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Week #4 in Machine Learning

Diabetes classification — Supervised ML classification problem

source

In this notebook, I am applying supervised machine learning classifications to a diabetic dataset. I aim to determine whether the tested data has diabetes or not. I will use KNN , decision tree , random forest ,Support vector machine, logistic regression and Naive Bayes algorithms. I will also make evaluation of all the models used by using confusion matrix.

Data Loading

```python
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression # Logistic regression
```

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```python
# loading the dataset
df = pd.read_csv("diabetes.csv")
df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
df.shape

(768, 9)
```

Descriptive statistics

This step shows the decriptive statistics of all the numerical columns in the dataset.

```
df.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

EDA

Exploratory Data Analysis

This step focuses on exploring throuhg the data to determine the data types, check for missing data point and fix them etc.

```
# Smmarize the characteristics of the data coluhmns to check for data types and missing values
df.info()
```

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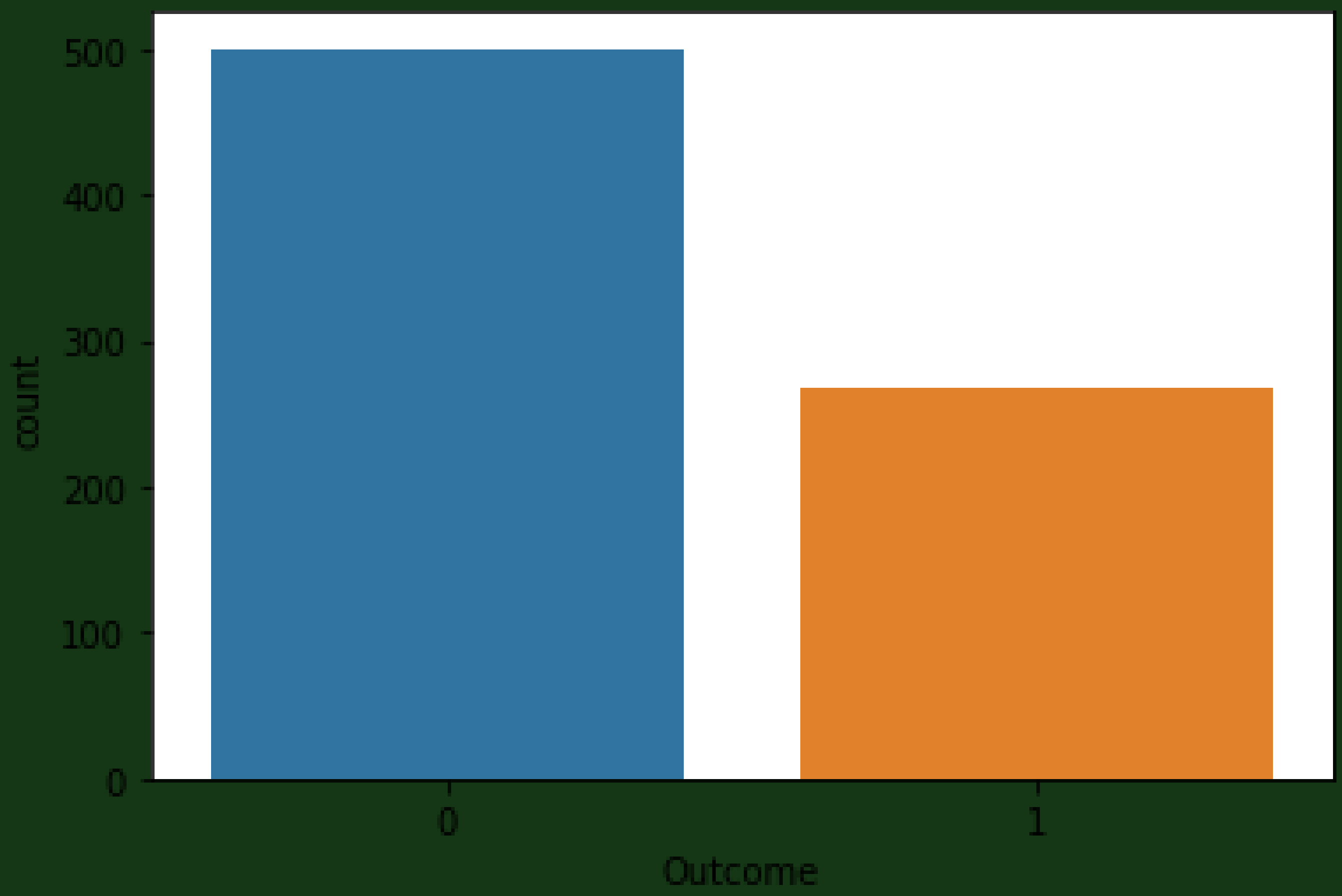
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
```



This chat shows how the Outcomes are classified. There are more Negative outcomes, 0, than postive outcomes, 1. There's not much cleaning to be done on our dataset. We can therefore go directly to the Machine learning processes.

Machine Learning

```
#Have the outcome data as y
y = df.Outcome.values

# remove the Outcome data from the dataset and have the remaining as x
x_data = df.drop(['Outcome'], axis=1)
```

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```
x_data.head()
```

