Machine Learning

Lab 7

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
df = pd.read_csv("Classified Data", index_col=0)
df.head()
```

Out[2]:

	WTT	PTI	EQW	SBI	LQE	QWG	FDJ	PJF	HQE	NXJ	TARGET CLASS
0	0.913917	1.162073	0.567946	0.755464	0.780862	0.352608	0.759697	0.643798	0.879422	1.231409	1
1	0.635632	1.003722	0.535342	0.825645	0.924109	0.648450	0.675334	1.013546	0.621552	1.492702	0
2	0.721360	1.201493	0.921990	0.855595	1.526629	0.720781	1.626351	1.154483	0.957877	1.285597	0
3	1.234204	1.386726	0.653046	0.825624	1.142504	0.875128	1.409708	1.380003	1.522692	1.153093	1
4	1.279491	0.949750	0.627280	0.668976	1.232537	0.703727	1.115596	0.646691	1.463812	1.419167	1

Scaling the data

In [3]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(df.drop('TARGET CLASS', axis=1))
scaled_features = scaler.transform(df.drop('TARGET CLASS', axis=1))
```

In [4]:
```
df_feat = pd.DataFrame(scaled_features, columns=df.columns[:-1])
df_feat.head()
```

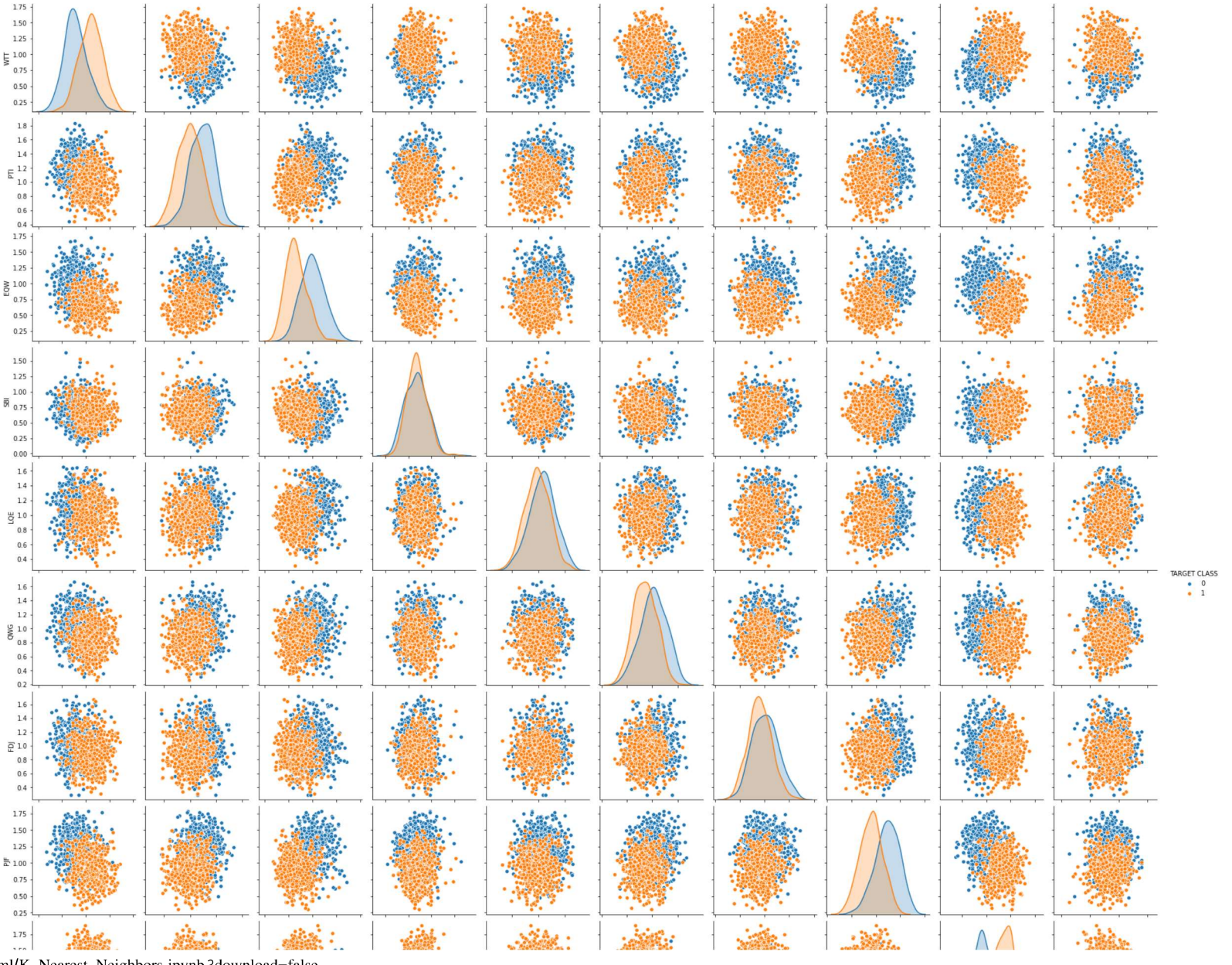
Out[4]:

