Iris Data set Analysis

Problem statement: Predict the class of flower by its chracteristics like sepal-length,petal-width etc.

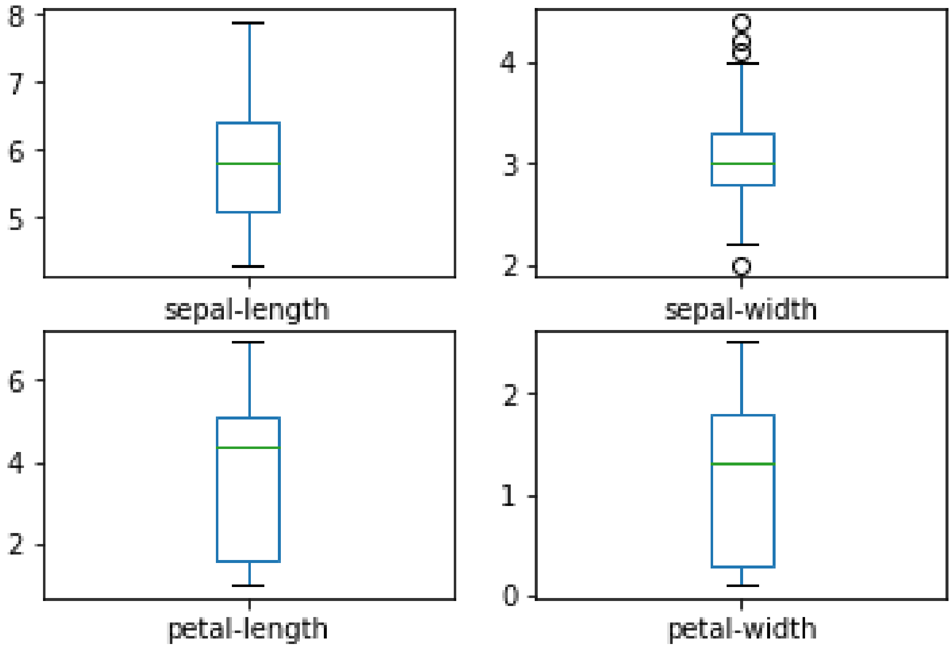
```
# Load libraries
import pandas
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model 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

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

# shape
print(dataset.shape)
```

```
(150, 5)
```

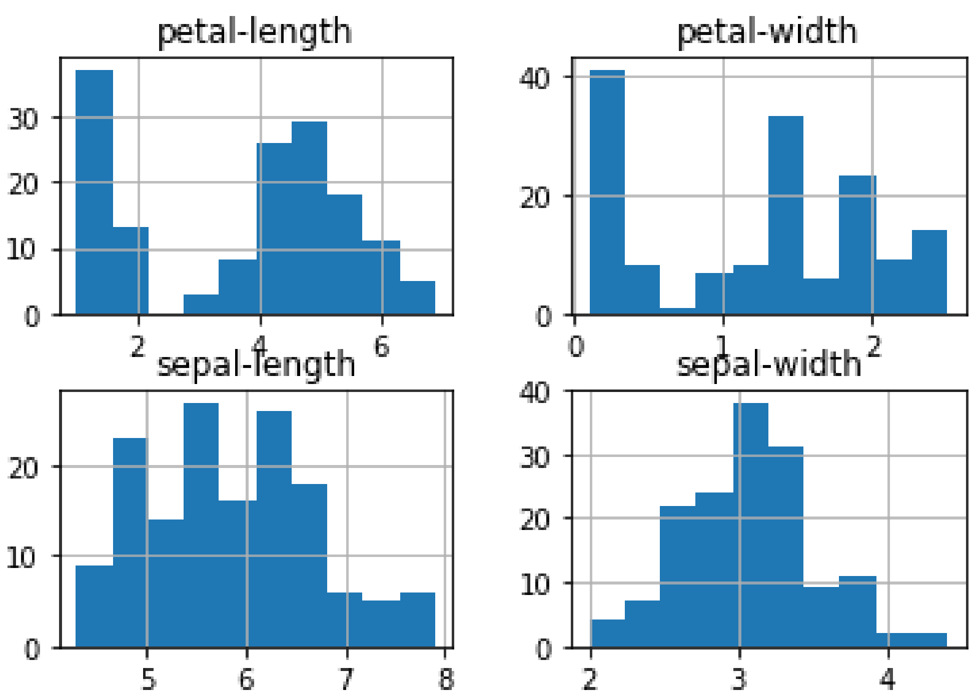
```
# head
print(dataset.head(30))
```

```
    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
```

