SEP 786 – Artificial Intelligence and Machine Learning Fundamentals

# Project Report

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# Dataset:

(https://archive.ics.uci.edu/ml/datasets/Wireless+Indoor+Localization#).

Wireless Indoor Localization Data, which is sourced from UCI ML, is the dataset utilised for this study. By analysing the WiFi signal levels in an interior setting, the data set is compiled. It is gathered by keeping an eye on the strengths shown on a smartphone. The dataset has one target variable and a total of seven characteristics. The WiFi signal strength as measured by a smartphone is each property. One of the four rooms is the goal value. Based on the seven signal intensities, the room is anticipated. There are a total of 2000 data points. 500 will be tested, and 1500 will be utilised for training.

| | | | | | |
|---|---|---|---|---|---|
| **Data Set Characteristics:** | Multivariate | **Number of Instances:** | 2000 | **Area:** | Computer |
| **Attribute Characteristics:** | Real | **Number of Attributes:** | 7 | **Date Donated** | 2017-12-04 |
| **Associated Tasks:** | Classification | **Missing Values?** | N/A | **Number of Web Hits:** | 67356 |

```
import numpy as np
import pandas as pd
import time
from numpy.linalg import eig
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
import warnings
warnings.filterwarnings('ignore')

cols = ["Smartphone 1", "Smartphone 2", "Smartphone 3", "Smartphone 4",
"Smartphone 5", "Smartphone 6", "Smartphone 7", "Room Number"]
data = pd.read_csv(r'wifi.csv', names = cols, index_col = False)
data.head()
```

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 | Room Number |
|---|---|---|---|---|---|---|---|---|
| **0** | -64 | -56 | -61 | -66 | -71 | -82 | -81 | 1 |
| **1** | -68 | -57 | -61 | -65 | -71 | -85 | -85 | 1 |
| **2** | -63 | -60 | -60 | -67 | -76 | -85 | -84 | 1 |
| **3** | -61 | -60 | -68 | -62 | -77 | -90 | -80 | 1 |
| **4** | -63 | -65 | -60 | -63 | -77 | -81 | -87 | 1 |

```
df = data.iloc[:,0:7]
op = data.iloc[:, -1]
df.head()
```

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 |
|---|---|---|---|---|---|---|---|
| 0 | -64 | -56 | -61 | -66 | -71 | -82 | -81 |
| 1 | -68 | -57 | -61 | -65 | -71 | -85 | -85 |
| 2 | -63 | -60 | -60 | -67 | -76 | -85 | -84 |
| 3 | -61 | -60 | -68 | -62 | -77 | -90 | -80 |
| 4 | -63 | -65 | -60 | -63 | -77 | -81 | -87 |

# PCA

## Centering the mean of the data for PCA:

```
df.mean().values
```

```
array([-52.3305, -55.6235, -54.964 , -53.5665, -62.6405, -80.985 ,
       -81.7265])
```

```
df_mc = pd.DataFrame()
# mc = Mean centered

for i in range(len(df.columns)):
    array = np.array(df.iloc[:,i] - df.mean().values[i])
    df_mc[df.columns[i]] = array
df_mc.head()
```

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 |
|---|---|---|---|---|---|---|---|
| 0 | -11.6695 | -0.3765 | -6.036 | -12.4335 | -8.3595 | -1.015 | 0.7265 |
| 1 | -15.6695 | -1.3765 | -6.036 | -11.4335 | -8.3595 | -4.015 | -3.2735 |
| 2 | -10.6695 | -4.3765 | -5.036 | -13.4335 | -13.3595 | -4.015 | -2.2735 |
| 3 | -8.6695 | -4.3765 | -13.036 | -8.4335 | -14.3595 | -9.015 | 1.7265 |
| 4 | -10.6695 | -9.3765 | -5.036 | -9.4335 | -14.3595 | -0.015 | -5.2735 |

## Scaling the data for PCA:

```
df.std().values
```

```
array([11.32167655,  3.41768753,  5.31618613, 11.47198243,  9.10509259,
        6.51667158,  6.51981225])
```

```
df_mcs = pd.DataFrame()
# mc = Mean centered scaled

for i in range(len(df_mc.columns)):
    array = np.array(df_mc.iloc[:,i] / df_mc.std().values[i])
    df_mcs[df_mc.columns[i]] = array
df_mcs.head()
```

