code

May 5, 2024

1 Predicting Hepatitis C

1.1 Importing Libraries

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter("ignore")
```

1.2 Loading up the data

[ ]:
```
df = pd.read_csv("/content/HepatitisCdata.csv")
df.head()
```

[ ]:
```
   Unnamed: 0      Category  Age Sex   ALB   ALP   ALT   AST   BIL    CHE  \
0           1  0=Blood Donor   32   m  38.5  52.5   7.7  22.1   7.5   6.93
1           2  0=Blood Donor   32   m  38.5  70.3  18.0  24.7   3.9  11.17
2           3  0=Blood Donor   32   m  46.9  74.7  36.2  52.6   6.1   8.84
3           4  0=Blood Donor   32   m  43.2  52.0  30.6  22.6  18.9   7.33
4           5  0=Blood Donor   32   m  39.2  74.1  32.6  24.8   9.6   9.15

   CHOL   CREA   GGT  PROT
0  3.23  106.0  12.1  69.0
1  4.80   74.0  15.6  76.5
2  5.20   86.0  33.2  79.3
3  4.74   80.0  33.8  75.7
4  4.32   76.0  29.9  68.7
```

[ ]:
```
df.drop("Unnamed: 0", axis=1, inplace=True)
```

[ ]:
```
df.dtypes
```

[ ]:
```
Category     object
Age           int64
Sex          object
```

```
ALB          float64
ALP          float64
ALT          float64
AST          float64
BIL          float64
CHE          float64
CHOL         float64
CREA         float64
GGT          float64
PROT         float64
dtype: object
```

[ ]:
```
df.Category.unique()
```

[ ]:
```
array(['0=Blood Donor', '0s=suspect Blood Donor', '1=Hepatitis',
       '2=Fibrosis', '3=Cirrhosis'], dtype=object)
```

[ ]:
```
# Mapping numeric values

df['Category'] = df['Category'].map({'0=Blood Donor': 0, '0s=suspect Blood␣
 ↪Donor': 0,
                                     "1=Hepatitis" : 1, "2=Fibrosis" : 1,␣
 ↪"3=Cirrhosis" : 1})

df['Sex'] = df['Sex'].map({'m': 1, 'f': 2})
```

[ ]:
```
df.head()
```

[ ]:
```
   Category  Age  Sex   ALB   ALP   ALT   AST   BIL    CHE  CHOL   CREA   GGT  \
0         0   32    1  38.5  52.5   7.7  22.1   7.5   6.93  3.23  106.0  12.1
1         0   32    1  38.5  70.3  18.0  24.7   3.9  11.17  4.80   74.0  15.6
2         0   32    1  46.9  74.7  36.2  52.6   6.1   8.84  5.20   86.0  33.2
3         0   32    1  43.2  52.0  30.6  22.6  18.9   7.33  4.74   80.0  33.8
4         0   32    1  39.2  74.1  32.6  24.8   9.6   9.15  4.32   76.0  29.9

   PROT
0  69.0
1  76.5
2  79.3
3  75.7
4  68.7
```

[ ]:
```
# Checking the data types again after the transformation
df.dtypes
```

[ ]:
```
Category       int64
Age            int64
```

```
Sex           int64
ALB         float64
ALP         float64
ALT         float64
AST         float64
BIL         float64
CHE         float64
CHOL        float64
CREA        float64
GGT         float64
PROT        float64
dtype: object
```

[ ]:
```
# Checking for missing values in the dataset
df.isna().sum()
```

[ ]:
```
Category     0
Age          0
Sex          0
ALB          1
ALP         18
ALT          1
AST          0
BIL          0
CHE          0
CHOL        10
CREA         0
GGT          0
PROT         1
dtype: int64
```

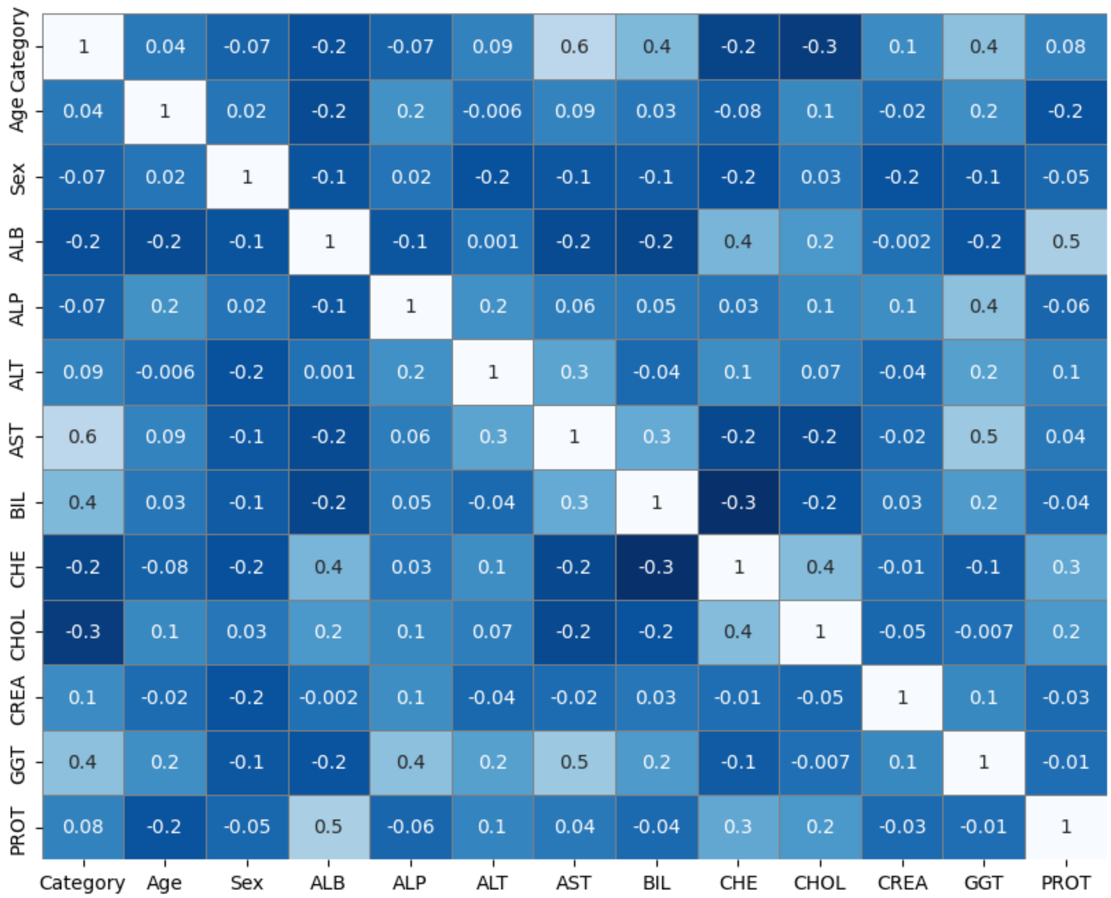
[ ]:
```
# Filling missing values with the median
df.fillna(df.median(), inplace=True)
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
Category    0
Age         0
Sex         0
ALB         0
ALP         0
ALT         0
AST         0
BIL         0
CHE         0
CHOL        0
CREA        0
```

