```python
# Import libraries and data
import pandas
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

```python
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iri
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'c
dataset = pandas.read_csv(url, names=names)
```

```python
# Summarize data
print(dataset.shape)
```

```
(150, 5)
```

```python
# View Data
print(dataset.head(20))
```

```
    sepal-length  sepal-width  petal-length  petal-width        class
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
5            5.4          3.9           1.7          0.4  Iris-setosa
6            4.6          3.4           1.4          0.3  Iris-setosa
7            5.0          3.4           1.5          0.2  Iris-setosa
8            4.4          2.9           1.4          0.2  Iris-setosa
9            4.9          3.1           1.5          0.1  Iris-setosa
10           5.4          3.7           1.5          0.2  Iris-setosa
11           4.8          3.4           1.6          0.2  Iris-setosa
12           4.8          3.0           1.4          0.1  Iris-setosa
13           4.3          3.0           1.1          0.1  Iris-setosa
14           5.8          4.0           1.2          0.2  Iris-setosa
15           5.7          4.4           1.5          0.4  Iris-setosa
16           5.4          3.9           1.3          0.4  Iris-setosa
17           5.1          3.5           1.4          0.3  Iris-setosa
```

```
18          5.7          3.8           1.7          0.3  Iris-setosa
19          5.1          3.8           1.5          0.3  Iris-setosa
```

```
[5]  # descriptions/stat summary
     print(dataset.describe())
```

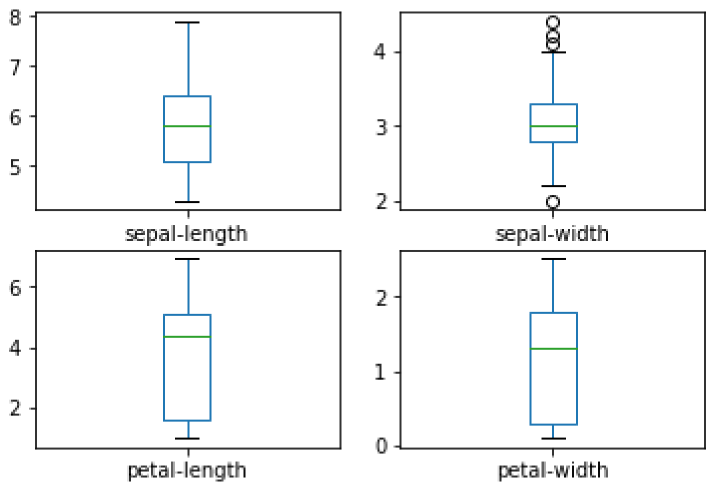
```
       sepal-length  sepal-width  petal-length  petal-width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
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
```

```
[6]  # class distribution
     print(dataset.groupby('class').size())
```

```
class
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

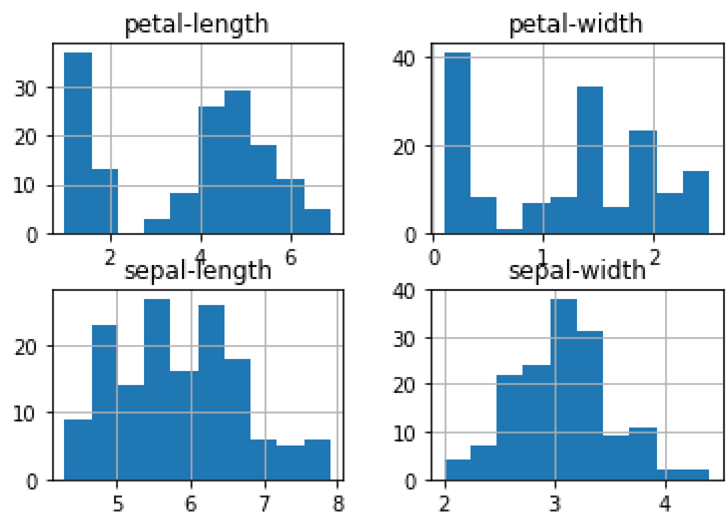
We can see that each class has the same number of instances (50 or 33% of the dataset).

```
[7]  # box and whisker plots
     dataset.plot(kind='box', subplots=True, layout=(2,2), sharex=False, share
     plt.show()
```