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 |
|---|---|---|---|---|---|---|---|
| 0 | -1.030722 | -0.110162 | -1.135400 | -1.083814 | -0.918113 | -0.155754 | 0.111430 |
| 1 | -1.384026 | -0.402758 | -1.135400 | -0.996646 | -0.918113 | -0.616112 | -0.502085 |
| 2 | -0.942396 | -1.280544 | -0.947296 | -1.170983 | -1.467256 | -0.616112 | -0.348706 |
| 3 | -0.765743 | -1.280544 | -2.452134 | -0.735139 | -1.577084 | -1.383375 | 0.264808 |
| 4 | -0.942396 | -2.743522 | -0.947296 | -0.822308 | -1.577084 | -0.002302 | -0.808842 |

```
df_mcs.mean()
```

```
Smartphone 1     4.263256e-17
Smartphone 2    -2.842171e-17
Smartphone 3    -2.842171e-16
Smartphone 4    -1.421085e-16
Smartphone 5     2.842171e-16
Smartphone 6     0.000000e+00
Smartphone 7     1.989520e-16
dtype: float64
```

```
df_mcs.std()
```

```
Smartphone 1    1.0
Smartphone 2    1.0
Smartphone 3    1.0
Smartphone 4    1.0
Smartphone 5    1.0
Smartphone 6    1.0
Smartphone 7    1.0
dtype: float64
```

## Finding the Covariance Matrix:

```
# covariance matrix

X = df_mcs.to_numpy()
Xt = X.transpose()

XtX = np.dot(Xt, X)
df_XtX = pd.DataFrame(XtX)
df_XtX/1999.0
```

[redacted]

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| **0** | 1.000000 | -0.003298 | 0.050814 | 0.921025 | -0.244932 | 0.718429 | 0.686955 |
| **1** | -0.003298 | 1.000000 | 0.282211 | 0.014604 | 0.200469 | 0.074002 | 0.048336 |
| **2** | 0.050814 | 0.282211 | 1.000000 | 0.078292 | 0.618984 | -0.091622 | -0.073141 |
| **3** | 0.921025 | 0.014604 | 0.078292 | 1.000000 | -0.236021 | 0.706039 | 0.673294 |
| **4** | -0.244932 | 0.200469 | 0.618984 | -0.236021 | 1.000000 | -0.416049 | -0.361621 |
| **5** | 0.718429 | 0.074002 | -0.091622 | 0.706039 | -0.416049 | 1.000000 | 0.723172 |
| **6** | 0.686955 | 0.048336 | -0.073141 | 0.673294 | -0.361621 | 0.723172 | 1.000000 |

## Calculating Eigen Values and Eigen Vectors:

```
eigen_Value, eigen_Vector = eig(XtX)
print('Eigen-value:\n', eigen_Value)
print('Eigen-vector:\n', eigen_Vector)
```

```
Eigen-value:
 [6787.68429243 3421.80053101 1741.77047985  155.95960672  741.76231514
  512.47144992  631.55132495]
Eigen-vector:
 [[-0.48948817  0.16468976  0.19791006 -0.71630001  0.41057236  0.10352193
   0.04169002]
 [ 0.00534144  0.42971465 -0.87398505 -0.01296522  0.20900505  0.07854757
   0.03802633]
 [ 0.07713055  0.6714255   0.24129382 -0.03120517 -0.32943421  0.16369837
  -0.59052363]
 [-0.48438445  0.18311678  0.19312126  0.69580645  0.43485981  0.14512339
  -0.01528574]
 [ 0.27160625  0.54881495  0.27858707  0.02857353  0.035565   -0.33069007
   0.66029099]
 [-0.47977075  0.02894363 -0.13116326  0.02263037 -0.25987816 -0.81040806
  -0.16422083]
 [-0.4645917   0.04293096 -0.08153934  0.0172405  -0.64908839  0.41126438
   0.43001331]]
```

