Iris Flower Classification

December 30, 2023

1 Iris Flower Classification

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
df = pd.read_csv('/content/drive/MyDrive/Datasets/IRIS.csv')
```

[3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

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

[6]:

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

[7]:
```python
df.shape
```

[7]: (150, 5)

[10]:
```
df.head()
```

[10]:
```
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
```

[12]:
```
#count the value
df['species'].value_counts()
```

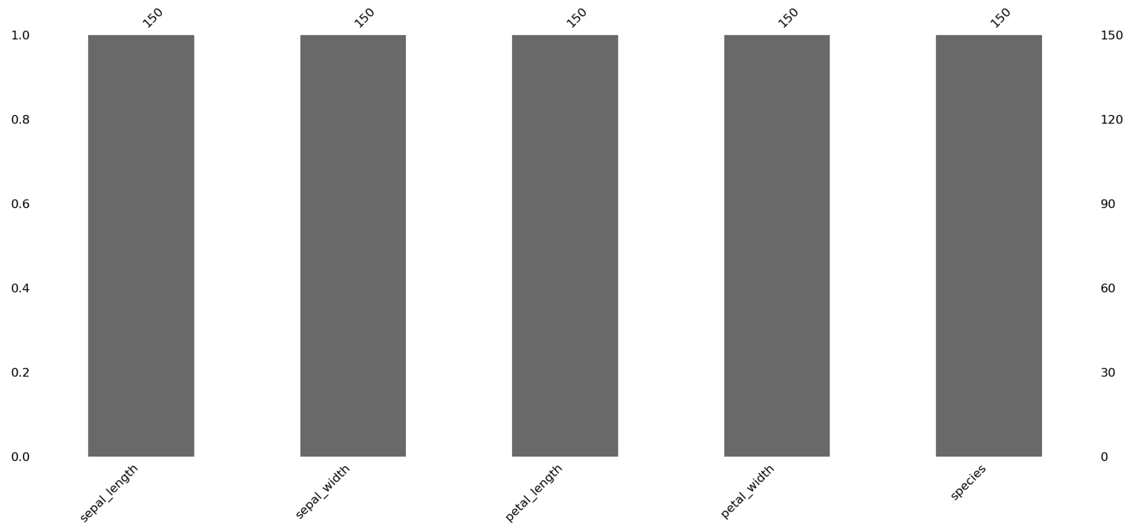
[12]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: species, dtype: int64
```