```
GGT         0
PROT        0
dtype: int64
```

[ ]:
```python
# Having a look at the correlation matrix

fig, ax = plt.subplots(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, fmt='.1g', cmap="Blues_r", cbar=False,
 ↪linewidths=0.5, linecolor='grey');
```

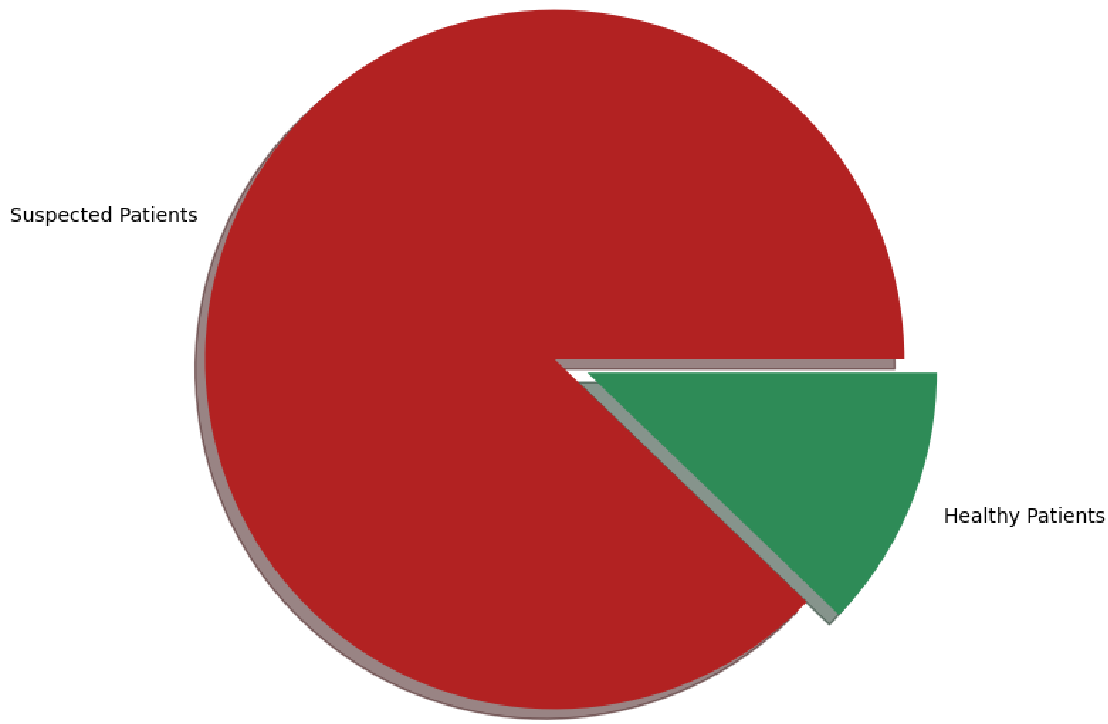


[ ]:
```python
print ('Total Suspected Patients : {} '.format(df.Category.value_counts()[0]))
print ('Total Healthy Patients : {} '.format(df.Category.value_counts()[1]))
```

```
Total Suspected Patients : 540
Total Healthy Patients : 75
```

[ ]:
```python
fig, ax = plt.subplots(figsize=(8,8))

plt.pie(x=df["Category"].value_counts(),
```

```
        colors=["firebrick","seagreen"],
        labels=["Suspected Patients","Healthy Patients"],
        shadow = True,
        explode = (0, 0.1)
        )

plt.show()
```

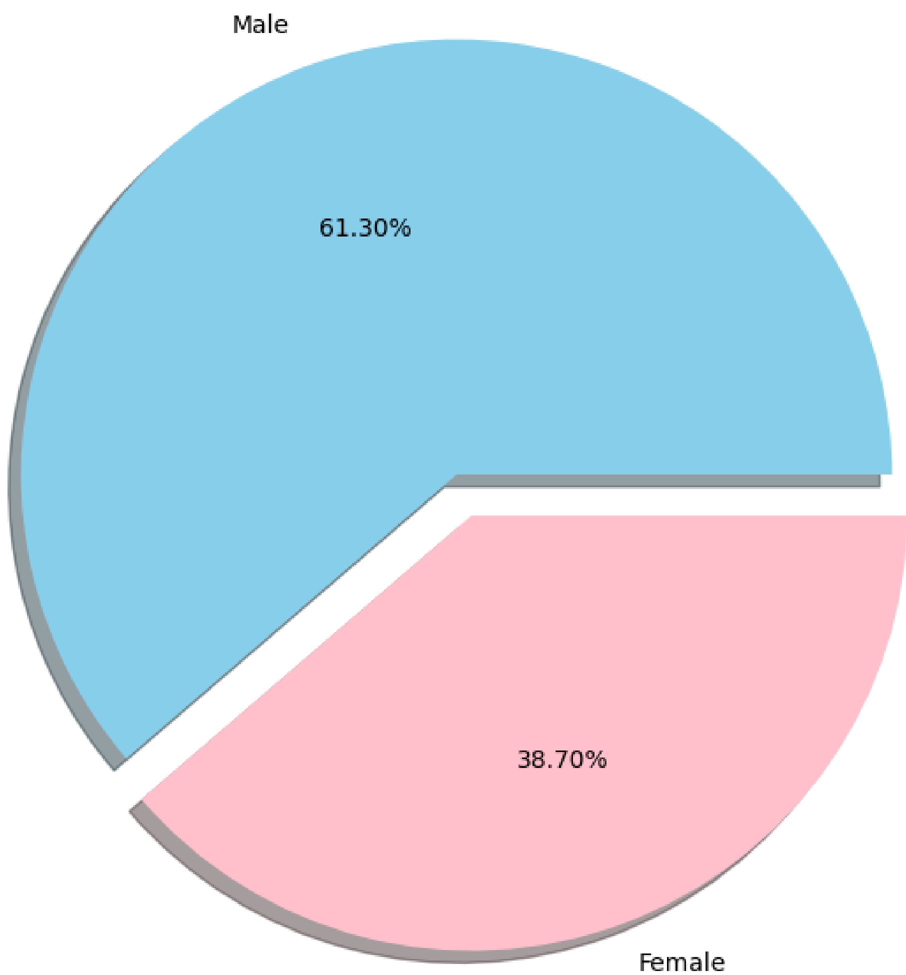


[ ]:
```
df.Sex.value_counts()
```

[ ]:
```
Sex
1    377
2    238
Name: count, dtype: int64
```

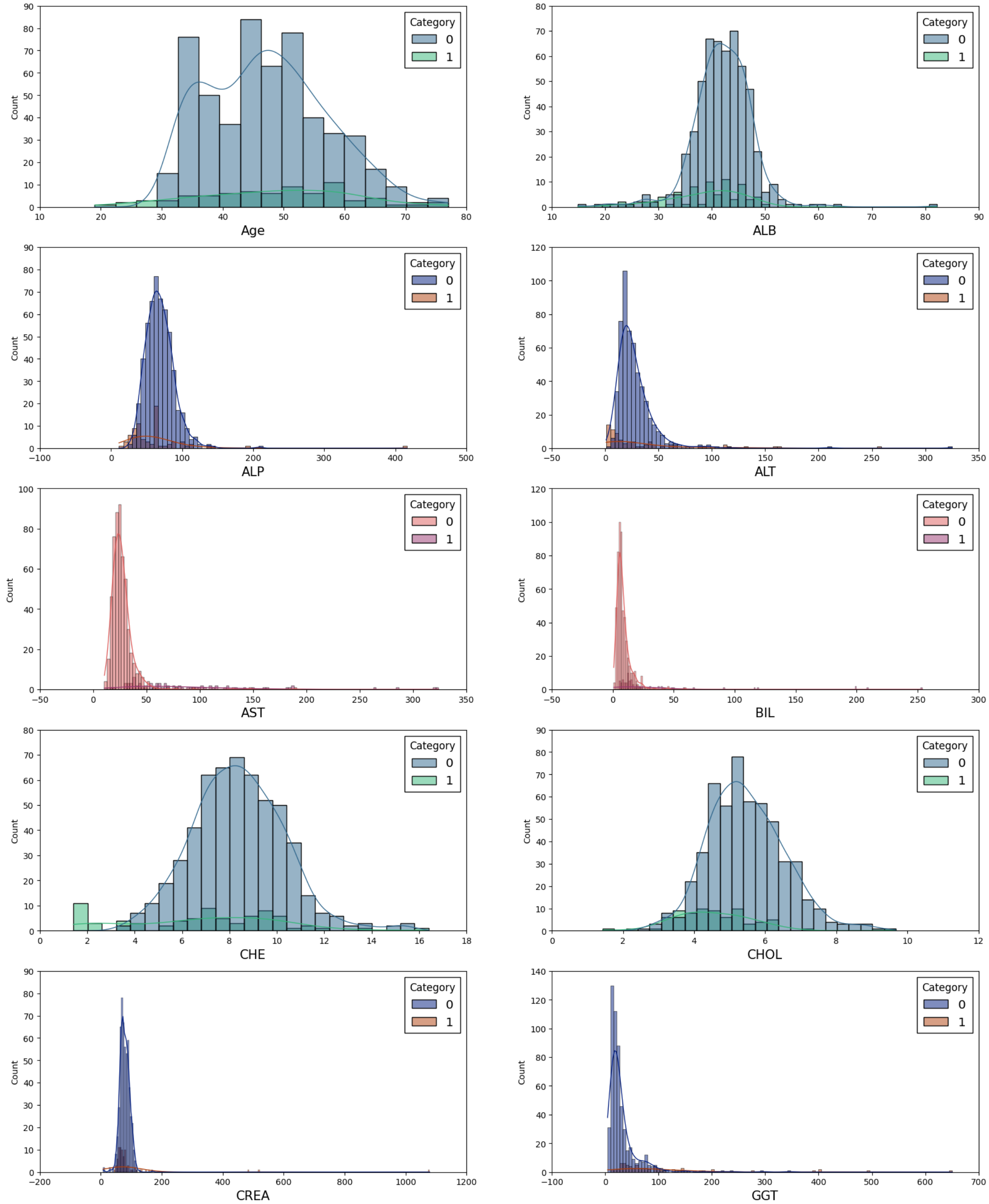
[ ]:
```
fig, ax = plt.subplots(figsize=(8,8))
plt.pie(x=df["Sex"].value_counts(),
        colors=["skyblue","pink"],
        labels=["Male","Female"],
```