## Principle Components:

```
# principle components

pcs = eigen_Vector.transpose()

p1 = pcs[0]
p2 = pcs[1]
p3 = pcs[2]
p4 = pcs[3]
p5 = pcs[4]
```

```
p6 = pcs[5]
p7 = pcs[6]


print("p1: ", p1)
print("p2: ", p2)
print("p3: ", p3)
print("p4: ", p4)
print("p5: ", p5)
print("p6: ", p6)
print("p7: ", p7)
```

```
p1:  [-0.48948817  0.00534144  0.07713055 -0.48438445  0.27160625 -0.47977075
 -0.4645917 ]
p2:  [0.16468976 0.42971465 0.6714255  0.18311678 0.54881495 0.02894363
 0.04293096]
p3:  [ 0.19791006 -0.87398505  0.24129382  0.19312126  0.27858707 -0.13116326
 -0.08153934]
p4:  [-0.71630001 -0.01296522 -0.03120517  0.69580645  0.02857353  0.02263037
  0.0172405 ]
p5:  [ 0.41057236  0.20900505 -0.32943421  0.43485981  0.035565   -0.25987816
 -0.64908839]
p6:  [ 0.10352193  0.07854757  0.16369837  0.14512339 -0.33069007 -0.81040806
  0.41126438]
p7:  [ 0.04169002  0.03802633 -0.59052363 -0.01528574  0.66029099 -0.16422083
  0.43001331]
```

### Calculating Scores:

We get the transformed data with scores calculated from all 7 principle components.

```
t = np.dot(X,eigen_Vector)
print(t)
```

```
[[ 0.71493855 -1.68148729 -0.83541376 ... -0.60798115  0.017157
   0.10716066]
 [ 1.34999078 -1.88910661 -0.52237044 ... -0.25842381  0.0910107
  -0.10824651]
 [ 1.00767508 -2.39399143  0.17843458 ... -0.51743149  0.31794851
  -0.52826882]
 ...
 [ 2.44169006  1.37971051  1.64808107 ... -0.61268396 -0.32302525
  -0.03658382]
 [ 2.31371957  1.05903344  1.33261272 ... -0.19150391 -0.01715813
   1.19923501]
 [ 2.13180815  2.7631949  -0.46381358 ...  0.11438007  0.19273188
   0.04801259]]
```

```
df_pca = pd.DataFrame(t, columns = cols[0:-1])
df_pca.head()
```

[redacted]

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 |
|---|---|---|---|---|---|---|---|
| 0 | 0.714939 | -1.681487 | -0.835414 | -0.006798 | -0.607981 | 0.017157 | 0.107161 |
| 1 | 1.349991 | -1.889107 | -0.522370 | 0.289725 | -0.258424 | 0.091011 | -0.108247 |
| 2 | 1.007675 | -2.393991 | 0.178435 | -0.155456 | -0.517431 | 0.317949 | -0.528269 |
| 3 | 0.647267 | -3.351619 | -0.045527 | 0.058306 | 0.037637 | 1.063579 | 0.678377 |
| 4 | 0.720425 | -3.021070 | 1.450805 | 0.108942 | -0.536329 | -0.396719 | -0.960414 |

## Function to find PCA with Logistic Regression and Decision Tree:

```
def regressionClassificationType(type):
    for i in range(df_pca.shape[1]):
        print("Number of principle components: ", i+1)
        X_train, X_test, y_train, y_test = train_test_split(df_pca.iloc[:,:i+1], op, test_size = 0.25)
        if(type == "Logistic Regression"):
            logreg = LogisticRegression()
            logreg.fit(X_train, y_train)
            y_pred = logreg.predict(X_test)
            print('Accuracy of Logistic Regression Classifier on Test set: {}'.format(logreg.score(X_test, y_test)))
            print()
        elif(type == "Decision Tree"):
            clf_model = DecisionTreeClassifier(criterion="gini")
            clf_model.fit(X_train,y_train)
            y_pred = clf_model.predict(X_test)
            print('Accuracy of Decision Tree Classifier on Test set: {}'.format(clf_model.score(X_test, y_test)))
            print()
```

# Logistic Regression with PCA

### Figuring out the best number of Principle Components for Logistic Regression:

We will calculate the Accuracy for model for each each number of principle components.