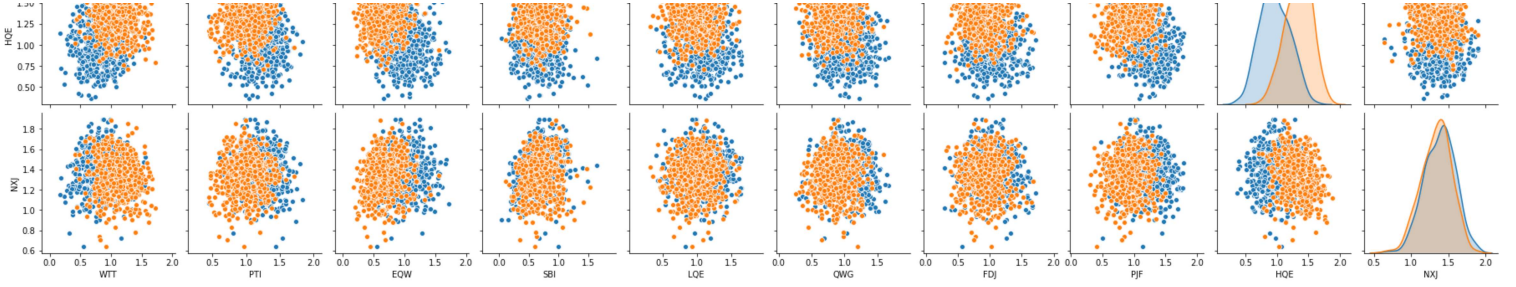
	WTT	PTI	EQW	SBI	LQE	QWG	FDJ	PJF	HQE	NXJ
0	-0.123542	0.185907	-0.913431	0.319629	-1.033637	-2.308375	-0.798951	-1.482368	-0.949719	-0.643314
1	-1.084836	-0.430348	-1.025313	0.625388	-0.444847	-1.152706	-1.129797	-0.202240	-1.828051	0.636759
2	-0.788702	0.339318	0.301511	0.755873	2.031693	-0.870156	2.599818	0.285707	-0.682494	-0.377850
3	0.982841	1.060193	-0.621399	0.625299	0.452820	-0.267220	1.750208	1.066491	1.241325	-1.026987
4	1.139275	-0.640392	-0.709819	-0.057175	0.822886	-0.936773	0.596782	-1.472352	1.040772	0.276510

Visualize

In [5]:
```
import seaborn as sns

sns.pairplot(df, hue='TARGET CLASS')
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x1e612eca9a0>


WTT
PTI
EQW
SBI
LQE
QWG
FDJ
PJF
TARGET CLASS
0
1



Here, data points are overlapped on eachother. So, We can't use Linear Regression.

In [6]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(scaled_features, df['TARGET CLASS'], test_size=0.3)
```

Check KNN with neighbour 1

In [7]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [8]:
```
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import cross_val_score

confusion_matrix(y_test, y_pred)
```