```
        shadow = True,
        autopct="%1.2f%%",
        explode = (0, 0.1)
        )
plt.show()
```



[ ]:
```
fig, ax =plt.subplots(5,2, figsize=(20,25))
plt.style.use("classic")


sns.histplot(x = df["Age"], hue = df["Category"], palette="viridis", kde=True,␣
 ↪ax=ax[0,0]);
ax[0,0].set_xlabel("Age",fontsize=15)
```

```
sns.histplot(x = df["ALB"], hue = df["Category"], palette="viridis", kde=True, ax=ax[0,1]);
ax[0,1].set_xlabel("ALB",fontsize=15)


sns.histplot(x = df["ALP"], hue = df["Category"], palette="dark", kde=True, ax=ax[1,0]);
ax[1,0].set_xlabel("ALP",fontsize=15)

sns.histplot(x = df["ALT"], hue = df["Category"], palette="dark", kde=True, ax=ax[1,1]);
ax[1,1].set_xlabel("ALT",fontsize=15)


sns.histplot(x = df["AST"], hue = df["Category"], palette="flare", kde=True, ax=ax[2,0]);
ax[2,0].set_xlabel("AST",fontsize=15)

sns.histplot(x = df["BIL"], hue = df["Category"], palette="flare", kde=True, ax=ax[2,1]);
ax[2,1].set_xlabel("BIL",fontsize=15)


sns.histplot(x = df["CHE"], hue = df["Category"], palette="viridis", kde=True, ax=ax[3,0]);
ax[3,0].set_xlabel("CHE",fontsize=15)

sns.histplot(x = df["CHOL"], hue = df["Category"], palette="viridis", kde=True, ax=ax[3,1]);
ax[3,1].set_xlabel("CHOL",fontsize=15);


sns.histplot(x = df["CREA"], hue = df["Category"], palette="dark", kde=True, ax=ax[4,0]);
ax[4,0].set_xlabel("CREA",fontsize=15)

sns.histplot(x = df["GGT"], hue = df["Category"], palette="dark", kde=True, ax=ax[4,1]);
ax[4,1].set_xlabel("GGT",fontsize=15);
```



1.3 Splitting the data into training and test datasets

Here, we are trying to predict whether the patient has Hepatitis C or not using the given data. Hence, the `Category` will be the y label and rest of the data will be the X or the input data.

[ ]:
```
# X data
X = df.drop("Category", axis=1)
X.head()
```

[ ]:

	Age	Sex	ALB	ALP	ALT	AST	BIL	CHE	CHOL	CREA	GGT	PROT
0	32	1	38.5	52.5	7.7	22.1	7.5	6.93	3.23	106.0	12.1	69.0
1	32	1	38.5	70.3	18.0	24.7	3.9	11.17	4.80	74.0	15.6	76.5
2	32	1	46.9	74.7	36.2	52.6	6.1	8.84	5.20	86.0	33.2	79.3
3	32	1	43.2	52.0	30.6	22.6	18.9	7.33	4.74	80.0	33.8	75.7
4	32	1	39.2	74.1	32.6	24.8	9.6	9.15	4.32	76.0	29.9	68.7

[ ]:
```
# y data
y = df["Category"]
y.head()
```

[ ]:
```
0    0
1    0
2    0
3    0
4    0
Name: Category, dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[ ]:
```
len(X_train), len(X_test)
```