1	1	85	66	29	0	26.6	0.351	31
2	8	183	64	0	0	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	0	137	40	35	168	43.1	2.288	33

```
y[1:10]

array([0, 1, 0, 1, 0, 1, 0, 1, 1])
```

```
#Normalization to handle unbalanced features
x = (x_data - np.min(x_data))/(np.max(x_data) -np.min(x_data)).values
```

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```
# Split the data into training and test set. We use 20% test data with a random state of 42
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size= 0.2, random_state=42)
```

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Logistic Regression Classification

Logistic regression is a powerful algorithm when you have a binary classification problem

```
lr = LogisticRegression()
lr.fit(x_train, y_train)
print("test accuracy {}".format(lr.score(x_test, y_test)))

lr_score=lr.score(x_test, y_test)
```

8023f7fd-4f14-4dda-b210-c6c0d4dbab96.py hosted with ❤ by GitHub view raw

```
test accuracy 0.7662337662337663
```

```
# using confusion matrix to evaluate the linear regression
from sklearn.metrics import confusion_matrix

y_prediction = lr.predict(x_test)
y_actual = y_test
cm = confusion_matrix(y_actual, y_prediction)

# heatmap visulization of confusion matrix
f, ax = plt.subplots(figsize =(5, 5))
sns.heatmap(cm, annot = True, linewidth=1, linecolor="green", fmt =".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```

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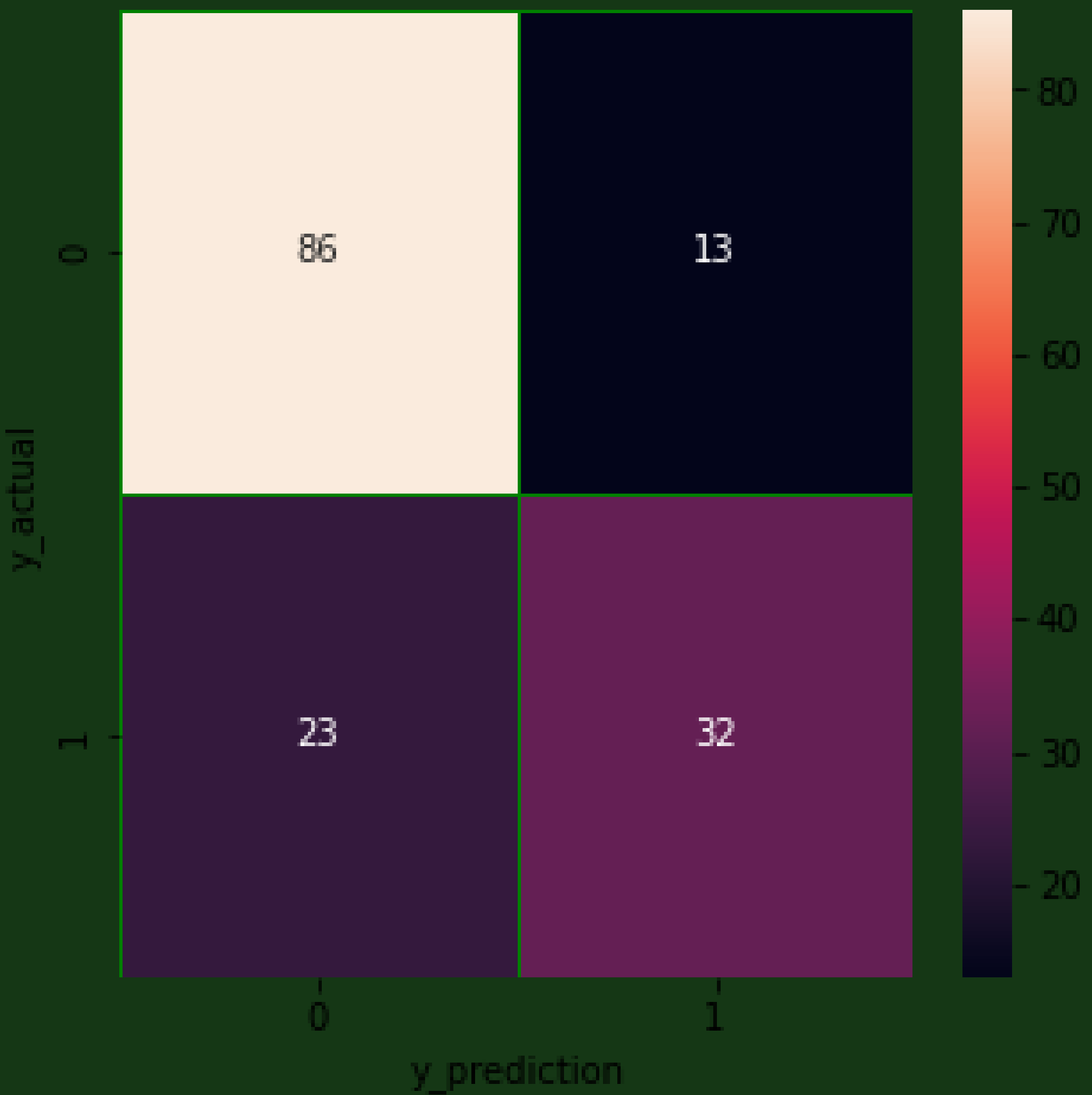