From the Output below, it is significant that the model starts to overfit if we use more than 3 principle components. So, we will build a model with first 3 scores.

```
regressionClassificationType("Logistic Regression")
```

```
Number of principle components:  1
Accuracy of Logistic Regression Classifier on Test set: 0.816

Number of principle components:  2
Accuracy of Logistic Regression Classifier on Test set: 0.93

Number of principle components:  3
Accuracy of Logistic Regression Classifier on Test set: 0.95

Number of principle components:  4
Accuracy of Logistic Regression Classifier on Test set: 0.978

Number of principle components:  5
Accuracy of Logistic Regression Classifier on Test set: 0.97

Number of principle components:  6
Accuracy of Logistic Regression Classifier on Test set: 0.978

Number of principle components:  7
Accuracy of Logistic Regression Classifier on Test set: 0.98
```

### Building logistic Regression model:

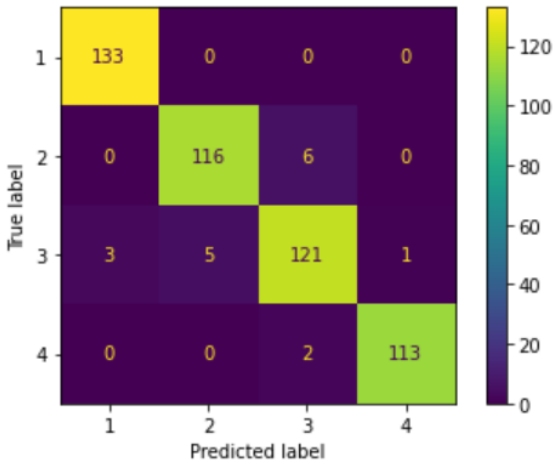
Principle components = 3

Calculating Accuracy, training and testing time, and Confusion matrix.

```
start = time.time()
```

```
X_train, X_test, y_train, y_test = train_test_split(df_pca.iloc[:,:3],
op, test_size = 0.25)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
stop = time.time()
print("Training Time: ", stop - start)
start = time.time()
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on Test set: {:.2f}'.
format(logreg.score(X_test, y_test)))
stop = time.time()
print("Testing Time: ", stop - start)
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", pd.DataFrame(confusion_matrix))
plot_confusion_matrix(logreg, X_test, y_test)
```

```
Training Time:  0.0363306999206543
Accuracy of Logistic Regression Classifier on Test set: 0.97
Testing Time:  0.005072832107543945
Confusion Matrix:
      0    1    2    3
0  133    0    0    0
1    0  116    6    0
2    3    5  121    1
3    0    0    2  113
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f2279f66590>
```



# Decision Tree with PCA

### Figuring out the best number of Principle Components for Decision Tree:

We will calculate the Accuracy for model for each each number of principle components.

From the Output below, it is significant that the model starts to overfit if we use more than 3 principle components. So, we will build a model with first 3 scores.

```
regressionClassificationType("Decision Tree")
```

```
Number of principle components:  1
Accuracy of Decision Tree Classifier on Test set: 0.748

Number of principle components:  2
Accuracy of Decision Tree Classifier on Test set: 0.896

Number of principle components:  3
Accuracy of Decision Tree Classifier on Test set: 0.948

Number of principle components:  4
Accuracy of Decision Tree Classifier on Test set: 0.944

Number of principle components:  5
Accuracy of Decision Tree Classifier on Test set: 0.962

Number of principle components:  6
Accuracy of Decision Tree Classifier on Test set: 0.932

Number of principle components:  7
Accuracy of Decision Tree Classifier on Test set: 0.948
```