[13]:
```
#finding the null value
df.isnull().sum()
```

[13]:
```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

[14]:
```
import missingno as msno
msno.bar(df)
```

[14]: <Axes: >



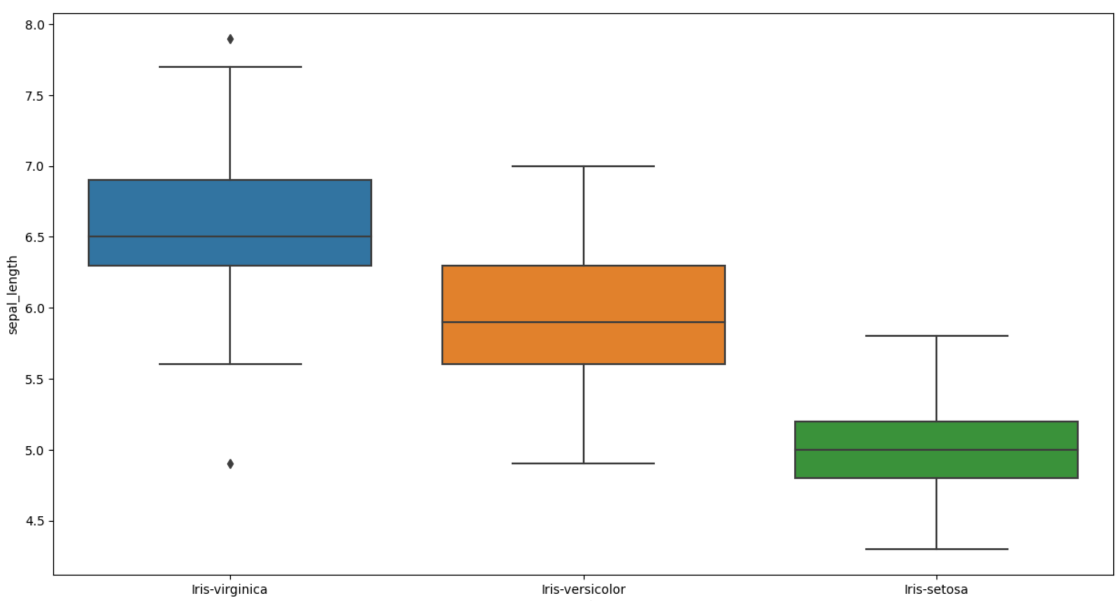
[15]:
```
df.drop_duplicates(inplace=True)
```

1.1 EDA

Relationship between species and sepal length

[18]:
```
plt.figure(figsize=(15,8))
sns.boxplot(x='species',y='sepal_length',data=df.
    ↪sort_values('sepal_length',ascending=False))
```

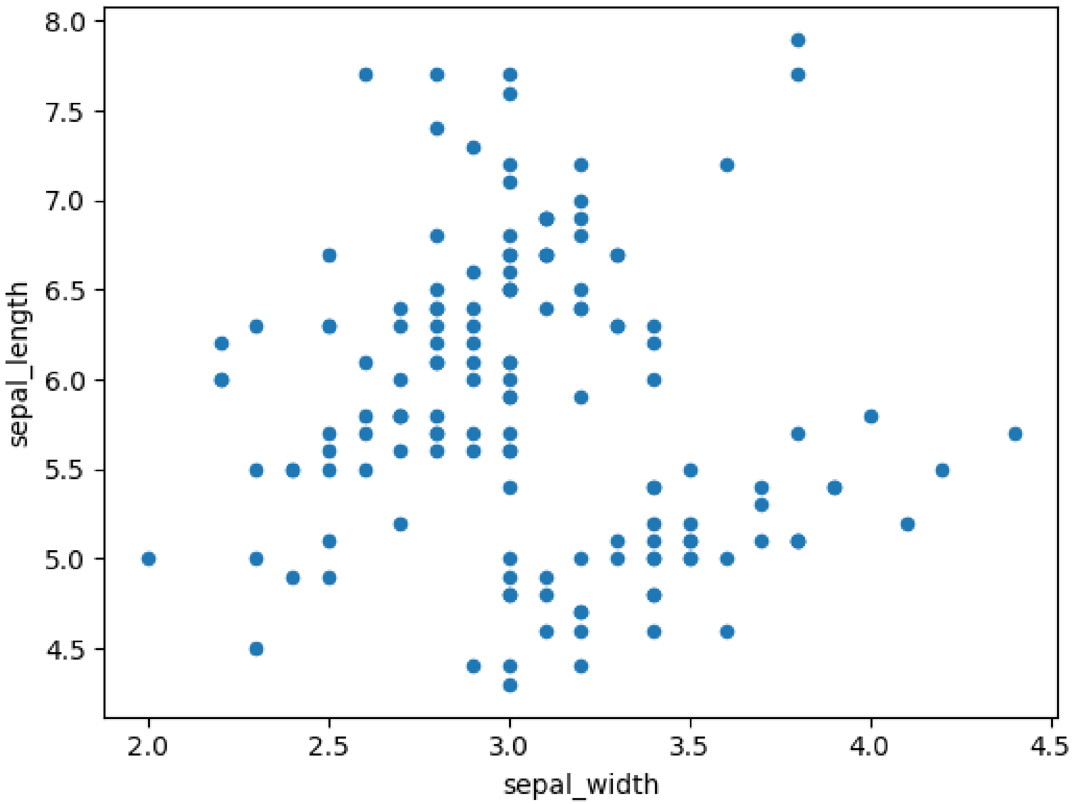
[18]: `<Axes: xlabel='species', ylabel='sepal_length'>`



Relationship between species and sepal width