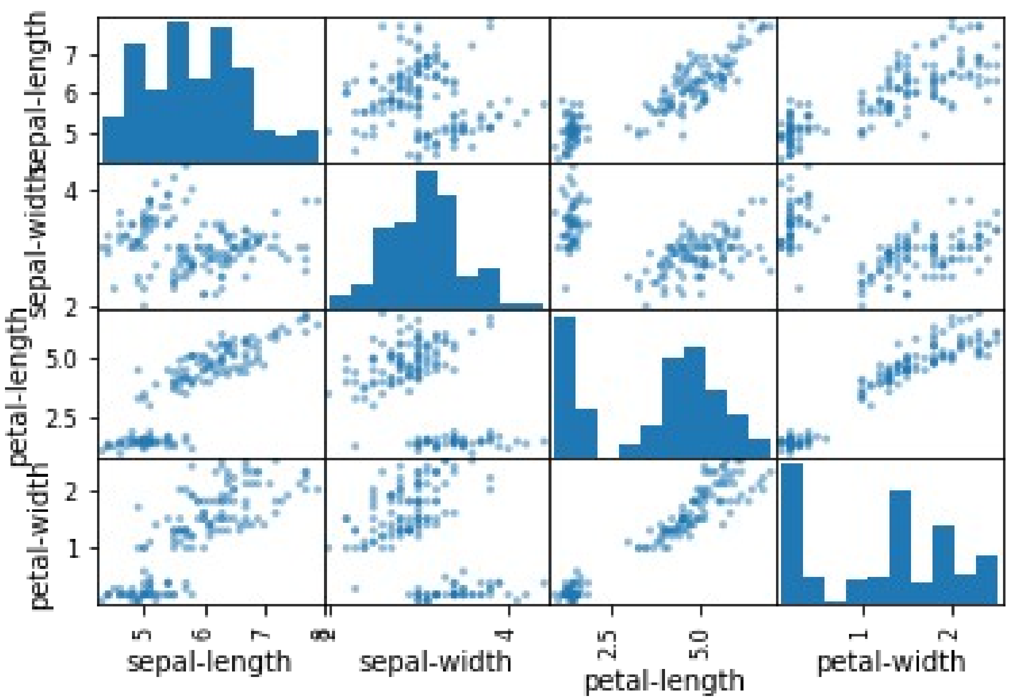
```
12              4.8           3.0           1.4           0.1   Iris-setosa
13              4.3           3.0           1.1           0.1   Iris-setosa
14              5.8           4.0           1.2           0.2   Iris-setosa
15              5.7           4.4           1.5           0.4   Iris-setosa
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
20              5.4           3.4           1.7           0.2   Iris-setosa
21              5.1           3.7           1.5           0.4   Iris-setosa
22              4.6           3.6           1.0           0.2   Iris-setosa
23              5.1           3.3           1.7           0.5   Iris-setosa
24              4.8           3.4           1.9           0.2   Iris-setosa
25              5.0           3.0           1.6           0.2   Iris-setosa
26              5.0           3.4           1.6           0.4   Iris-setosa
27              5.2           3.5           1.5           0.2   Iris-setosa
28              5.2           3.4           1.4           0.2   Iris-setosa
29              4.7           3.2           1.6           0.2   Iris-setosa

# class distribution
print(dataset.groupby('class').size())

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

# Univariate plots to better understand each attribute
# box and whisker plots
dataset.plot(kind='box', subplots=True, layout=(2,2), sharex=False,
sharey=False)
plt.show()
```




```
# histograms
dataset.hist()
plt.show()
# It looks like perhaps two of the input variables have a Gaussian
distribution.
#This is useful to note as we can use algorithms
#that can exploit this assumption.
```



```
# Multivariate plots to better understand the relationships between attributes.
# scatter plot matrix
scatter_matrix(dataset)
plt.show()
#The diagonal grouping of some pairs of attributes. This suggests a high correlation and a predictable relationship.
```