### Building Decision Tree model:

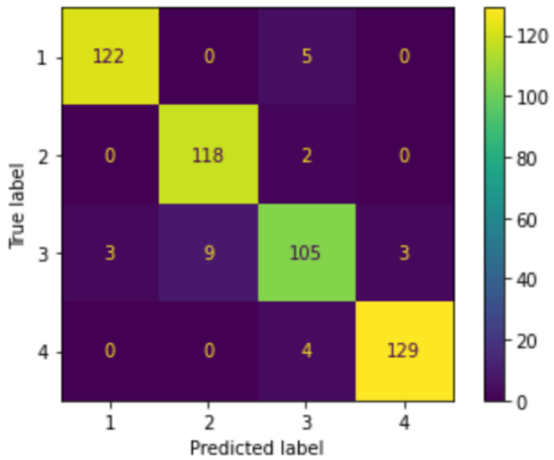
Principle components = 3

Calculating Accuracy, training and testing time, and Confusion matrix.

```
start = time.time()
```

```
X_train, X_test, y_train, y_test = train_test_split(df_pca.iloc[:,:3],
op, test_size = 0.25)
clf_model = DecisionTreeClassifier(criterion="gini")
clf_model.fit(X_train,y_train)
stop = time.time()
print("Training Time: ", stop - start)
from sklearn.metrics import confusion_matrix
start = time.time()
y_pred = clf_model.predict(X_test)
print('Accuracy of Decision Tree classifier on test set: ', end='')
print(accuracy_score(y_test,y_pred))
stop = time.time()
print("Testing Time: ", stop - start)
confusion_Matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", confusion_Matrix)
plot_confusion_matrix(clf_model, X_test, y_test)
```

```
Training Time:  0.007017612457275391
Accuracy of Decision Tree classifier on test set: 0.948
Testing Time:  0.0031337738037109375
Confusion Matrix:
 [[122   0   5   0]
 [  0 118   2   0]
 [  3   9 105   3]
 [  0   0   4 129]]
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f2279ed6b90>
```



# Feature Selection

```
features = pd.DataFrame(df)
removed_index = []
features.head()
```

| | Smartphone 1 | Smartphone 2 | Smartphone 3 | Smartphone 4 | Smartphone 5 | Smartphone 6 | Smartphone 7 |
|---|---|---|---|---|---|---|---|
| 0 | -64 | -56 | -61 | -66 | -71 | -82 | -81 |
| 1 | -68 | -57 | -61 | -65 | -71 | -85 | -85 |
| 2 | -63 | -60 | -60 | -67 | -76 | -85 | -84 |
| 3 | -61 | -60 | -68 | -62 | -77 | -90 | -80 |
| 4 | -63 | -65 | -60 | -63 | -77 | -81 | -87 |

### Selecting Features

The following code will find the indexes for best to worst attributes.

The method used is Backward Search.

```
for i in range(7):
    accuracy = []
    for i in range(7):
        if i in removed_index:
            print("Already Removed... Hence, Accuracy = 0")
            accuracy.append(0)
            continue

        x = features.drop(features.columns[i],axis=1)
        X_train, X_test, y_train, y_test = train_test_split(x, op, test
_size = 0.25)
        logreg = LogisticRegression()
        logreg.fit(X_train, y_train)
        y_pred = logreg.predict(X_test)
        accuracy.append(logreg.score(X_test, y_test))
        print('Accuracy of logistic regression classifier on test set:
{}'.format(accuracy[i]))
    max_index = np.argmax(accuracy)
    print()
```

```
removed_index.append(max_index)
print(removed_index)
```

```
Accuracy of logistic regression classifier on test set: 0.946
Accuracy of logistic regression classifier on test set: 0.978
Accuracy of logistic regression classifier on test set: 0.986
Accuracy of logistic regression classifier on test set: 0.976
Accuracy of logistic regression classifier on test set: 0.958
Accuracy of logistic regression classifier on test set: 0.98
Accuracy of logistic regression classifier on test set: 0.972

[2]
Accuracy of logistic regression classifier on test set: 0.956
Accuracy of logistic regression classifier on test set: 0.966
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.976
Accuracy of logistic regression classifier on test set: 0.932
Accuracy of logistic regression classifier on test set: 0.972
Accuracy of logistic regression classifier on test set: 0.98

[2, 6]
Accuracy of logistic regression classifier on test set: 0.96
Accuracy of logistic regression classifier on test set: 0.96
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.978
Accuracy of logistic regression classifier on test set: 0.926
Accuracy of logistic regression classifier on test set: 0.972
Already Removed... Hence, Accuracy = 0
```

```
[2, 6, 3]
Accuracy of logistic regression classifier on test set: 0.964
Accuracy of logistic regression classifier on test set: 0.976
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.942
Accuracy of logistic regression classifier on test set: 0.98
Already Removed... Hence, Accuracy = 0

[2, 6, 3, 5]
Accuracy of logistic regression classifier on test set: 0.956
Accuracy of logistic regression classifier on test set: 0.974
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.956
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0

[2, 6, 3, 5, 1]
Accuracy of logistic regression classifier on test set: 0.956
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.95
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
```

```
[2, 6, 3, 5, 1, 0]
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0
Accuracy of logistic regression classifier on test set: 0.926
Already Removed... Hence, Accuracy = 0
Already Removed... Hence, Accuracy = 0

[2, 6, 3, 5, 1, 0, 4]
```

```
significant_features = removed_index[::-1]
significant_features
```

```
[4, 0, 1, 5, 3, 6, 2]
```