[19]:
```
df.plot(kind='scatter',x='sepal_width',y='sepal_length')
```

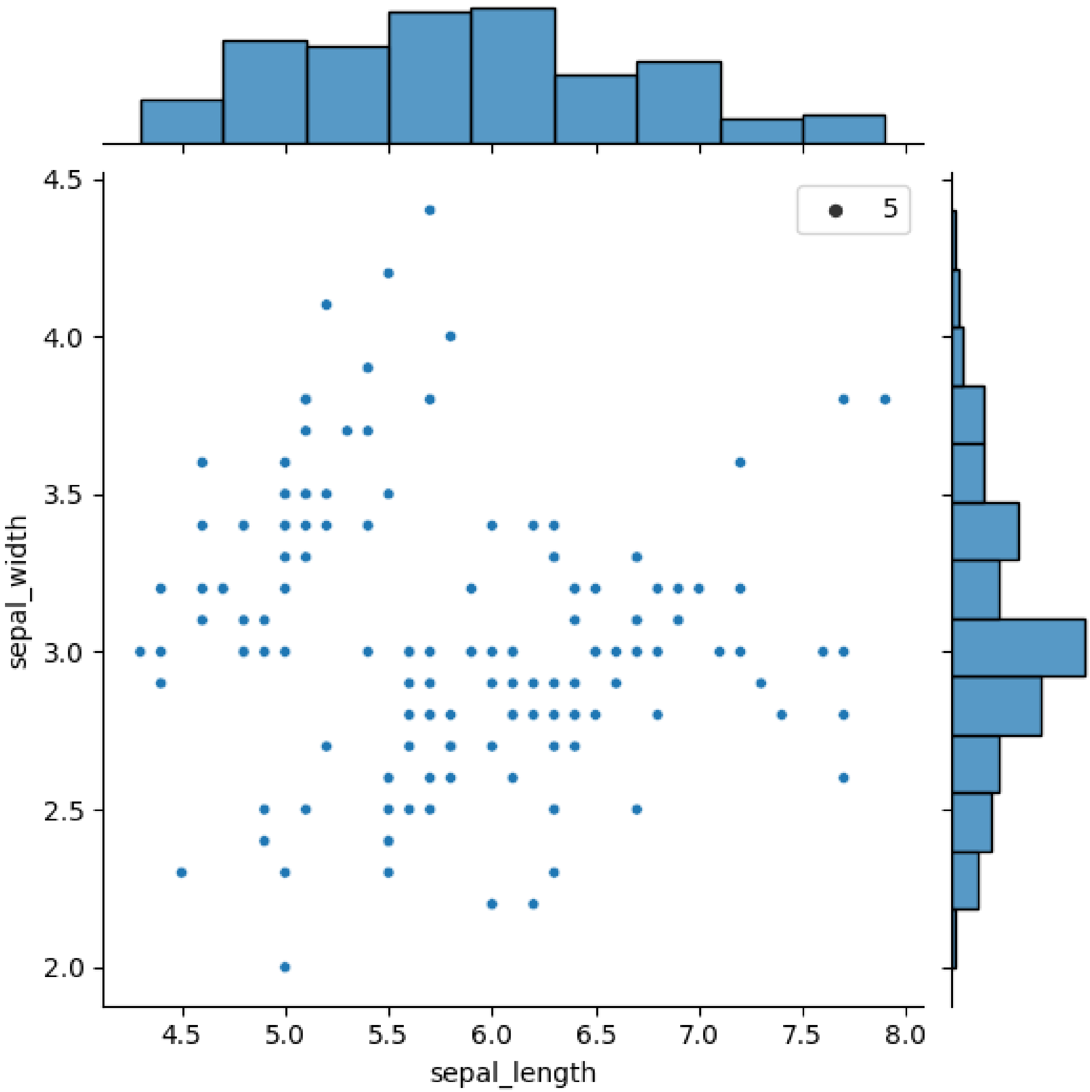
[19]: <Axes: xlabel='sepal_width', ylabel='sepal_length'>



Relationship between sepal width and sepal length

[20]:
```
sns.jointplot(x="sepal_length", y="sepal_width", data=df, size=5)
```

[20]: <seaborn.axisgrid.JointGrid at 0x7d5c3887a5c0>

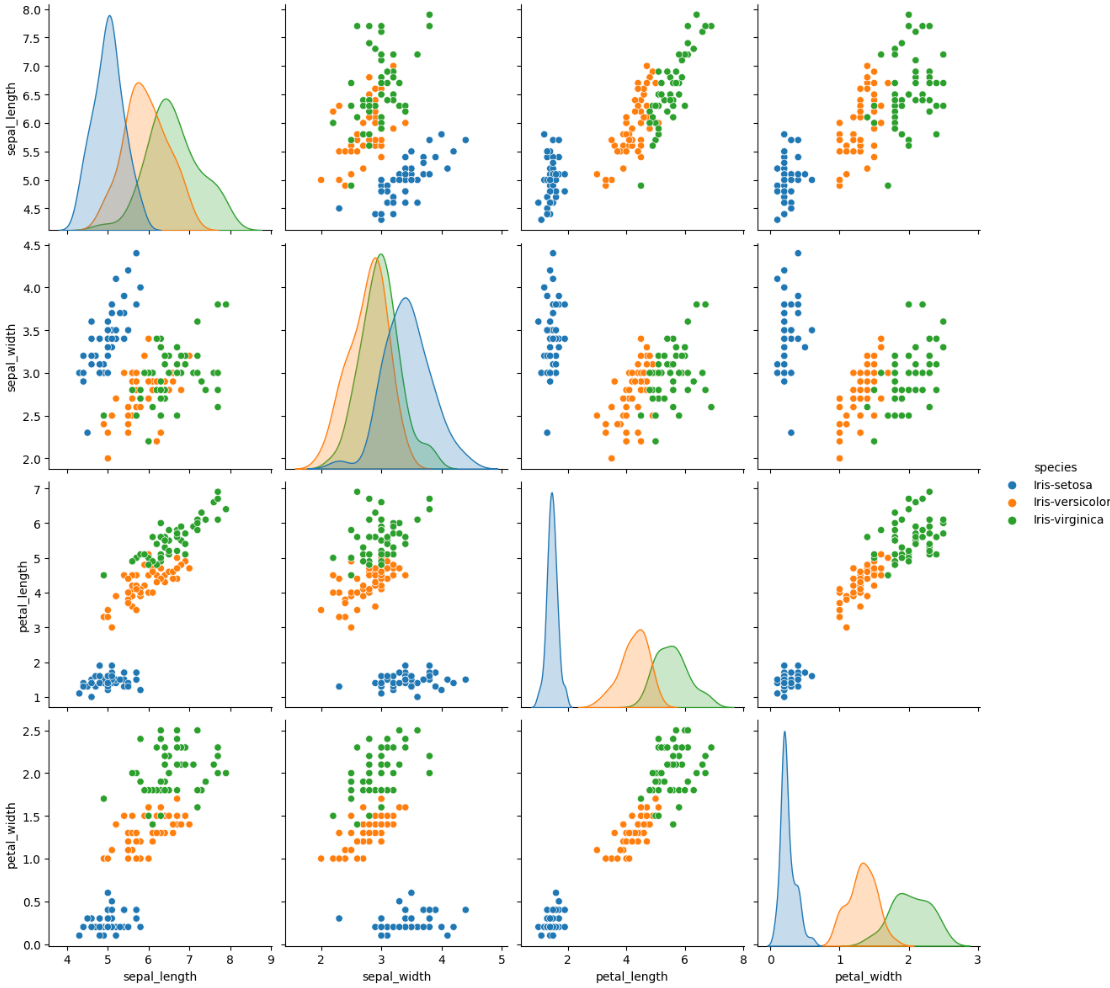


Pairplot

[26]:
```
plt.figure(figsize=(15,8))
sns.pairplot(df, hue="species", size=3)
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:2095: UserWarning:
The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