[ ]:
```
(492, 123)
```

[ ]:
```
# Scaling the data

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

1.4 Logistic Regression

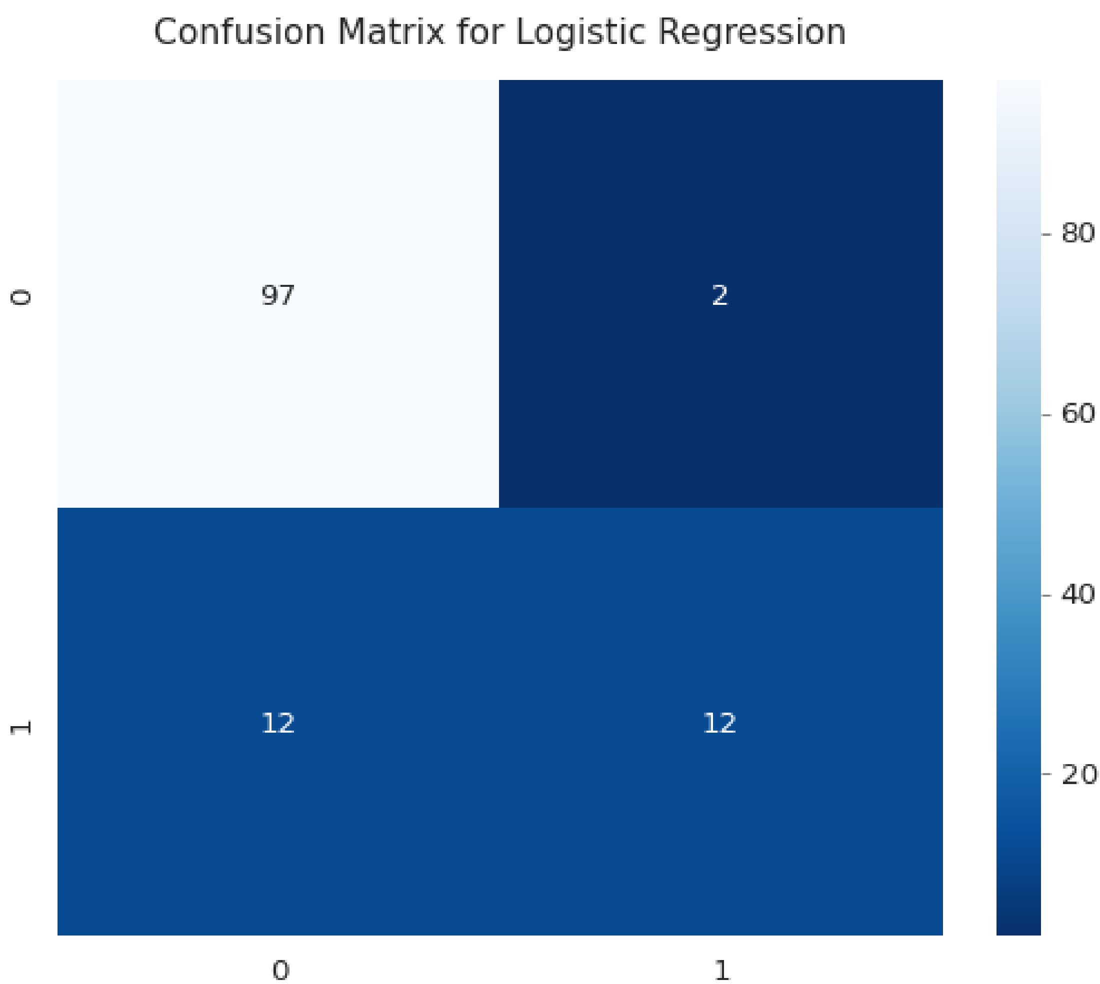
[ ]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train, y_train)
```

[ ]:
```
LogisticRegression()
```

```
[ ]: LogisticRegressionScore = lr.score(X_test, y_test)
     print("Accuracy obtained by Logistic Regression model:
      ↪",LogisticRegressionScore*100)
```

```
Accuracy obtained by Logistic Regression model: 88.6178861788618
```

```
[ ]: # Having a look at the confusion matrix for Logistic Regression

     from sklearn.metrics import confusion_matrix, classification_report
     sns.set_style("white")
     y_pred_lr = lr.predict(X_test)
     cf_matrix = confusion_matrix(y_test, y_pred_lr)
     sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
     plt.title("Confusion Matrix for Logistic Regression", fontsize=14, y=1.03);
```



```
[ ]: # Having a look at the classification report of Logistic Regression

from sklearn import metrics
print(metrics.classification_report(y_test, y_pred_lr))
```

```
              precision    recall  f1-score   support

           0       0.89      0.98      0.93        99
           1       0.86      0.50      0.63        24

    accuracy                           0.89       123
   macro avg       0.87      0.74      0.78       123
weighted avg       0.88      0.89      0.87       123
```

1.5 Random Forest Classifier

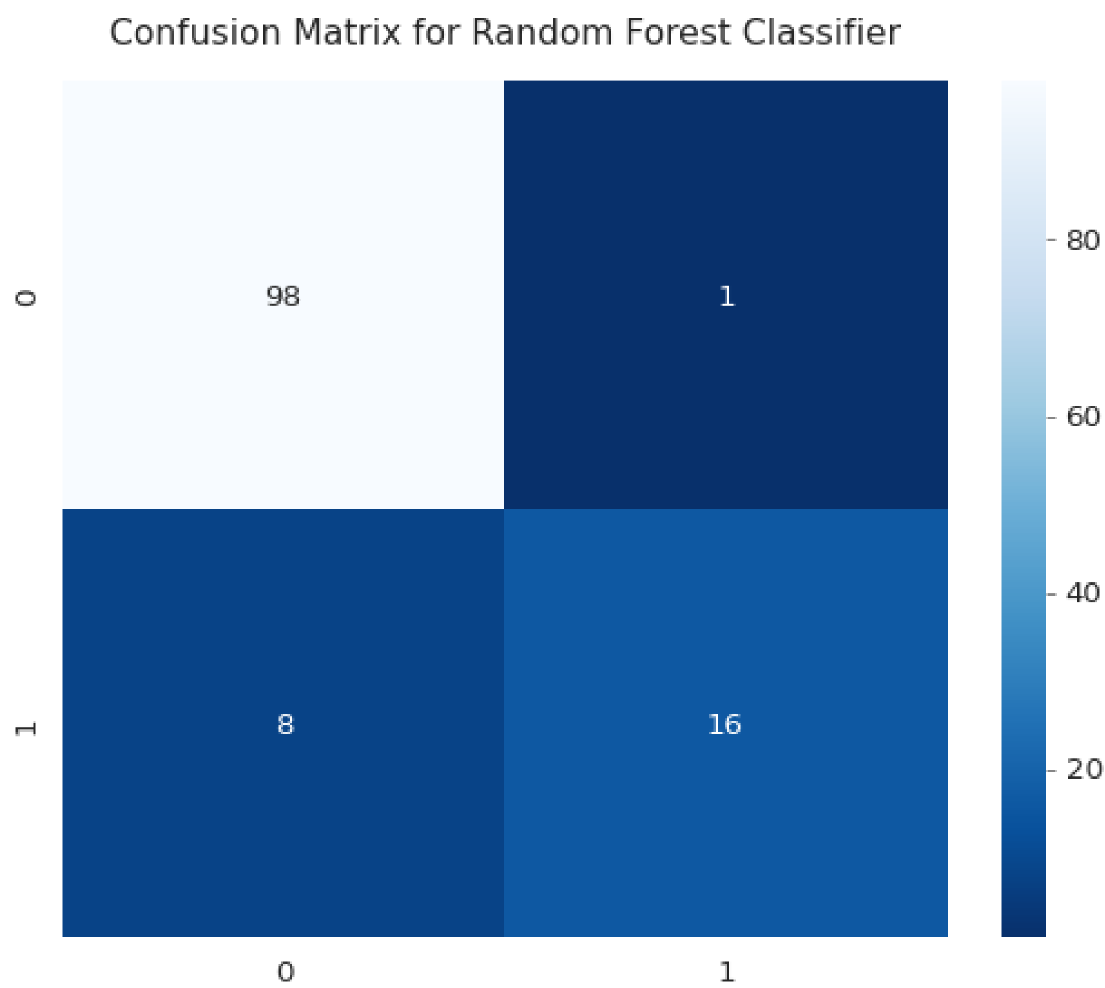
```
[ ]: from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train, y_train)
```

```
[ ]: RandomForestClassifier()
```

```
[ ]: RandomForestClassifierScore = rfc.score(X_test,y_test)
print("Accacy obtained by Random Forest Classifier :",␣
 ↪RandomForestClassifierScore*100)
```

```
Accacy obtained by Random Forest Classifier : 92.6829268292683
```

```
[ ]: # Confusion Matrix of Random Forest Classifier
y_pred_rfc = rfc.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_rfc)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for Random Forest Classifier", fontsize=14, y=1.03);
```