KNN Classification

We need to choose a small k value but not too small that it causes overfitting while big k value causes underfitting. The K value we choose needs to be as close to our test points as possible. For this case, we use the standard k value whcih is k=3

```
# import KNN classification model
from sklearn.neighbors import KNeighborsClassifier
k=11
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(x_train, y_train)
prediction = knn.predict(x_test)
print("{} nn score: {}".format(k, knn.score(x_test, y_test)))

knn_score = knn.score(x_test, y_test)
```

```
11 nn score: 0.7207792207792207
```

```python
# testing different vaues of k with accuracy to determine the most favorable
# k ranges from 1-15
score_list = []
for each in range(1, 15):
    knn2 = KNeighborsClassifier(n_neighbors= each)
    knn2.fit(x_train, y_train)
    score_list.append(knn2.score(x_test, y_test))

plt.plot(range(1, 15), score_list)
plt.xlabel("kvalues")
plt.ylabel("accuracy")
plt.show()
```

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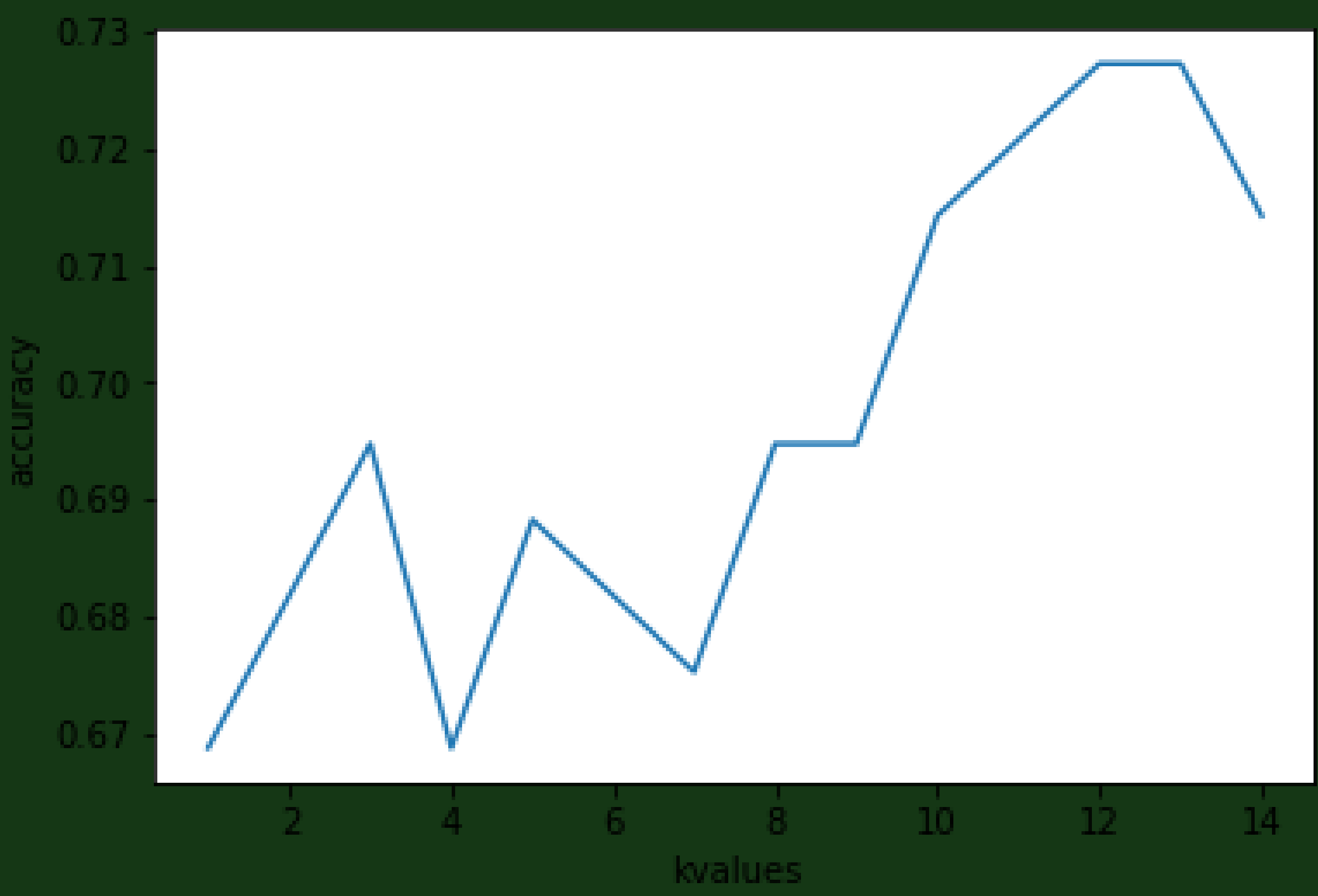
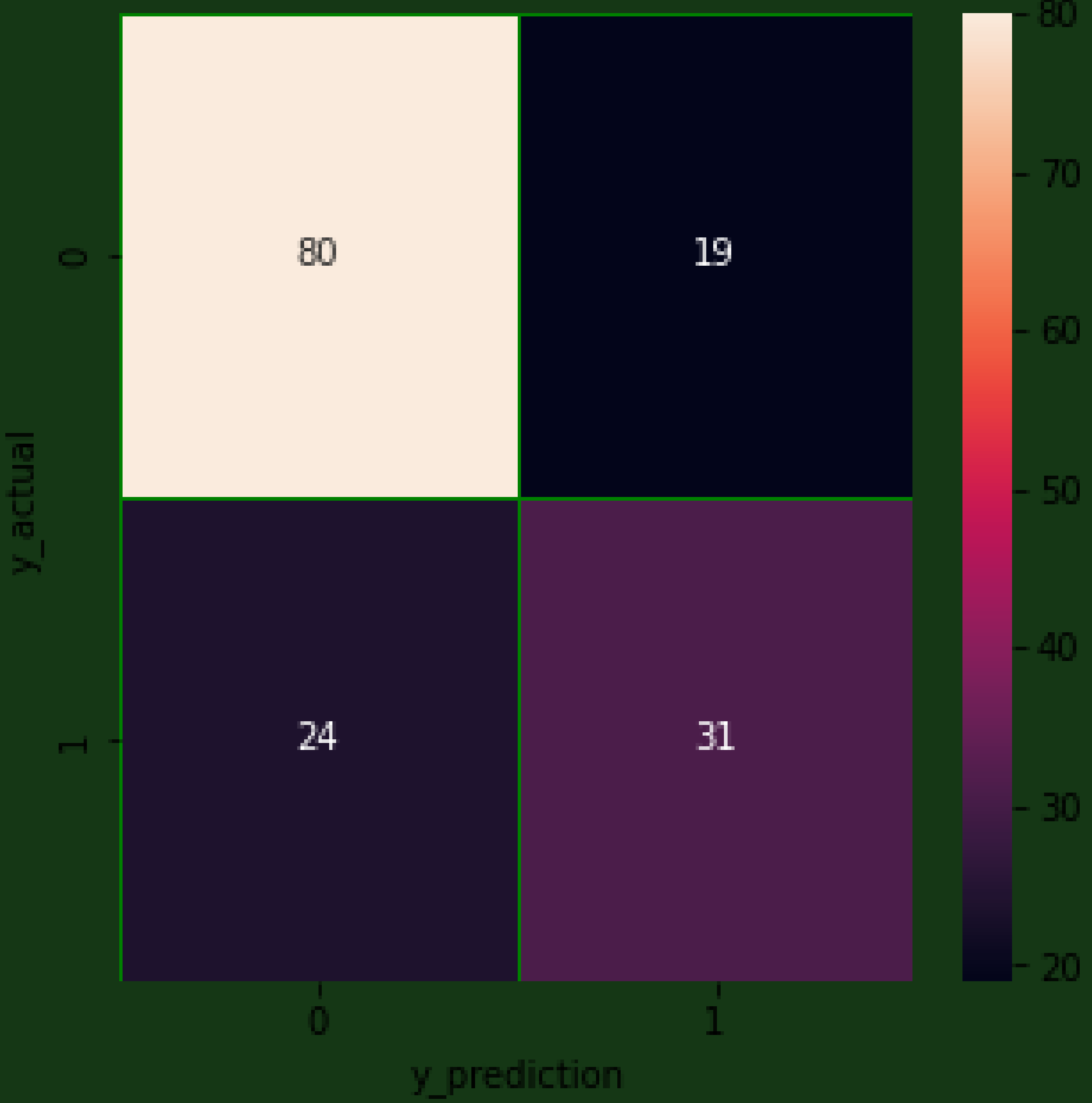