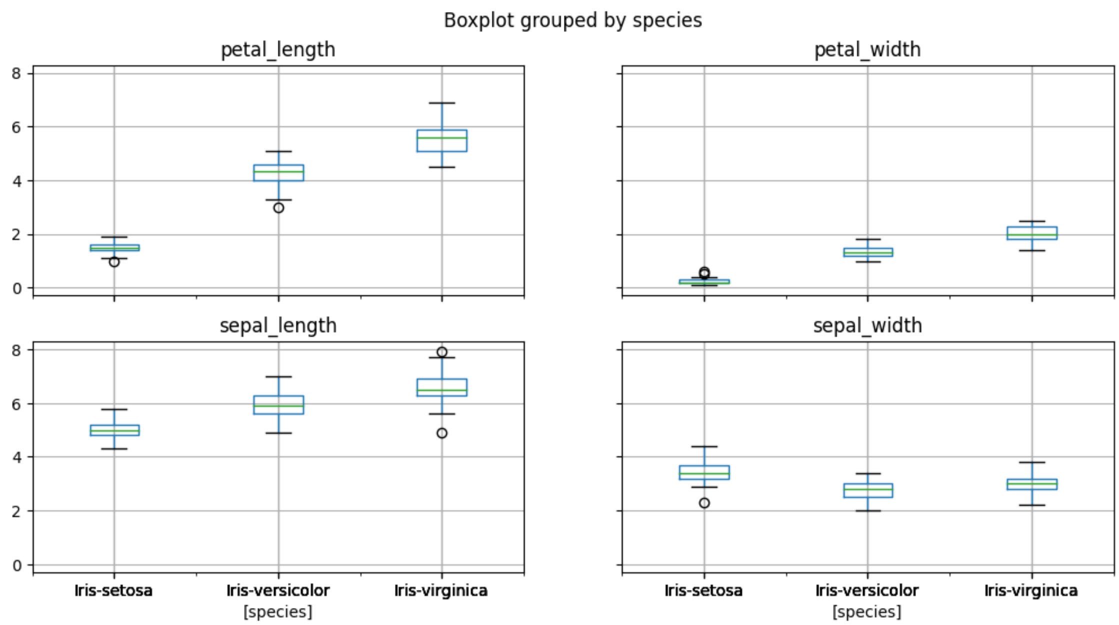
```
<Figure size 1500x800 with 0 Axes>
```