Create a Validation Dataset

```
#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.
# 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_split(X, Y, test_size=validation_size, random_state=seed)

X_train
```

```
array([[6.2, 2.8, 4.8, 1.8],
       [5.7, 2.6, 3.5, 1.0],
       [4.6, 3.6, 1.0, 0.2],
       [6.9, 3.1, 5.4, 2.1],
       [6.4, 2.9, 4.3, 1.3],
       [4.8, 3.0, 1.4, 0.3],
       [5.5, 3.5, 1.3, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [7.1, 3.0, 5.9, 2.1],
       [6.7, 3.3, 5.7, 2.1],
       [6.8, 2.8, 4.8, 1.4],
       [6.4, 2.8, 5.6, 2.2],
       [6.5, 3.0, 5.5, 1.8],
       [5.7, 3.0, 4.2, 1.2],
       [5.0, 3.3, 1.4, 0.2],
       [6.7, 3.1, 4.4, 1.4],
       [6.0, 2.2, 4.0, 1.0],
       [6.4, 2.7, 5.3, 1.9],
       [4.7, 3.2, 1.6, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [7.7, 3.8, 6.7, 2.2],
       [4.3, 3.0, 1.1, 0.1],
       [6.3, 3.3, 6.0, 2.5],
       [5.5, 2.4, 3.7, 1.0],
       [5.0, 2.0, 3.5, 1.0],
       [6.5, 2.8, 4.6, 1.5],
       [5.0, 3.4, 1.6, 0.4],
       [4.4, 2.9, 1.4, 0.2],
       [5.0, 3.5, 1.6, 0.6],
       [6.7, 3.1, 4.7, 1.5],
       [7.3, 2.9, 6.3, 1.8],
       [5.5, 2.6, 4.4, 1.2],
       [5.2, 2.7, 3.9, 1.4],
       [5.7, 4.4, 1.5, 0.4],
       [7.2, 3.2, 6.0, 1.8],
       [5.4, 3.4, 1.7, 0.2],
       [5.8, 4.0, 1.2, 0.2],
       [6.1, 2.6, 5.6, 1.4],
       [5.7, 2.5, 5.0, 2.0],
       [4.8, 3.0, 1.4, 0.1],
       [6.5, 3.0, 5.8, 2.2],
       [4.6, 3.2, 1.4, 0.2],
       [6.6, 2.9, 4.6, 1.3],
       [6.7, 3.0, 5.2, 2.3],
       [6.1, 3.0, 4.6, 1.4],
       [5.7, 3.8, 1.7, 0.3],
       [7.0, 3.2, 4.7, 1.4],
       [4.7, 3.2, 1.3, 0.2],
```

```
          [6.5, 3.0, 5.2, 2.0],
          [7.7, 2.6, 6.9, 2.3],
          [4.9, 2.4, 3.3, 1.0],
          [4.8, 3.1, 1.6, 0.2],
          [5.5, 4.2, 1.4, 0.2],
          [5.6, 3.0, 4.1, 1.3],
          [6.4, 3.2, 5.3, 2.3],
          [5.2, 3.5, 1.5, 0.2],
          [7.9, 3.8, 6.4, 2.0],
          [5.8, 2.8, 5.1, 2.4],
          [5.7, 2.9, 4.2, 1.3],
          [5.1, 3.7, 1.5, 0.4],
          [5.1, 2.5, 3.0, 1.1],
          [5.0, 3.4, 1.5, 0.2],
          [7.7, 2.8, 6.7, 2.0],
          [7.6, 3.0, 6.6, 2.1],
          [5.0, 3.2, 1.2, 0.2],
          [5.4, 3.7, 1.5, 0.2],
          [6.7, 3.3, 5.7, 2.5],
          [6.1, 2.8, 4.0, 1.3],
          [6.3, 2.5, 5.0, 1.9],
          [7.4, 2.8, 6.1, 1.9],
          [5.0, 2.3, 3.3, 1.0],
          [5.4, 3.4, 1.5, 0.4],
          [5.4, 3.9, 1.3, 0.4],
          [5.6, 2.8, 4.9, 2.0],
          [4.9, 3.0, 1.4, 0.2],
          [5.3, 3.7, 1.5, 0.2],
          [6.0, 2.7, 5.1, 1.6],
          [6.8, 3.2, 5.9, 2.3],
          [6.2, 3.4, 5.4, 2.3],
          [5.7, 2.8, 4.1, 1.3],
          [6.3, 2.3, 4.4, 1.3],
          [4.9, 3.1, 1.5, 0.1],
          [6.9, 3.1, 5.1, 2.3],
          [5.0, 3.6, 1.4, 0.2],
          [4.4, 3.0, 1.3, 0.2],
          [6.0, 2.9, 4.5, 1.5],
          [6.1, 2.8, 4.7, 1.2],
          [6.4, 2.8, 5.6, 2.1],
          [4.9, 3.1, 1.5, 0.1],
          [5.6, 2.9, 3.6, 1.3],
          [5.9, 3.0, 4.2, 1.5],
          [6.3, 2.7, 4.9, 1.8],
          [6.8, 3.0, 5.5, 2.1],
          [5.5, 2.3, 4.0, 1.3],
          [6.3, 2.8, 5.1, 1.5],
          [4.8, 3.4, 1.9, 0.2],
          [6.3, 3.3, 4.7, 1.6],
          [5.6, 2.5, 3.9, 1.1],
```

```
       [5.1, 3.8, 1.9, 0.4],
       [5.1, 3.8, 1.5, 0.3],
       [4.6, 3.4, 1.4, 0.3],
       [5.7, 2.8, 4.5, 1.3],
       [6.6, 3.0, 4.4, 1.4],
       [5.1, 3.5, 1.4, 0.2],
       [7.7, 3.0, 6.1, 2.3],
       [6.1, 3.0, 4.9, 1.8],
       [6.2, 2.2, 4.5, 1.5],
       [6.3, 3.4, 5.6, 2.4],
       [4.4, 3.2, 1.3, 0.2],
       [6.5, 3.2, 5.1, 2.0],
       [5.5, 2.5, 4.0, 1.3],
       [6.3, 2.5, 4.9, 1.5],
       [5.1, 3.3, 1.7, 0.5],
       [5.8, 2.7, 5.1, 1.9],
       [5.8, 2.6, 4.0, 1.2],
       [6.3, 2.9, 5.6, 1.8],
       [5.8, 2.7, 4.1, 1.0],
       [5.0, 3.0, 1.6, 0.2]], dtype=object)
```

```
print (len(Y_train),len(Y_validation))
#so our training and validation set is ready with 80:20 ratio
```

```
120 30
```

```
# Test options and evaluation metric
seed = 7
scoring = 'accuracy'
#We will use 10-fold cross validation to estimate accuracy.
#This will split our dataset into 10 parts, train on 9 and test on 1
#and repeat for all combinations of train-test splits.
```