K=11, 12 gives the best accuracy for our case

```
# Heatmap visualization of conusion matrix
f, ax = plt.subplots(figsize = (5, 5))
sns.heatmap(cm, annot =  True, linewidths=1, linecolor = "green", fmt = ".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```

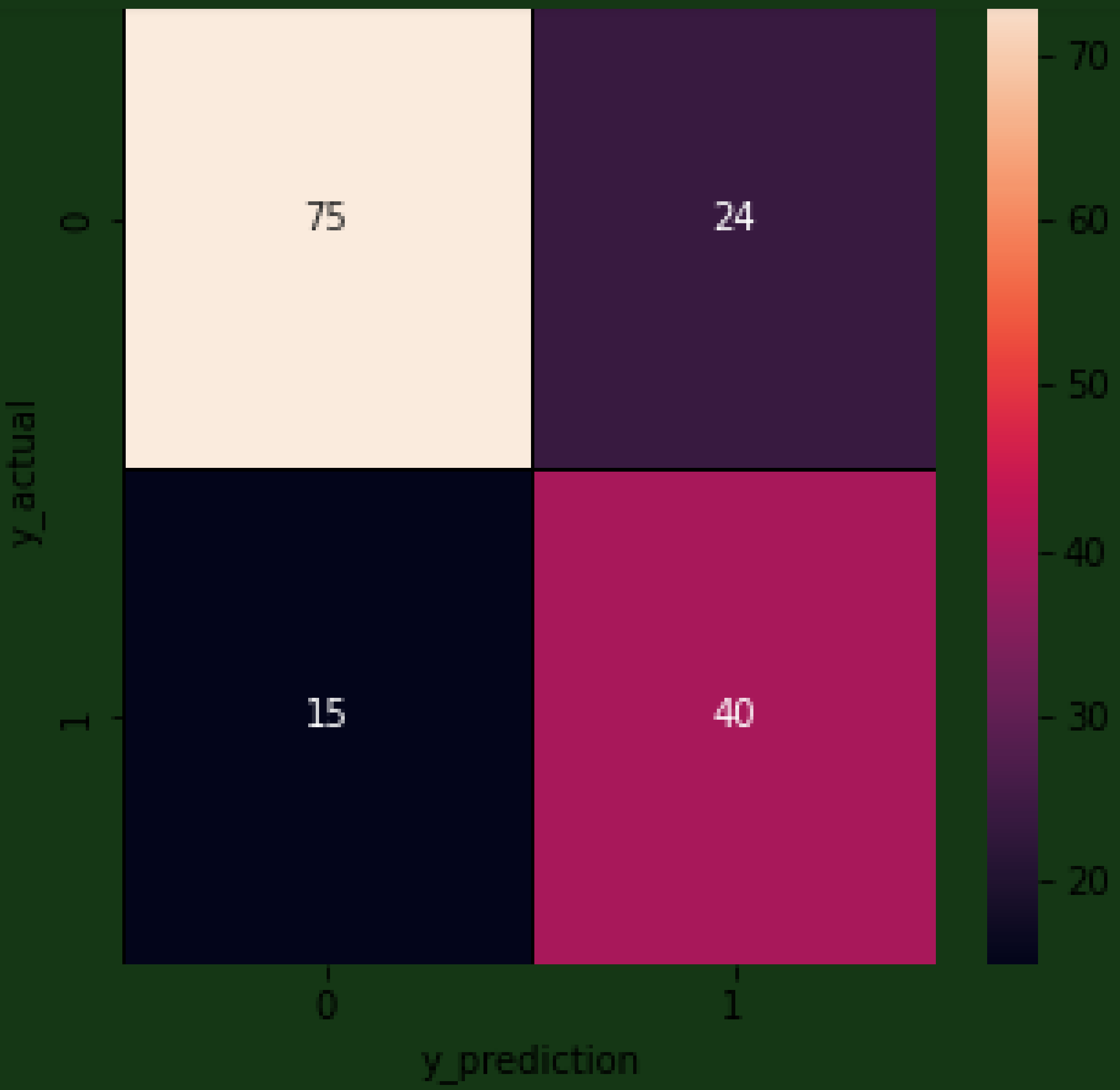
Decision Tree Classification