Out[8]:
```
array([[135,  19],
       [ 12, 134]], dtype=int64)
```

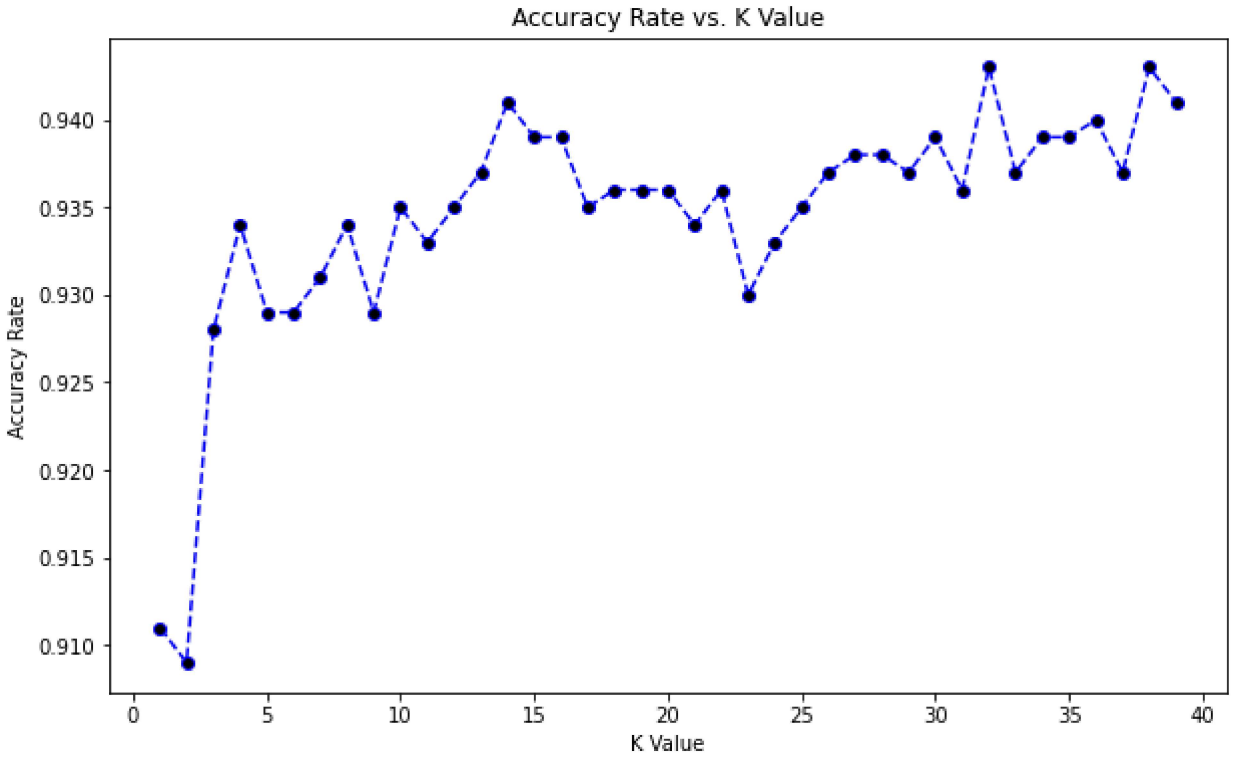
Choosing K value

In [9]:
```
accuracy_rate = []

for i in range(1,40):
    knn = KNeighborsClassifier(n_neighbors=i)
    score = cross_val_score(knn, df_feat, df['TARGET CLASS'], cv=10)
    accuracy_rate.append(score.mean())
```

In [10]:
```
error_rate = []

for i in range(1,40):
    knn = KNeighborsClassifier(n_neighbors=i)
    score = cross_val_score(knn, df_feat, df['TARGET CLASS'], cv=10)
    error_rate.append(1-score.mean())
```