[ ]:
```
print(metrics.classification_report(y_test, y_pred_rfc))
```

```
              precision    recall  f1-score   support

           0       0.92      0.99      0.96        99
           1       0.94      0.67      0.78        24

    accuracy                           0.93       123
   macro avg       0.93      0.83      0.87       123
weighted avg       0.93      0.93      0.92       123
```

1.6 K Neighbors Classifier

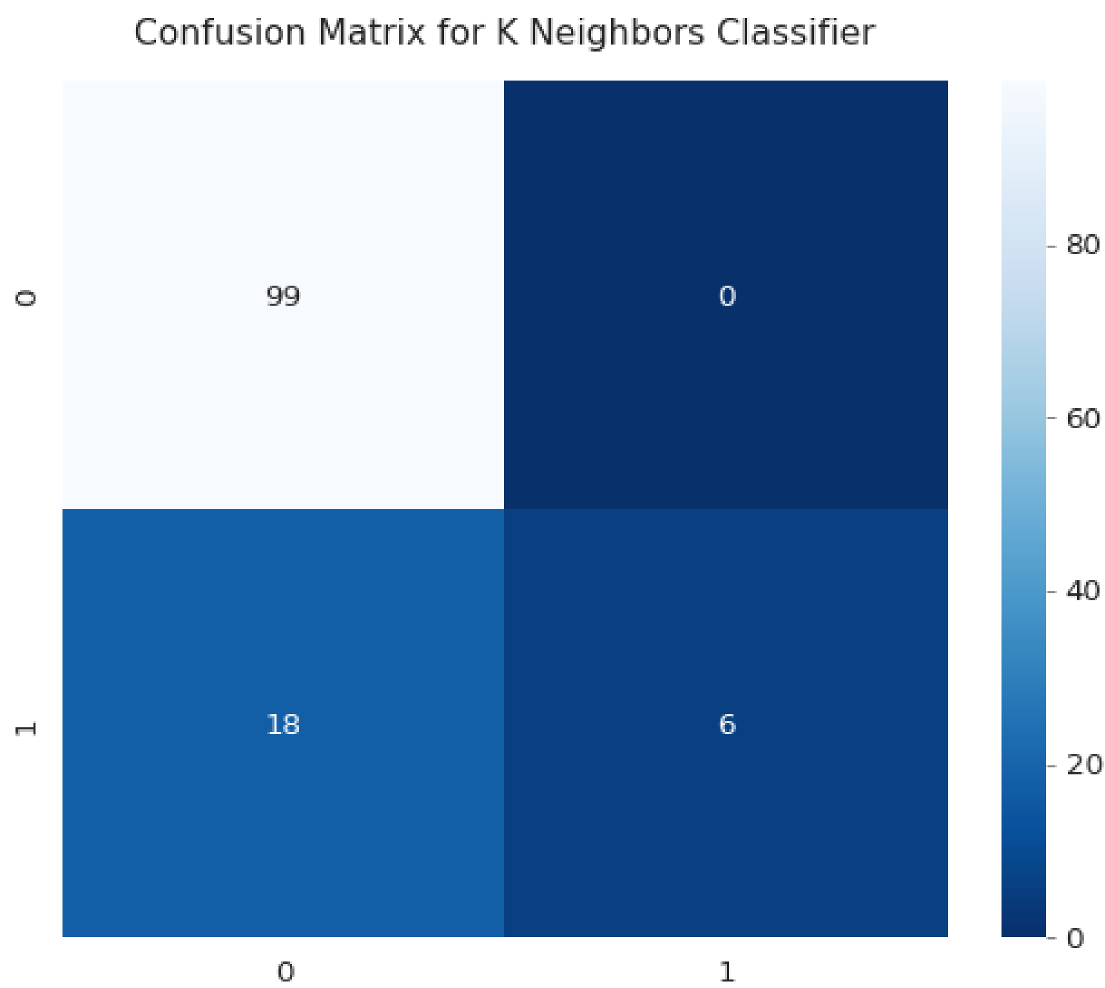
[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
```

[ ]:
```
KNeighborsClassifier()
```

[ ]:
```
KNeighborsClassifierScore = knn.score(X_test, y_test)
print("Accuracy obtained by K Neighbors Classifier :",␣
 ↪KNeighborsClassifierScore*100)
```

```
Accuracy obtained by K Neighbors Classifier : 85.36585365853658
```

[ ]:
```
# Confustion Matrix

y_pred_knn = knn.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_knn)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for K Neighbors Classifier", fontsize=14, y=1.03);
```




```
[ ]: print(metrics.classification_report(y_test,y_pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.85      1.00      0.92        99
           1       1.00      0.25      0.40        24

    accuracy                           0.85       123
   macro avg       0.92      0.62      0.66       123
weighted avg       0.88      0.85      0.82       123
```

1.7 Decision Tree Classifier

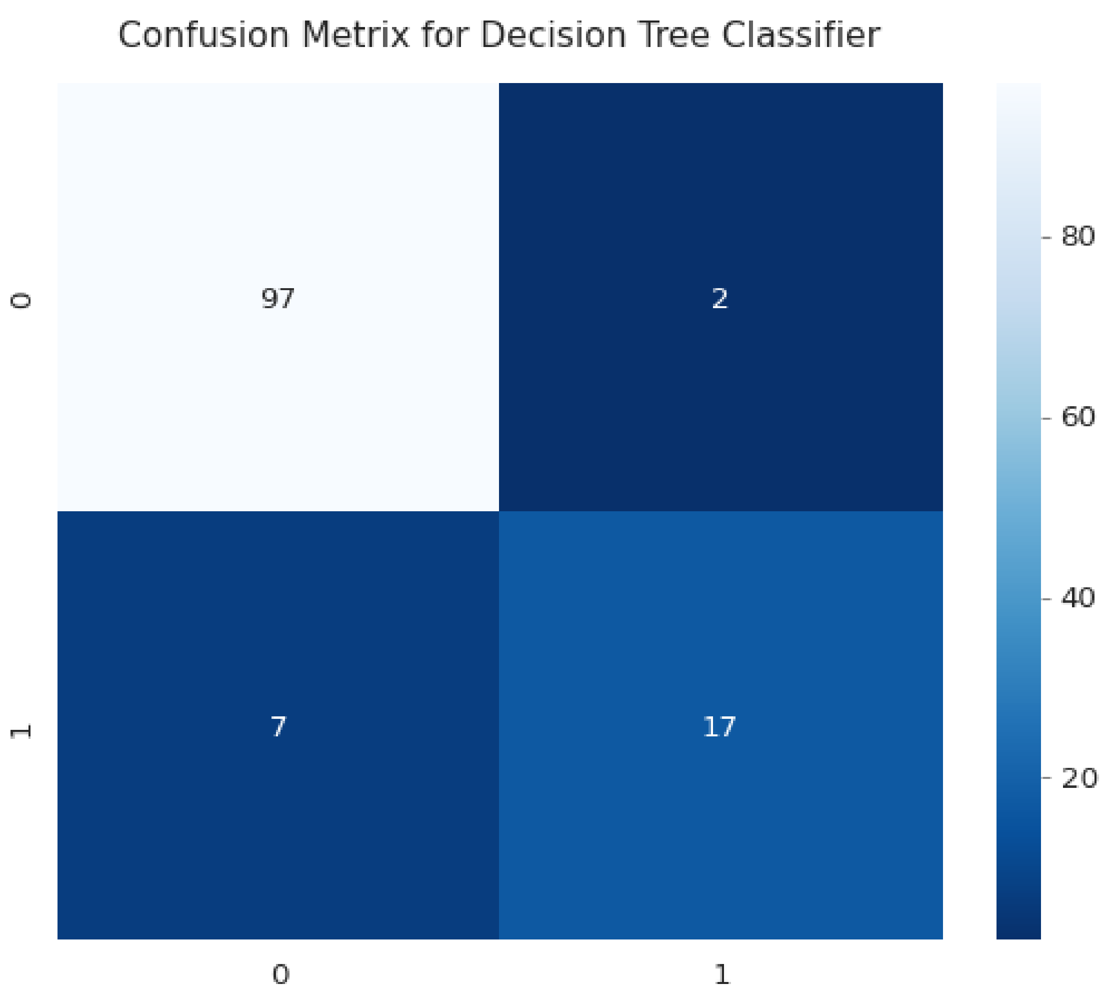
[ ]:
```
from sklearn.tree import DecisionTreeClassifier
tree = DecisionTreeClassifier()
tree.fit(X_train, y_train)
```

[ ]:
```
DecisionTreeClassifier()
```

[ ]:
```
DecisionTreeClassifierScore = tree.score(X_test,y_test)
print("Accuracy obtained by Decision Tree Classifier :",␣
 ↪DecisionTreeClassifierScore*100)
```