```python
dt = DecisionTreeClassifier(random_state = 42)
dt.fit(x_train, y_train)

print("score: ", dt.score(x_test, y_test))

dt_score = dt.score(x_test, y_test)
```



```
score:  0.7467532467532467
```

```python
# confsion matrix
y_prediction = dt.predict(x_test)
y_actual = y_test
cm = confusion_matrix(y_actual, y_prediction)

# heatmap
f, ax = plt.subplots(figsize = (5, 5))
sns.heatmap(cm, annot = True, linewidths=1, linecolor="black", fmt =".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```



Random Forest Classification

This approach uses multiple decision trees and take the averge of the results of these decison trees. this average is used to determien the calss of the test points. It is one fo the ensember methods that uses multiple classes to predict the target

```python
# random forest classification
from sklearn.ensemble import RandomForestClassifier
# set n_estimators to 100 whcih means the model will use 100 subsets
rf = RandomForestClassifier(n_estimators = 100, random_state = 42)
rf.fit(x_train, y_train)
print("random forest model score: ", rf.score(x_test, y_test))
rf_score= rf.score(x_test, y_test)
```

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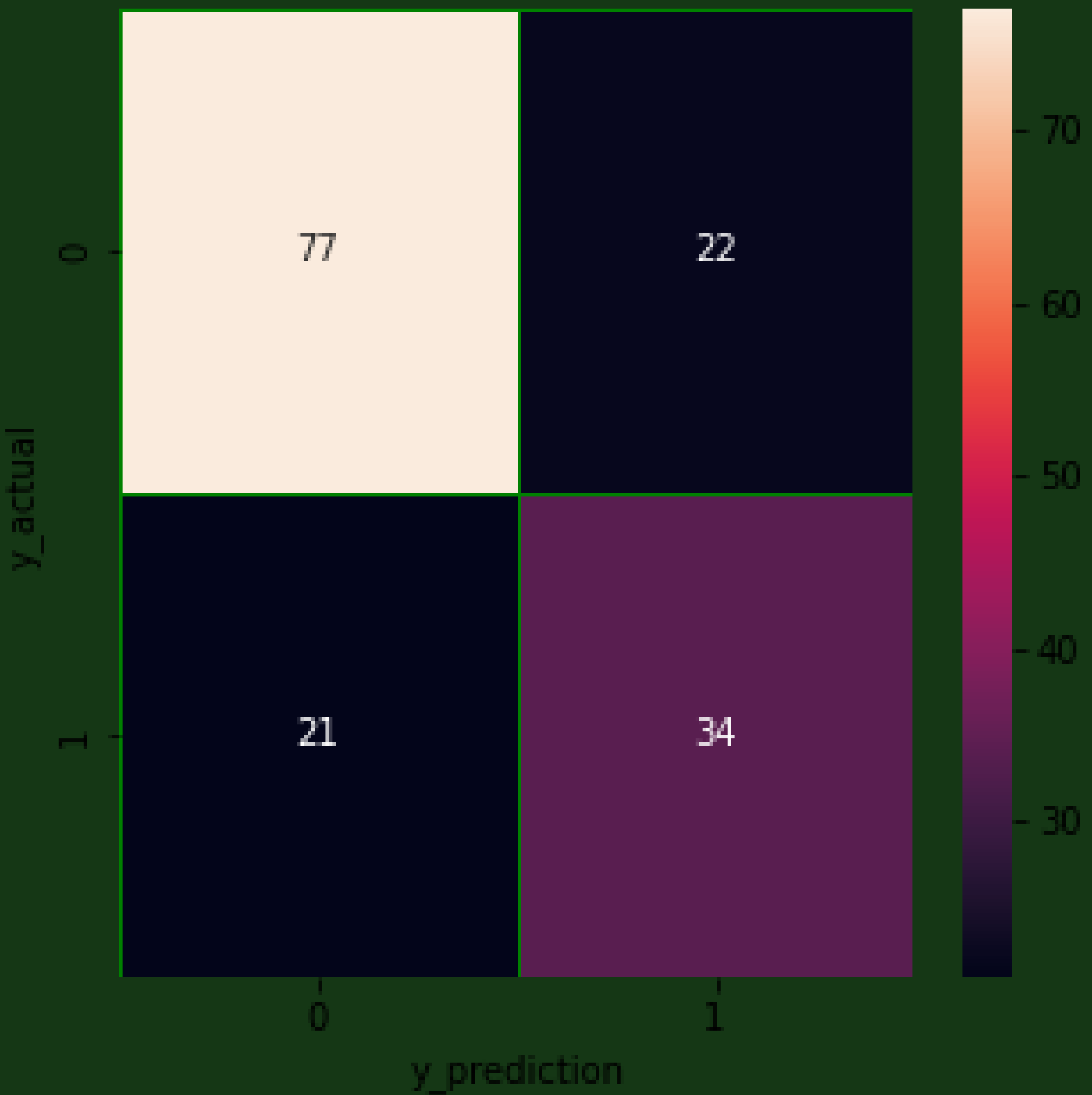
```
y_actual = y_test
cm = confusion_matrix(y_actual, y_prediction)

# Heatmap
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(cm, annot = True, linewidths=0.5, linecolor = "green", fmt = ".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```

best value

