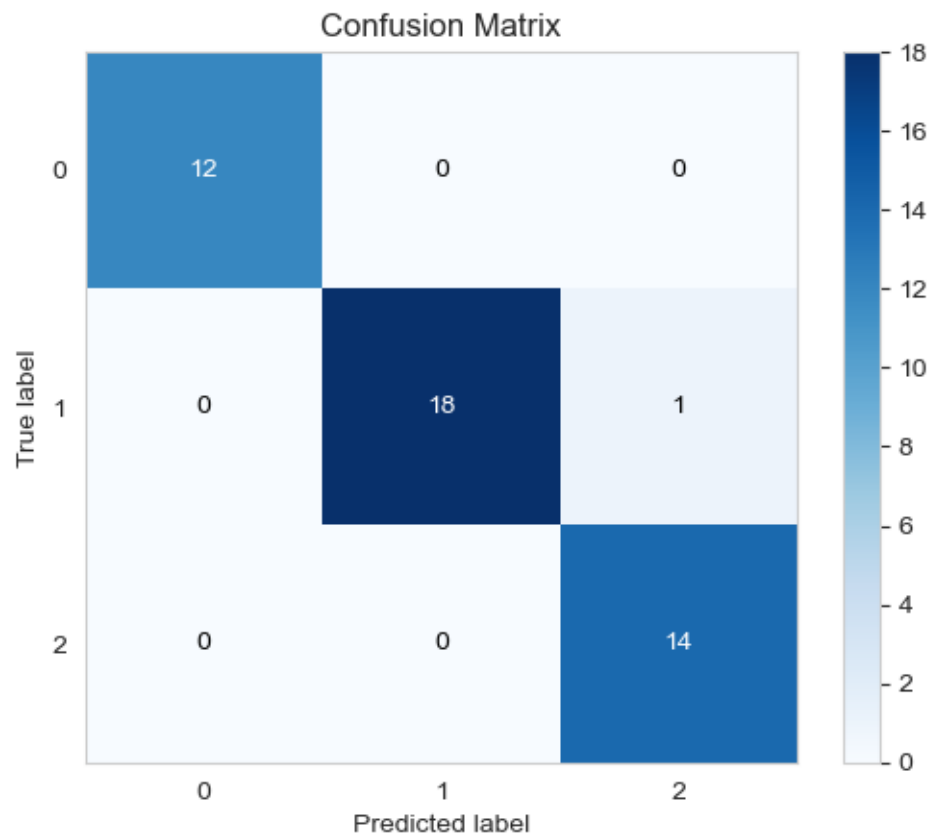
```
print(classification_report(y_test_am, y_pred, labels=[0,1,2]))

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

2/2 [=====] - 0s 3ms/step

```
[[12  0  0]
 [ 0 18  1]
 [ 0  0 14]]
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	12
1	1.00	0.95	0.97	19
2	0.93	1.00	0.97	14
accuracy			0.98	45
macro avg	0.98	0.98	0.98	45
weighted avg	0.98	0.98	0.98	45



```
[18]: 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
↳100% vs. 98%, 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 100% vs. 98%, so that's better obviously but really not a huge difference. All in all, I think the model is well fit.

```
[ ]:
```