### Arranging DataFrame according to significance:

```
df_fs = pd.DataFrame()
for i in significant_features:
    df_fs = pd.concat([df_fs,features.iloc[: , i]], axis = 1)
df_fs.head()
```

| | Smartphone 5 | Smartphone 1 | Smartphone 2 | Smartphone 6 | Smartphone 4 | Smartphone 7 | Smartphone 3 |
|---|---|---|---|---|---|---|---|
| 0 | -71 | -64 | -56 | -82 | -66 | -81 | -61 |
| 1 | -71 | -68 | -57 | -85 | -65 | -85 | -61 |
| 2 | -76 | -63 | -60 | -85 | -67 | -84 | -60 |
| 3 | -77 | -61 | -60 | -90 | -62 | -80 | -68 |
| 4 | -77 | -63 | -65 | -81 | -63 | -87 | -60 |

# Logistic Regression with Feature Selection

### Figuring out the best number of Features to be used for Logistic Regression:

We will calculate the Accuracy for model for each each number of features.

From the Output below, it is significant that the model starts to overfit if we use more than 2 features. So, we will build a model with first 2 significant features.

```
for i in range(7):
    print( "Number of principle components: ", i+1)
    X_train, X_test, y_train, y_test = train_test_split(df_fs.iloc[:,:i
+1], op, test_size = 0.25)
    logreg = LogisticRegression()
    logreg.fit(X_train, y_train)
    y_pred = logreg.predict(X_test)
    print('Accuracy of Logistic Regression Classifier on test set: {}'.
format(logreg.score(X_test, y_test)))
    print()
```

```
Number of principle components:  1
Accuracy of Logistic Regression Classifier on test set: 0.614

Number of principle components:  2
Accuracy of Logistic Regression Classifier on test set: 0.958

Number of principle components:  3
Accuracy of Logistic Regression Classifier on test set: 0.954

Number of principle components:  4
Accuracy of Logistic Regression Classifier on test set: 0.97

Number of principle components:  5
Accuracy of Logistic Regression Classifier on test set: 0.968

Number of principle components:  6
Accuracy of Logistic Regression Classifier on test set: 0.974

Number of principle components:  7
Accuracy of Logistic Regression Classifier on test set: 0.98
```

## Building logistic Regression model:

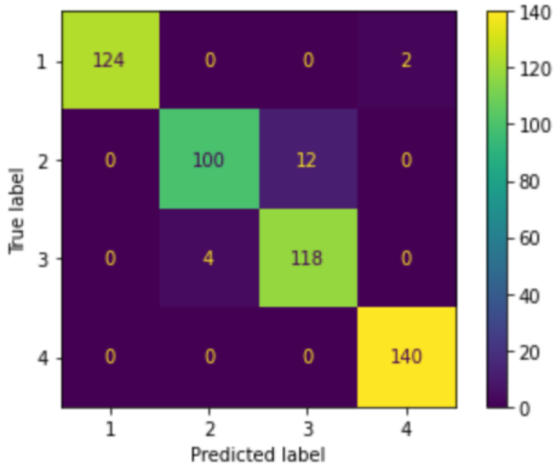
Features = 2

Calculating Accuracy, training and testing time, and Confusion matrix.

```
start = time.time()
X_train, X_test, y_train, y_test = train_test_split(df_fs.iloc[:,:2], o
p, test_size = 0.25)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
stop = time.time()
print("Training Time: ", stop - start)
start = time.time()
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on test set: {:.2f}'.
format(logreg.score(X_test, y_test)))
stop = time.time()
print("Testing Time: ", stop - start)
```

```
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", pd.DataFrame(confusion_matrix))
plot_confusion_matrix(logreg, X_test, y_test)
```

```
Training Time:  0.21881532669067383
Accuracy of Logistic Regression Classifier on test set: 0.96
Testing Time:  0.016811847686767578
Confusion Matrix:
      0    1    2    3
0  124    0    0    2
1    0  100   12    0
2    0    4  118    0
3    0    0    0  140
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f2279921c50>
```




# Decision Tree with Feature Selection

### Figuring out the best number of Features to be used for Logistic Regression:

We will calculate the Accuracy for model for each each number of features.