In [11]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40), accuracy_rate, markerfacecolor='black', marker='o', color='blue', linestyle='dash
ed')
plt.title('Accuracy Rate vs. K Value')
plt.xlabel('K Value')
plt.ylabel('Accuracy Rate')
```

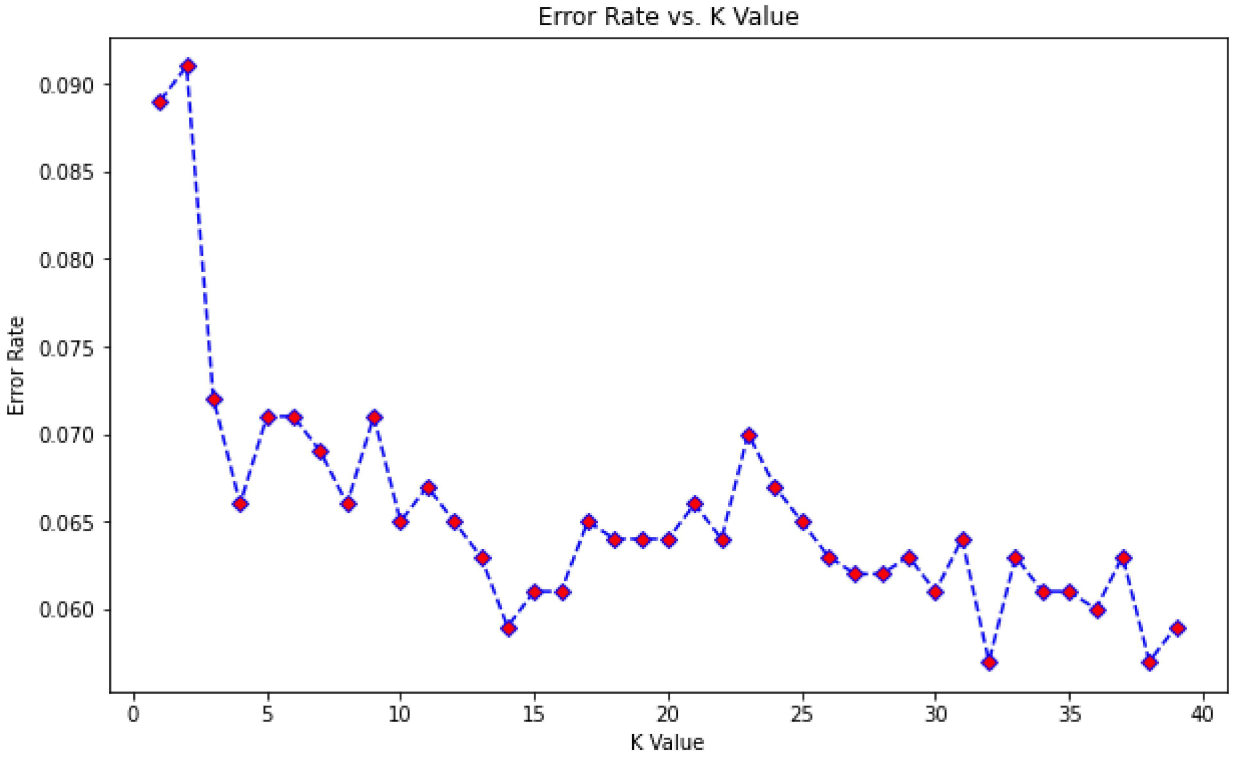
Out[11]: Text(0, 0.5, 'Accuracy Rate')



Plotting Accuracy rate and Error rate

In [12]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40), error_rate, color='blue', marker='D', markerfacecolor='red', linestyle='dashed')
plt.title('Error Rate vs. K Value')
plt.xlabel('K Value')
plt.ylabel('Error Rate')
```

Out[12]:
```
Text(0, 0.5, 'Error Rate')
```



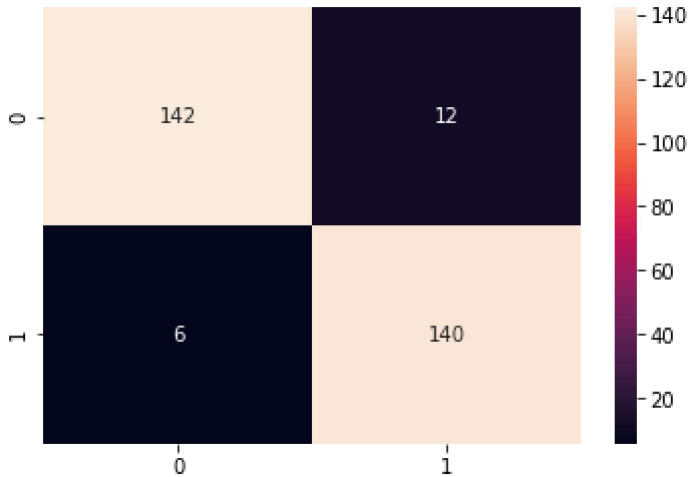
By observing above plots, the accuracy increases after the K=24.

In [13]:
```
knn = KNeighborsClassifier(n_neighbors=24)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [14]:
```
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[14]:
```
array([[142,  12],
       [  6, 140]], dtype=int64)
```

In [15]:
```
sns.heatmap(cm, annot=True, fmt='d')
plt.show()
```



In [16]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      0.92      0.94       154
           1       0.92      0.96      0.94       146

    accuracy                           0.94       300
   macro avg       0.94      0.94      0.94       300
weighted avg       0.94      0.94      0.94       300
```

In [ ]:
```

```