```python
# SVM approach
from sklearn.svm import SVC
svm = SVC(random_state = 42)
svm.fit(x_train, y_train)

print("Accuracy of SVM: ", svm.score(x_test, y_test))

svm_score = svm.score(x_test, y_test)
```

678e3eb7-8f3d-430e-afc4-37fd870f29ca.py hosted with ❤ by GitHub view raw

```
Accuracy of SVM:  0.7467532467532467
```

```python
# Confusion matrix
y_prediction = svm.predict(x_test)
y_actual = y_test
cm = confusion_matrix(y_actual, y_prediction)

# Heatmap
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(cm, annot = True, linewidths=0.5, linecolor = "green", fmt = ".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```

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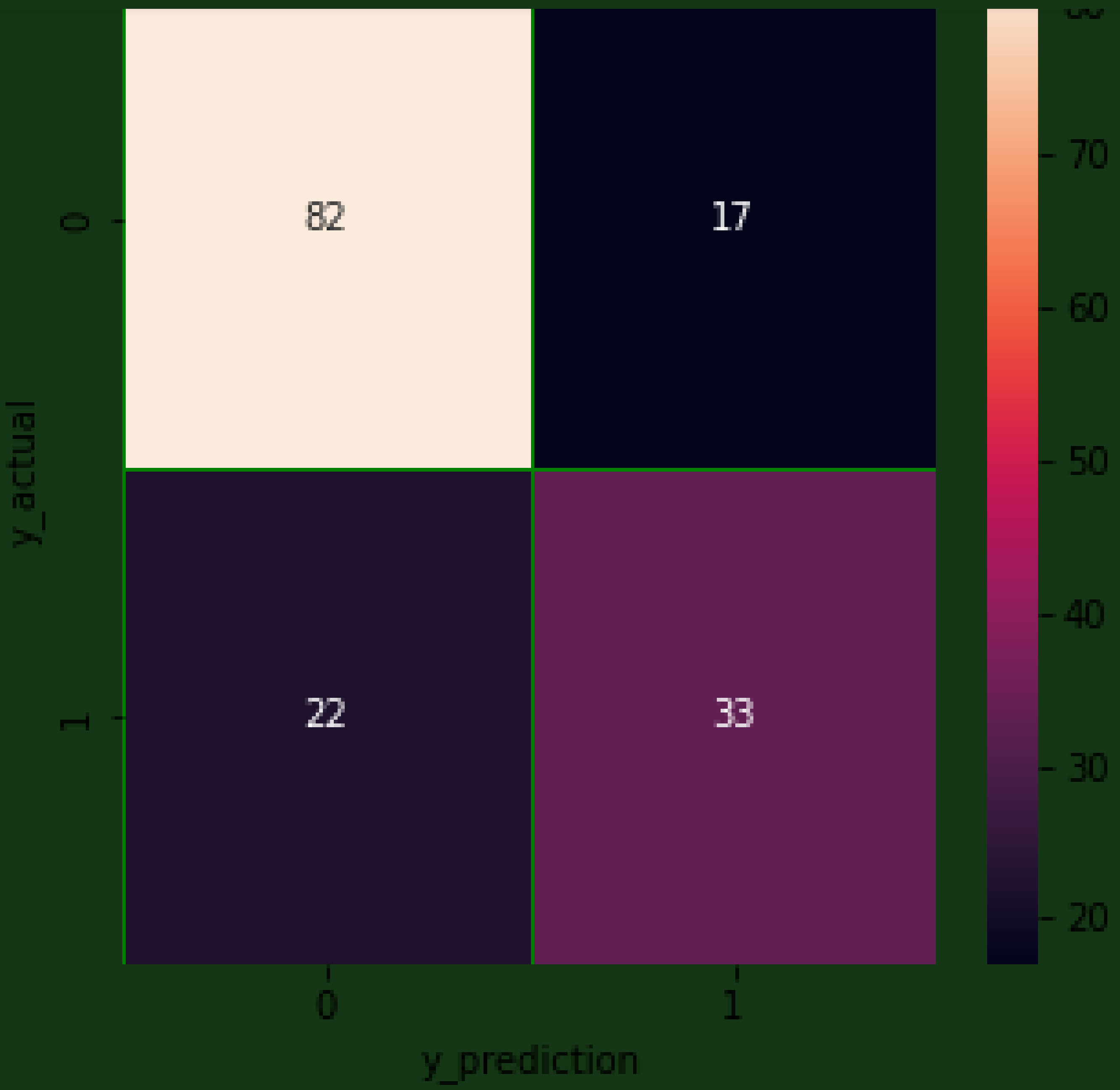