From the Output below, it is significant that the model starts to overfit if we use more than 2 features. So, we will build a model with first 2 significant features.

```
for i in range(7):
    print( "no. of principle components: ", i+1)
```

```
    X_train, X_test, y_train, y_test = train_test_split(df_fs.iloc[:,:i
+1], op, test_size = 0.25)
    decTree = DecisionTreeClassifier(criterion="gini")
    decTree.fit(X_train,y_train)
    y_pred = decTree.predict(X_test)
    print('Accuracy of Decision Tree classifier on test set: ', end='')
    print(accuracy_score(y_test,y_pred))
    print()
```

```
no. of principle components:  1
Accuracy of Decision Tree classifier on test set: 0.652

no. of principle components:  2
Accuracy of Decision Tree classifier on test set: 0.952

no. of principle components:  3
Accuracy of Decision Tree classifier on test set: 0.954

no. of principle components:  4
Accuracy of Decision Tree classifier on test set: 0.962

no. of principle components:  5
Accuracy of Decision Tree classifier on test set: 0.978

no. of principle components:  6
Accuracy of Decision Tree classifier on test set: 0.976

no. of principle components:  7
Accuracy of Decision Tree classifier on test set: 0.972
```

## Building decision tree model:

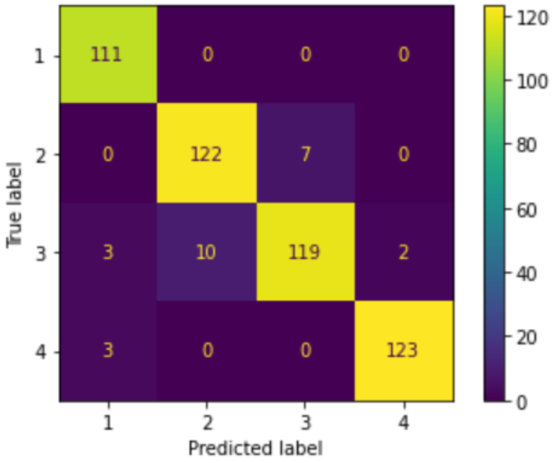
Principle components = 2

Calculating Accuracy, training and testing time, and Confusion matrix.

```
start = time.time()
X_train, X_test, y_train, y_test = train_test_split(df_fs.iloc[:,:2], o
p, test_size = 0.25)
clf_model = DecisionTreeClassifier(criterion="gini")
clf_model.fit(X_train,y_train)
stop = time.time()
print("Training Time: ", stop - start)
from sklearn.metrics import confusion_matrix
start = time.time()
y_pred = clf_model.predict(X_test)
print('Accuracy of Decision Tree classifier on test set: ', end='')
print(accuracy_score(y_test,y_pred))
stop = time.time()
```

```
print("Testing Time: ", stop - start)
confusion_Matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", confusion_Matrix)
plot_confusion_matrix(clf_model, X_test, y_test)
```

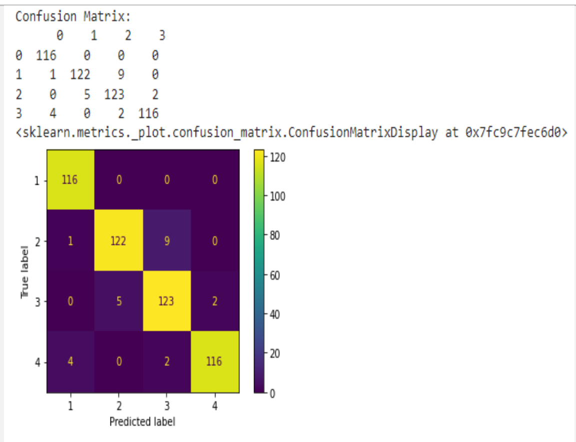
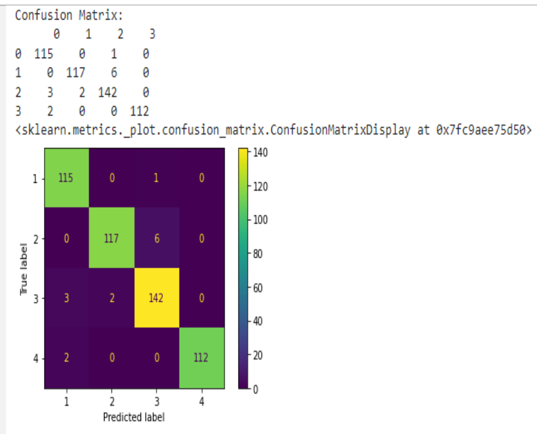
```
Training Time:  0.018146276473999023
Accuracy of Decision Tree classifier on test set: 0.95
Testing Time:  0.023658990859985 35
Confusion Matrix:
 [[111   0   0   0]
 [  0 122   7   0]
 [  3  10 119   2]
 [  3   0   0 123]]
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f227986f650>
```