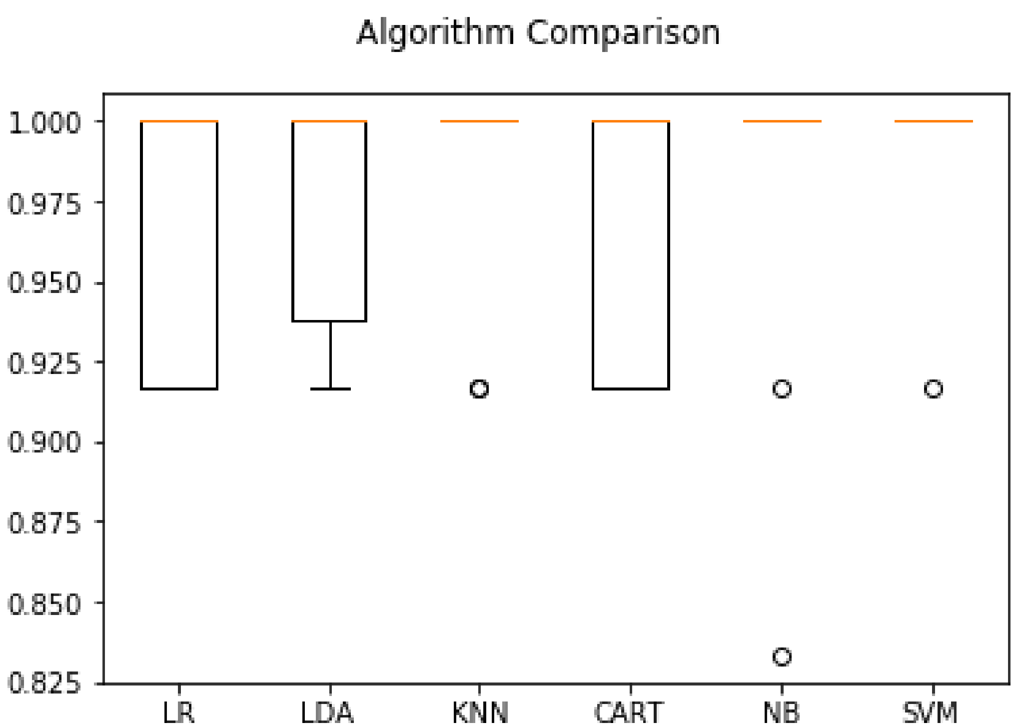
Build Models

```
# we will evaluate using  6 different 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)#here
```

```
e use kfold validation for scoring
    cv_results = model_selection.cross_val_score(model, X_train,
Y_train, cv=kfold, scoring=scoring)#apply dataset on train data
    results.append(cv_results)
    names.append(name)
    #here we are using supervised method as we are giving what could
be the result to given characteristics
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
    #here we can see  KNN has the largest estimated accuracy score.
```

```
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)
```

```
# Compare Algorithms
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
# The box and whisker plots are squashed at the top of the range, with
many samples achieving 100% accuracy
```



Make Predictions

```
# Make predictions on validation dataset
# Here we apply our built model on test data set so to see that our
model does not overfit and it gives an
# idea whether our model is appropiate for prediction on other
datasets
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
```

Conclusion

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.