Naive Bayes Classification

this is a probabilistic classifier whcih applies Bayes theorem with strong independence assumption between the features. It works by determinign similarity range and calculating probability of the X points in the A feature P(A_feature|x)

```
# Naive Bayes
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train, y_train)

print("accuracy of naive bayes: ", nb.score(x_test, y_test))

nb_score = nb.score(x_test, y_test)
```

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```python
# Confusion matrix
y_prediction = nb.predict(x_test)
y_actual = y_test
cm = confusion_matrix(y_actual, y_prediction)

# heatmap
f, ax = plt.subplots(figsize=(5,5))
sns.heatmap(cm, annot = True, linewidths=0.5, linecolor = "green", fmt = ".0f", ax=ax)
plt.xlabel("y_prediction")
plt.ylabel("y_actual")
plt.show()
```

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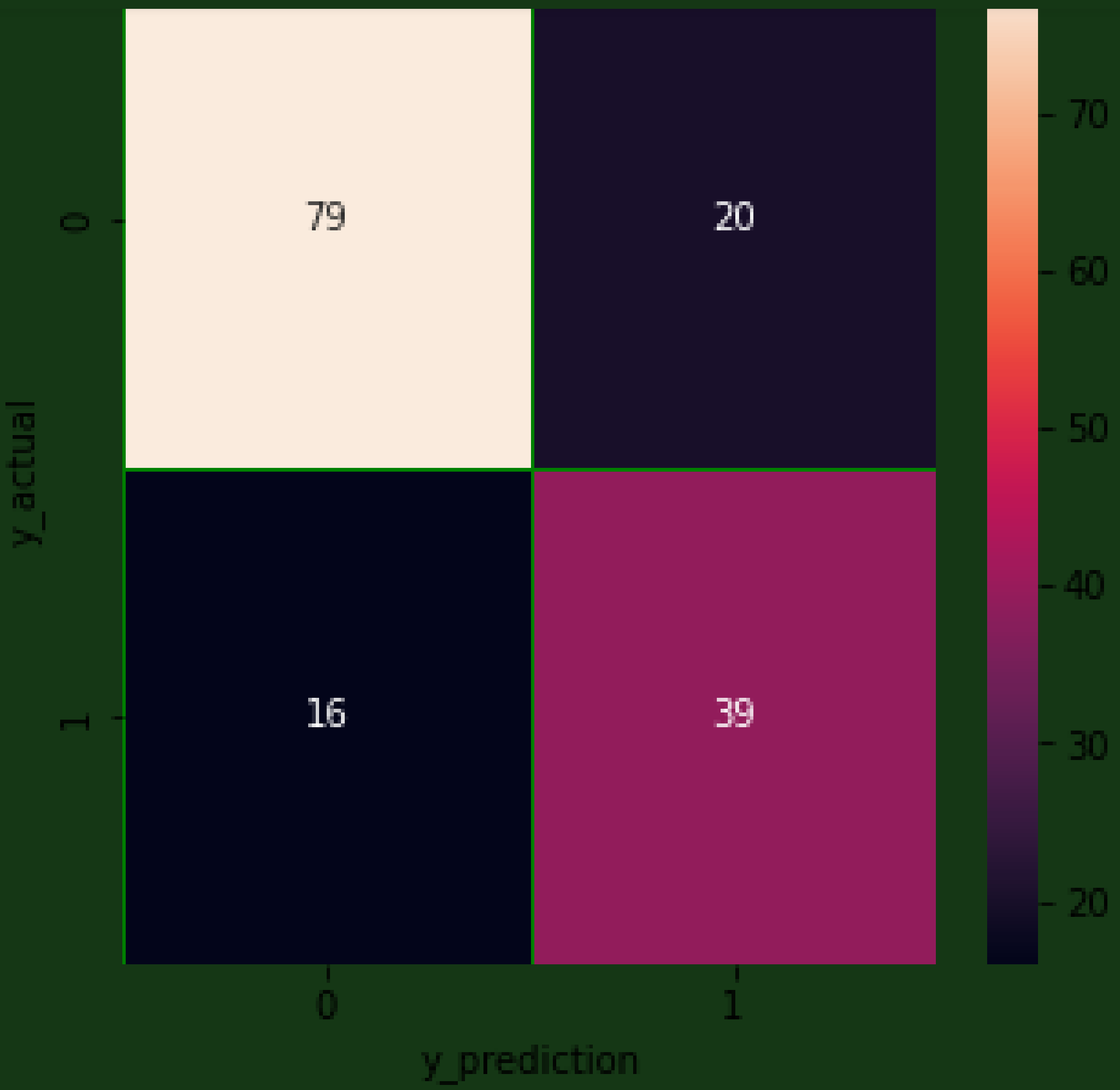