```
Accuracy obtained by Decision Tree Classifier : 92.6829268292683
```

[ ]:
```
y_pred_tree = tree.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_tree)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Metrix for Decision Tree Classifier", fontsize=14,  y=1.
 ↪03);
```



```
[ ]: print(metrics.classification_report(y_test, y_pred_tree));
```

```
              precision    recall  f1-score   support

           0       0.93      0.98      0.96        99
           1       0.89      0.71      0.79        24

    accuracy                           0.93       123
   macro avg       0.91      0.84      0.87       123
weighted avg       0.93      0.93      0.92       123
```

1.8 CatBoost Classifier

```
[ ]: pip install catboost
```

```
Collecting catboost
  Downloading catboost-1.2.5-cp310-cp310-manylinux2014_x86_64.whl (98.2 MB)
                           98.2/98.2 MB
5.6 MB/s eta 0:00:00
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-
packages (from catboost) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (from catboost) (3.7.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-
packages (from catboost) (1.25.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-
packages (from catboost) (2.0.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from catboost) (1.11.4)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages
(from catboost) (5.15.0)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.24->catboost) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.24->catboost) (2024.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->catboost) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
```

```
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (4.51.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (24.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->catboost) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (3.1.2)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from plotly->catboost) (8.2.3)
Installing collected packages: catboost
Successfully installed catboost-1.2.5
```

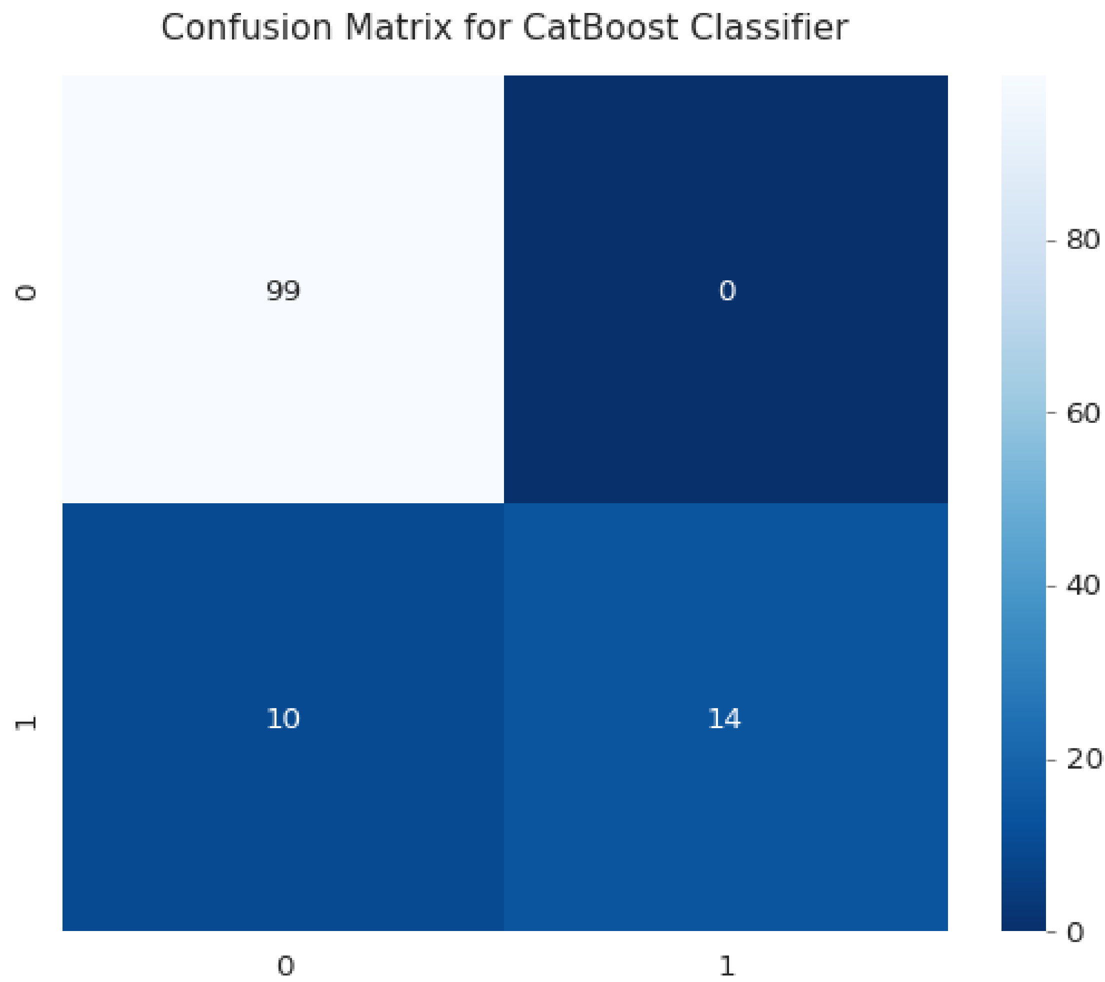
[ ]:
```
from catboost import CatBoostClassifier
cat = CatBoostClassifier(iterations=10)
cat.fit(X_train, y_train);
```