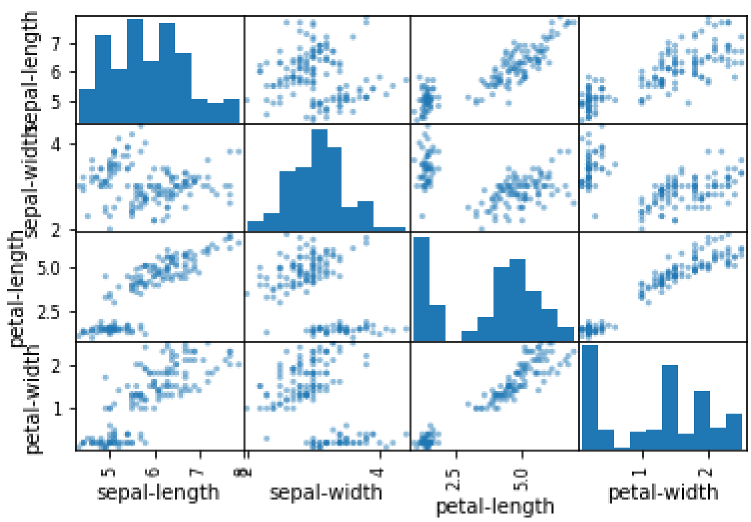


This gives us a much clearer idea of the distribution of the input attributes:

```
[8]  # histograms
     dataset.hist()
     plt.show()
```




```
[9]  # scatter plot matrix
     scatter_matrix(dataset)
     plt.show()
```



Note the diagonal grouping of some pairs of attributes. This suggests a high correlation and a predictable relationship.

We will split the loaded dataset into two, 80% of which we will use to train our models and 20% that we will hold back as a validation dataset.

```
[10] # Split-out validation dataset
     array = dataset.values
     X = array[:,0:4]
     Y = array[:,4]
     validation_size = 0.20
```

```
seed = 7
X_train, X_validation, Y_train, Y_validation = model_selection.train_test
```

This will split our dataset into 10 parts, train on 9 and test on 1 and repeat for all combinations of train-test splits.

[11]

```
# Test options and evaluation metric
seed = 7
scoring = 'accuracy'
```

Build Models!

[12]

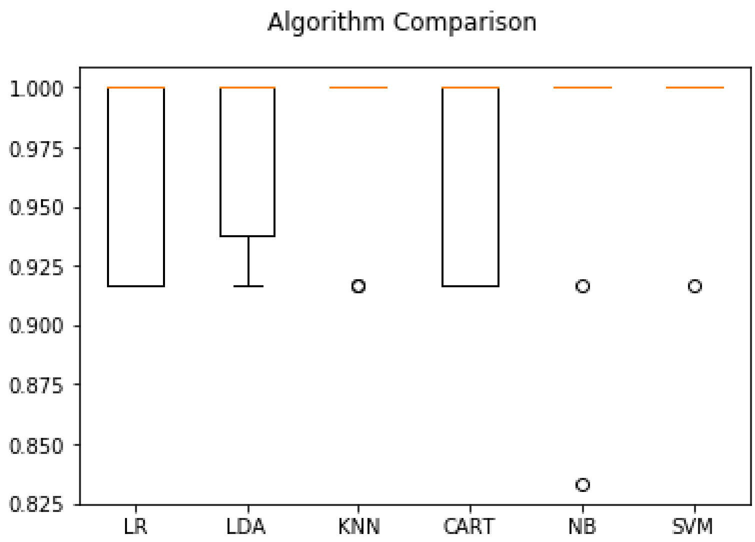
```
# Spot Check Algorithms
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, Y_train,
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.966667 (0.040825)
LDA: 0.975000 (0.038188)
KNN: 0.983333 (0.033333)
CART: 0.966667 (0.040825)
NB: 0.975000 (0.053359)
SVM: 0.991667 (0.025000)
```

[13]

```
# Compare Algorithms
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
```

```
plt.show()
```



You can see that the box and whisker plots are squashed at the top of the range, with many samples achieving 100% accuracy.

```
[14]  # Make predictions on validation dataset
knn = KNeighborsClassifier()
knn.fit(X_train, Y_train)
predictions = knn.predict(X_validation)
print(accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
```

```
0.9
[[ 7  0  0]
 [ 0 11  1]
 [ 0  2  9]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       0.85      0.92      0.88        12
 Iris-virginica       0.90      0.82      0.86        11

    avg / total       0.90      0.90      0.90        30
```

We can see that the accuracy is 0.9 or 90%. The confusion matrix provides an indication of the three errors made. Finally, the classification report provides a breakdown of each class by precision, recall, f1-score and support showing excellent results (granted the validation dataset was small).