Boxplot

[28]:
```
df.boxplot(by="species", figsize=(12, 6))
```

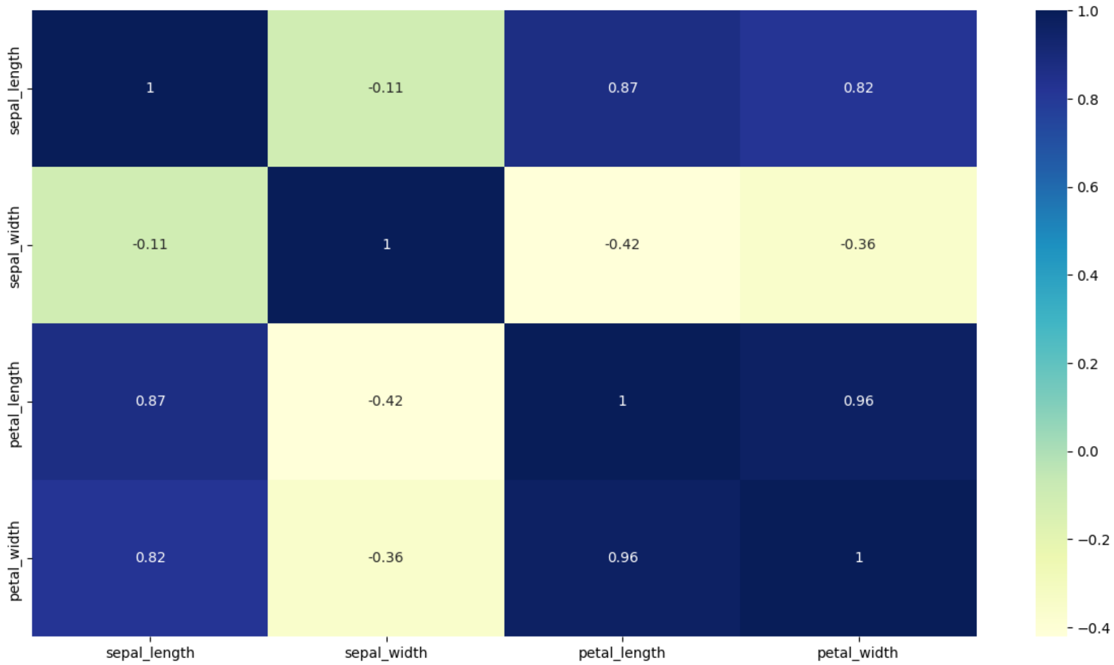
[28]:
```
array([[<Axes: title={'center': 'petal_length'}, xlabel='[species]'>,
        <Axes: title={'center': 'petal_width'}, xlabel='[species]'>],
       [<Axes: title={'center': 'sepal_length'}, xlabel='[species]'>,
        <Axes: title={'center': 'sepal_width'}, xlabel='[species]'>]],
      dtype=object)
```



[32]:

```
plt.figure(figsize=(15,8))
sns.heatmap(df.corr(),annot=True,cmap="YlGnBu")
plt.show()
```

```
<ipython-input-32-6b51bb3694af>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(),annot=True,cmap="YlGnBu")
```



1.2 Model Training with Sequential

[35]:
```
X=df.drop('species',axis=1)
y=df['species']
```

[37]:
```
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical
```

[42]:
```
df['species'] = pd.Categorical(df.species)
df['species'] = df.species.cat.codes
# Turn response variable into one-hot response vectory = to_categorical(df.
↪response)
y = to_categorical(df.species)
```