```
Learning rate set to 0.5
0:      learn: 0.4056594        total: 49.9ms   remaining: 449ms
1:      learn: 0.3052358        total: 52.4ms   remaining: 210ms
2:      learn: 0.2281643        total: 54.9ms   remaining: 128ms
3:      learn: 0.1874827        total: 57.7ms   remaining: 86.5ms
4:      learn: 0.1540611        total: 61.4ms   remaining: 61.4ms
5:      learn: 0.1302461        total: 65ms     remaining: 43.3ms
6:      learn: 0.1100836        total: 67.1ms   remaining: 28.8ms
7:      learn: 0.0993443        total: 69.5ms   remaining: 17.4ms
8:      learn: 0.0894244        total: 71.9ms   remaining: 7.98ms
9:      learn: 0.0820818        total: 74.3ms   remaining: 0us
```

[ ]:
```
CatBoostClassifierScore = cat.score(X_test,y_test)
print("Accuracy obtained by CatBoost Classifier model:
 ↪",CatBoostClassifierScore*100)
```

```
Accuracy obtained by CatBoost Classifier model: 91.869918699187
```

[ ]:
```
# Confusion matrix
y_pred_cat = cat.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_cat)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for CatBoost Classifier", fontsize=14, y=1.03);
```



[ ]:
```
# Classification Report of CatBoost Classifier
print(metrics.classification_report(y_test, y_pred_cat))
```

```
              precision    recall  f1-score   support

           0       0.91      1.00      0.95        99
           1       1.00      0.58      0.74        24

    accuracy                           0.92       123
   macro avg       0.95      0.79      0.84       123
weighted avg       0.93      0.92      0.91       123
```

1.9 Gradient Boosting Classifier

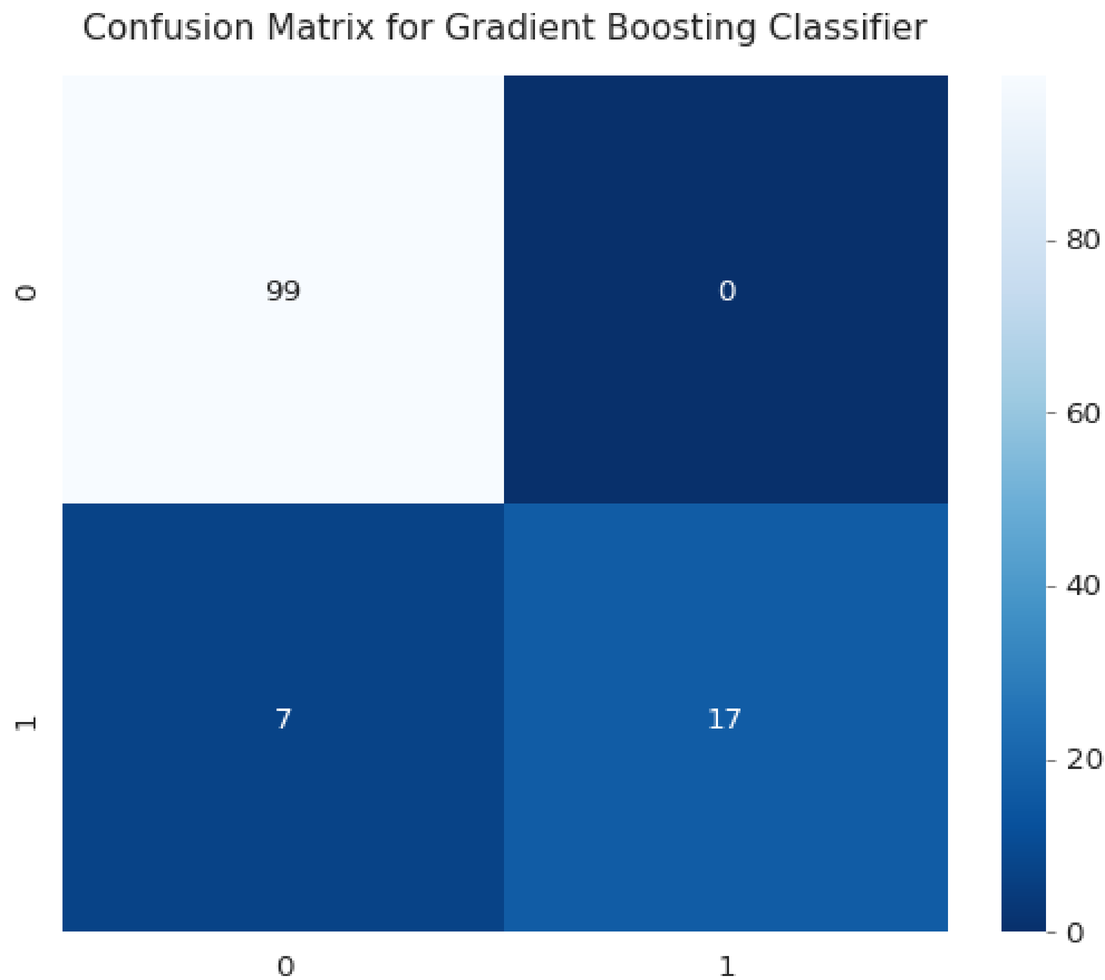
[ ]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)
```

[ ]:
```
GradientBoostingClassifier()
```

[ ]:
```
GradientBoostingClassifierScore = gb.score(X_test,y_test)
print("Accuracy obtained by Gradient Boosting Classifier model:
↪",GradientBoostingClassifierScore*100)
```

```
Accuracy obtained by Gradient Boosting Classifier model: 94.3089430894309
```

[ ]:
```
# Confusion matrix
y_pred_gb = gb.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_gb)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for Gradient Boosting Classifier", fontsize=14, y=1.
↪03);
```




```
[ ]: # Classification Report of Gradient Boosting Classifier
print(metrics.classification_report(y_test, y_pred_gb))
```

```
              precision    recall  f1-score   support

           0       0.93      1.00      0.97        99
           1       1.00      0.71      0.83        24

    accuracy                           0.94       123
   macro avg       0.97      0.85      0.90       123
weighted avg       0.95      0.94      0.94       123
```