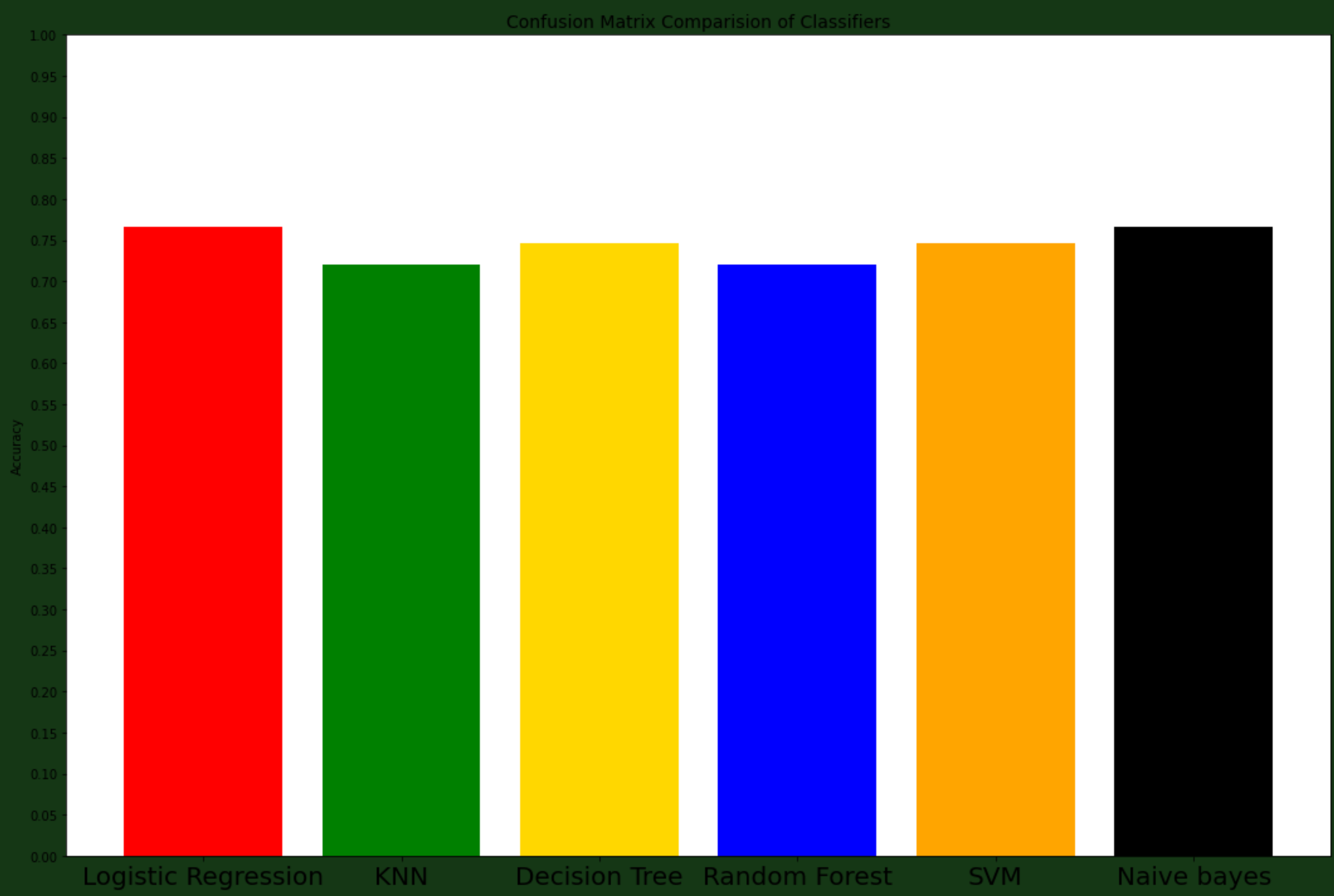


Comparision Using Confusion matrix

Below I visualize all confusion matrices to all classifiers

```python
class_name = ("Logistic Regression", "KNN", "Decision Tree", "Random Forest", "SVM", "Naive bayes")
class_score = (lr_score, knn_score, dt_score, rf_score, svm_score, nb_score)
y_pos = np.arange(len(class_score))
colors = ("red", "green", "gold","blue", "orange","black")
plt.figure(figsize=(18, 12))
plt.bar(y_pos, class_score, color=colors)
plt.xticks(y_pos, class_name, fontsize=20)
plt.yticks(np.arange(0.00, 1.05, step = 0.05))
plt.ylabel("Accuracy")

plt.title("Confusion Matrix Comparision of Classifiers", fontsize=14)
plt.savefig("graph.png")
plt.show()
```



Conclusion

From the past 3 week's posts, we have looked at the theoretical part of classification algorithms, here we have applied the algorithms. Check out for next weeks post.

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