[44]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
↪2,stratify=y,random_state=123)
```

[45]:
```
model=Sequential()
model.add(Dense(100,activation='relu',input_shape=(4,)))

model.add(Dense(3,activation='softmax'))
```

[46]:
```
model.
 ↪compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
```

[56]:
```
history=model.fit(X_train,y_train,epochs=45,validation_data=(X_test, y_test))
```

```
Epoch 1/45
4/4 [==============================] - 0s 28ms/step - loss: 0.4276 - accuracy:
0.9829 - val_loss: 0.4316 - val_accuracy: 0.9000
Epoch 2/45
4/4 [==============================] - 0s 11ms/step - loss: 0.4215 - accuracy:
0.9829 - val_loss: 0.4269 - val_accuracy: 0.9000
Epoch 3/45
4/4 [==============================] - 0s 11ms/step - loss: 0.4164 - accuracy:
0.9829 - val_loss: 0.4235 - val_accuracy: 0.9000
Epoch 4/45
4/4 [==============================] - 0s 11ms/step - loss: 0.4106 - accuracy:
0.9658 - val_loss: 0.4188 - val_accuracy: 0.9000
Epoch 5/45
4/4 [==============================] - 0s 11ms/step - loss: 0.4054 - accuracy:
0.9829 - val_loss: 0.4136 - val_accuracy: 0.9000
Epoch 6/45
4/4 [==============================] - 0s 11ms/step - loss: 0.4017 - accuracy:
0.9829 - val_loss: 0.4086 - val_accuracy: 0.9000
Epoch 7/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3956 - accuracy:
0.9829 - val_loss: 0.4042 - val_accuracy: 0.9333
Epoch 8/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3899 - accuracy:
0.9829 - val_loss: 0.4002 - val_accuracy: 0.9000
Epoch 9/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3863 - accuracy:
0.9829 - val_loss: 0.3961 - val_accuracy: 0.9000
Epoch 10/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3799 - accuracy:
0.9829 - val_loss: 0.3931 - val_accuracy: 0.9000
Epoch 11/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3759 - accuracy:
0.9829 - val_loss: 0.3892 - val_accuracy: 0.9000
Epoch 12/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3721 - accuracy:
0.9744 - val_loss: 0.3854 - val_accuracy: 0.9000
Epoch 13/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3671 - accuracy:
0.9829 - val_loss: 0.3812 - val_accuracy: 0.9000
Epoch 14/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3625 - accuracy:
0.9829 - val_loss: 0.3773 - val_accuracy: 0.9000
```

```
Epoch 15/45
4/4 [==============================] - 0s 12ms/step - loss: 0.3587 - accuracy:
0.9829 - val_loss: 0.3735 - val_accuracy: 0.9000
Epoch 16/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3534 - accuracy:
0.9829 - val_loss: 0.3687 - val_accuracy: 0.9000
Epoch 17/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3534 - accuracy:
0.9744 - val_loss: 0.3656 - val_accuracy: 0.9000
Epoch 18/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3448 - accuracy:
0.9829 - val_loss: 0.3619 - val_accuracy: 0.9000
Epoch 19/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3403 - accuracy:
0.9744 - val_loss: 0.3609 - val_accuracy: 0.9000
Epoch 20/45
4/4 [==============================] - 0s 12ms/step - loss: 0.3380 - accuracy:
0.9744 - val_loss: 0.3568 - val_accuracy: 0.9000
Epoch 21/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3340 - accuracy:
0.9744 - val_loss: 0.3528 - val_accuracy: 0.9000
Epoch 22/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3279 - accuracy:
0.9829 - val_loss: 0.3476 - val_accuracy: 0.9333
Epoch 23/45
4/4 [==============================] - 0s 15ms/step - loss: 0.3255 - accuracy:
0.9744 - val_loss: 0.3446 - val_accuracy: 0.9333
Epoch 24/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3223 - accuracy:
0.9744 - val_loss: 0.3410 - val_accuracy: 0.9000
Epoch 25/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3177 - accuracy:
0.9829 - val_loss: 0.3377 - val_accuracy: 0.9333
Epoch 26/45
4/4 [==============================] - 0s 12ms/step - loss: 0.3126 - accuracy:
0.9829 - val_loss: 0.3349 - val_accuracy: 0.9333
Epoch 27/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3096 - accuracy:
0.9829 - val_loss: 0.3319 - val_accuracy: 0.9000
Epoch 28/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3059 - accuracy:
0.9829 - val_loss: 0.3279 - val_accuracy: 0.9000
Epoch 29/45
4/4 [==============================] - 0s 11ms/step - loss: 0.3022 - accuracy:
0.9829 - val_loss: 0.3246 - val_accuracy: 0.9000
Epoch 30/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2980 - accuracy:
0.9829 - val_loss: 0.3218 - val_accuracy: 0.9333
```