# Results :

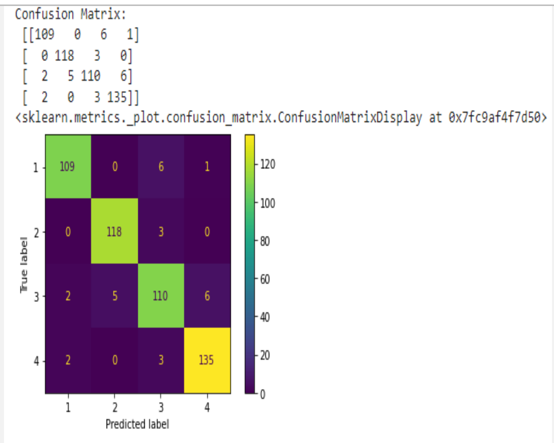
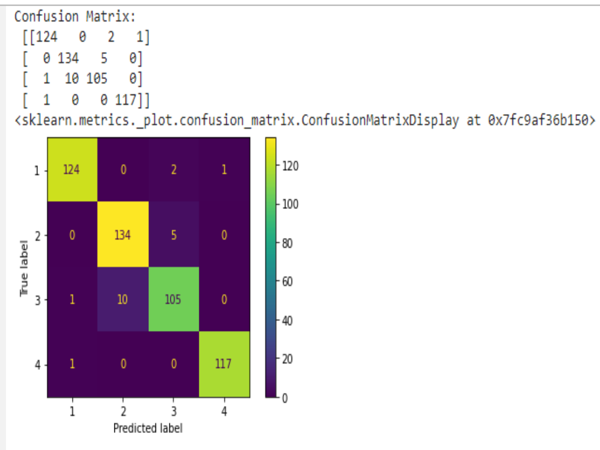
**Logistic Regression**

| | PCA | Feature Selection |
|---|---|---|
| **Accuracy** | 0.95 | 0.97 |
| **Number of Features** | 3 | 2 |
| **Training Time** | 0.033 | 0.287 |

| | | |
|---|---|---|
| **Testing Time** | 0.003 | 0.007 |
| **Confusion Matrix** |  |  |

### Decision Tree

| | PCA | Feature Selection |
|---|---|---|
| **Accuracy** | 0.94 | 0.96 |
| **Number of Features** | 3 | 2 |
| **Training Time** | 0.024 | 0.017 |
| **Testing Time** | 0.007 | 0.004 |

| | | |
|---|---|---|
| **Confusion Matrix** |  |  |

# Conclusion :

On the data, we had to use PCA and Feature Selection. Logistic Regression and Decision Tree were the two classifiers we employed. The dataset was mean-centred and scaled for PCA. The Principle components were then determined using the Covariance matrix, Eigen Values, and Vectors. The scores for all of the principle components were determined using the Eigen Vector (principal components) and the data. Next, we developed models for all values of n (n = number of Principle components) to identify the number of Principle components to be employed.

We could detect which component the model was overfitting based on the accuracies. The model was overfitting after the third component in both Logistic Regression and Decision Tree. So we created both models for n = 3. The results were recorded (training time, testing time, accuracy, and confusion matrix). We used the backward search strategy to select the greatest to worst features for the Feature Selection. The data was organised from best to worst columns. Next, we developed models for all values of n (n = number of features) to decide the number of features to be employed. We could assess how many characteristics the model was overfitting by looking at the accuracies.

The model was overfitting after two features in both Logistic Regression and Decision Tree. So we created both models for n = 2. The results were recorded (training time, testing time, accuracy, and confusion matrix). According to the data (shown in results.docx), Feature Selection outperforms PCA for both classifiers. The goal of PCA is to reduce dimensionality. We eliminate characteristics with a low variance. As a result, information will be lost. In addition, the PCA does not take into account the target variable in this technique. On the other hand, in Feature Selection, we remove the characteristic based on accuracy while keeping the desired value in mind.