```
Epoch 31/45
4/4 [==============================] - 0s 12ms/step - loss: 0.2962 - accuracy:
0.9829 - val_loss: 0.3206 - val_accuracy: 0.9000
Epoch 32/45
4/4 [==============================] - 0s 12ms/step - loss: 0.2922 - accuracy:
0.9829 - val_loss: 0.3161 - val_accuracy: 0.9333
Epoch 33/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2881 - accuracy:
0.9829 - val_loss: 0.3132 - val_accuracy: 0.9333
Epoch 34/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2889 - accuracy:
0.9744 - val_loss: 0.3098 - val_accuracy: 0.9667
Epoch 35/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2828 - accuracy:
0.9829 - val_loss: 0.3077 - val_accuracy: 0.9333
Epoch 36/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2777 - accuracy:
0.9829 - val_loss: 0.3053 - val_accuracy: 0.9333
Epoch 37/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2751 - accuracy:
0.9829 - val_loss: 0.3029 - val_accuracy: 0.9333
Epoch 38/45
4/4 [==============================] - 0s 12ms/step - loss: 0.2719 - accuracy:
0.9829 - val_loss: 0.2994 - val_accuracy: 0.9333
Epoch 39/45
4/4 [==============================] - 0s 12ms/step - loss: 0.2687 - accuracy:
0.9829 - val_loss: 0.2965 - val_accuracy: 0.9000
Epoch 40/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2654 - accuracy:
0.9829 - val_loss: 0.2943 - val_accuracy: 0.9333
Epoch 41/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2626 - accuracy:
0.9829 - val_loss: 0.2920 - val_accuracy: 0.9333
Epoch 42/45
4/4 [==============================] - 0s 12ms/step - loss: 0.2594 - accuracy:
0.9829 - val_loss: 0.2892 - val_accuracy: 0.9333
Epoch 43/45
4/4 [==============================] - 0s 13ms/step - loss: 0.2563 - accuracy:
0.9829 - val_loss: 0.2862 - val_accuracy: 0.9000
Epoch 44/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2549 - accuracy:
0.9744 - val_loss: 0.2840 - val_accuracy: 0.9667
Epoch 45/45
4/4 [==============================] - 0s 11ms/step - loss: 0.2519 - accuracy:
0.9744 - val_loss: 0.2813 - val_accuracy: 0.9333
```

[57]:

```
model.evaluate(X_test,y_test)
```

```
1/1 [==============================] - 0s 24ms/step - loss: 0.2813 - accuracy:
0.9333
```

[57]:
```
[0.2812903821468353, 0.9333333373069763]
```

[58]:
```
pred = model.predict(X_test[:10])
print(pred)
```

```
1/1 [==============================] - 0s 18ms/step
[[4.4205684e-02 7.4035019e-01 2.1544413e-01]
 [4.6080411e-03 2.7307117e-01 7.2232085e-01]
 [9.4151229e-01 5.7721719e-02 7.6599861e-04]
 [9.7722459e-01 2.2616867e-02 1.5854144e-04]
 [1.0456862e-02 4.2329228e-01 5.6625086e-01]
 [1.9926867e-03 2.2487162e-01 7.7313578e-01]
 [9.3268001e-01 6.6229850e-02 1.0901118e-03]
 [1.0335593e-02 4.8913625e-01 5.0052810e-01]
 [9.6969181e-01 2.9984126e-02 3.2402345e-04]
 [4.7446853e-03 3.7676704e-01 6.1848831e-01]]
```

[59]:
```
p=np.argmax(pred,axis=1)
print(p)
print(y_test[:10])
```

```
[1 2 0 0 2 2 0 2 0 2]
[[0. 1. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 1. 0.]
 [1. 0. 0.]
 [0. 0. 1.]]
```

[60]:
```
history.history['accuracy']
```

[60]:
```
[0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9658119678497314,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
```

```
 0.9829059839248657,
 0.9743589758872986,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9743589758872986,
 0.9829059839248657,
 0.9743589758872986,
 0.9743589758872986,
 0.9743589758872986,
 0.9829059839248657,
 0.9743589758872986,
 0.9743589758872986,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9743589758872986,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9829059839248657,
 0.9743589758872986,
 0.9743589758872986]
```

[61]:
```
history.history['val_accuracy']
```

[61]:
```
[0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.9333333373069763,
 0.8999999761581421,
 0.8999999761581421,
```

```
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.9333333373069763,
 0.9333333373069763,
 0.8999999761581421,
 0.9333333373069763,
 0.9333333373069763,
 0.8999999761581421,
 0.8999999761581421,
 0.8999999761581421,
 0.9333333373069763,
 0.8999999761581421,
 0.9333333373069763,
 0.9333333373069763,
 0.9666666388511658,
 0.9333333373069763,
 0.9333333373069763,
 0.9333333373069763,
 0.9333333373069763,
 0.8999999761581421,
 0.9333333373069763,
 0.9333333373069763,
 0.9333333373069763,
 0.8999999761581421,
 0.9666666388511658,
 0.9333333373069763]
```

[62]:

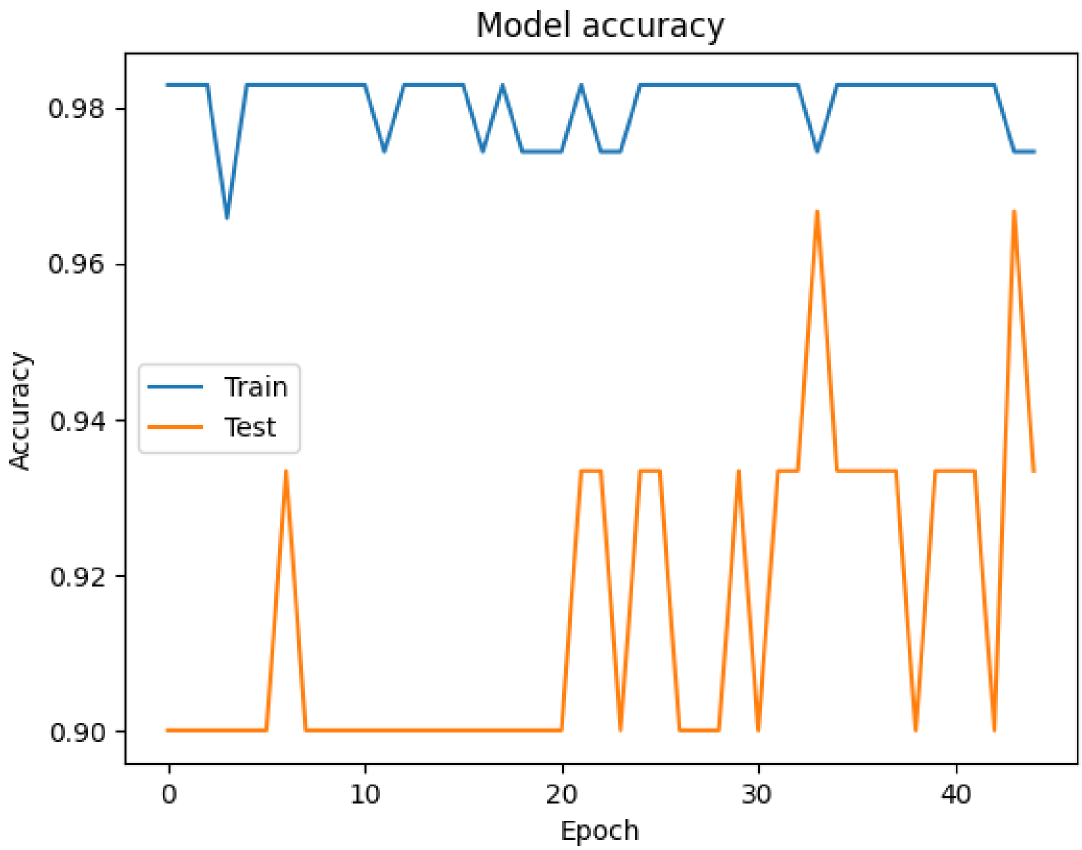
```
plt.figure()



plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])

plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'])
```

```
plt.show()
```



Model accuracy
0.98
0.96
0.94
0.92
0.90
Accuracy
Train
Test
0
10
20
30
40
Epoch