1.10 Gausian Naive Bayes Classifier

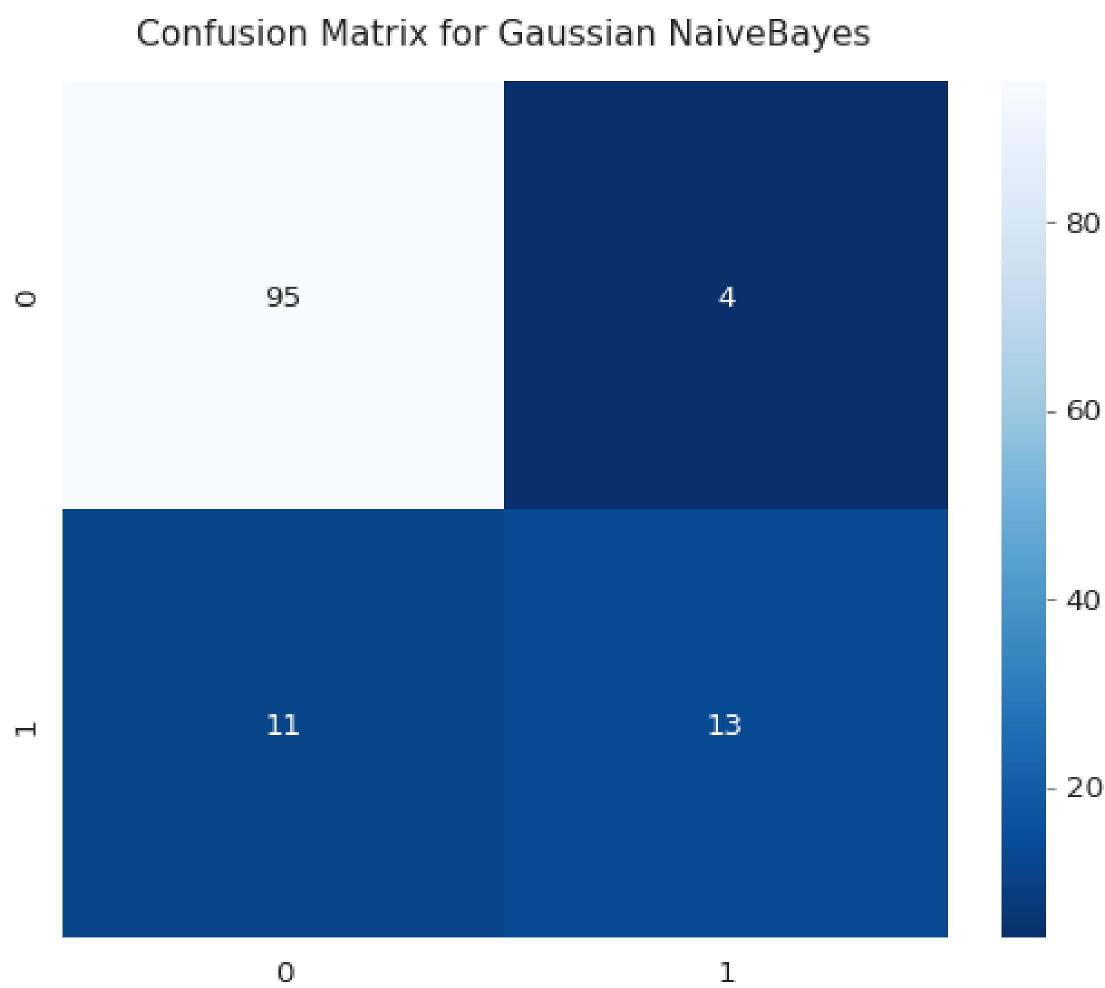
[ ]:
```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(X_train, y_train)
```

[ ]:
```
GaussianNB()
```

[ ]:
```
nb_score = nb.score(X_test, y_test)
print("Accuracy obtained by Gaussian NaiveBayes model:", nb_score*100)
```

```
Accuracy obtained by Gaussian NaiveBayes model: 87.8048780487805
```

[ ]:
```
# Confusion matrix for Naive Bayes
y_pred_nb = nb.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_nb)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for Gaussian NaiveBayes", fontsize=14, y=1.03);
```



[ ]:
```
# Classification Report for Naive Bayes
print(metrics.classification_report(y_test, y_pred_nb))
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93        99
           1       0.76      0.54      0.63        24

    accuracy                           0.88       123
   macro avg       0.83      0.75      0.78       123
weighted avg       0.87      0.88      0.87       123
```

1.11 SupportVectorMachine Classifier

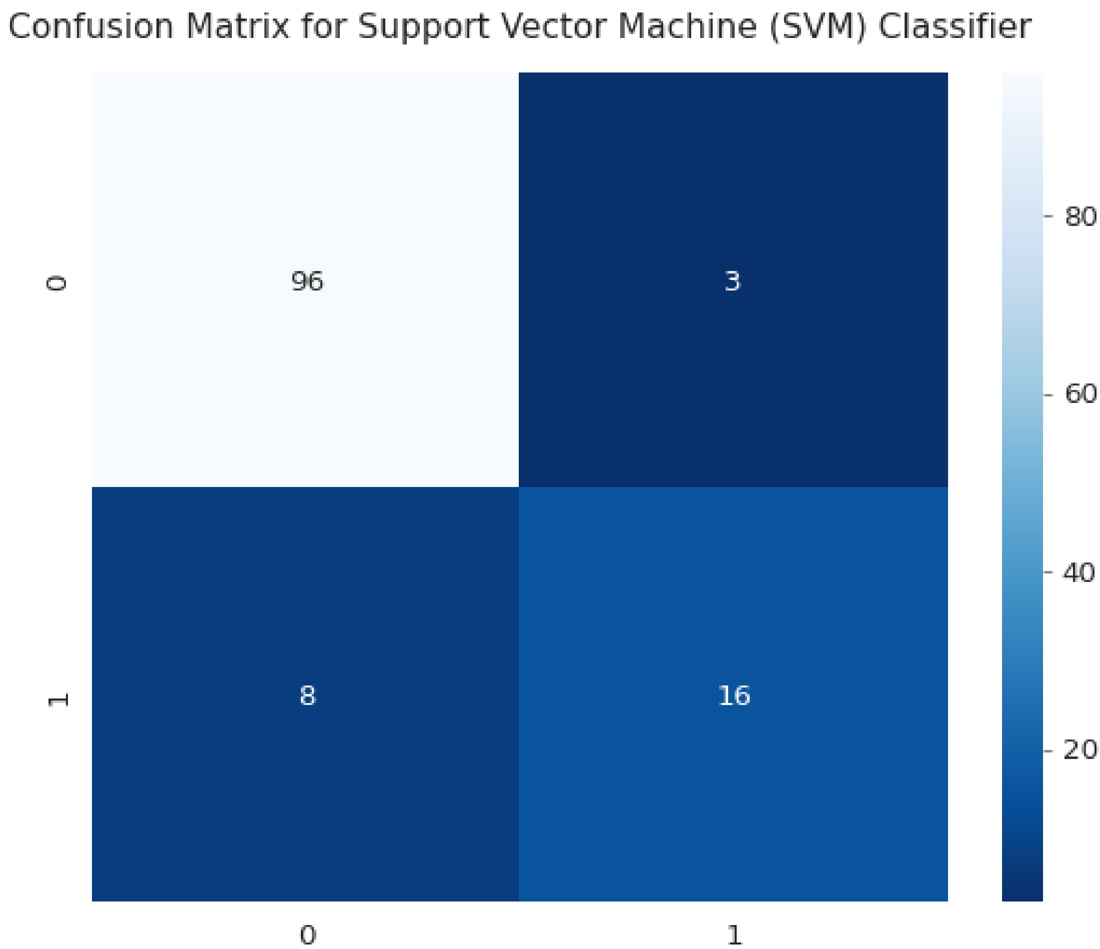
[ ]:
```
from sklearn.svm import SVC
SupportVectorClassifier = SVC()
SupportVectorClassifier.fit(X_train, y_train)
```

[ ]:
```
SVC()
```

[ ]:
```
SVMScore = SupportVectorClassifier.score(X_test, y_test)
print("Accuracy obtained by Support Vector Machine (SVM) Classifier:", SVMScore␣
↪* 100)
```

```
Accuracy obtained by Support Vector Machine (SVM) Classifier: 91.05691056910568
```

[ ]:
```
# Confusion matrix for SVM Classifier
y_pred_svm = SupportVectorClassifier.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_svm)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for Support Vector Machine (SVM) Classifier",␣
↪fontsize=14, y=1.03)
plt.show()
```



[ ]:
```
# Classification Report for SVM Classifier
print(classification_report(y_test, y_pred_svm))
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.95        99
           1       0.84      0.67      0.74        24

    accuracy                           0.91       123
   macro avg       0.88      0.82      0.84       123
weighted avg       0.91      0.91      0.91       123
```

1.12 MultiLayer Perceptron Classifier

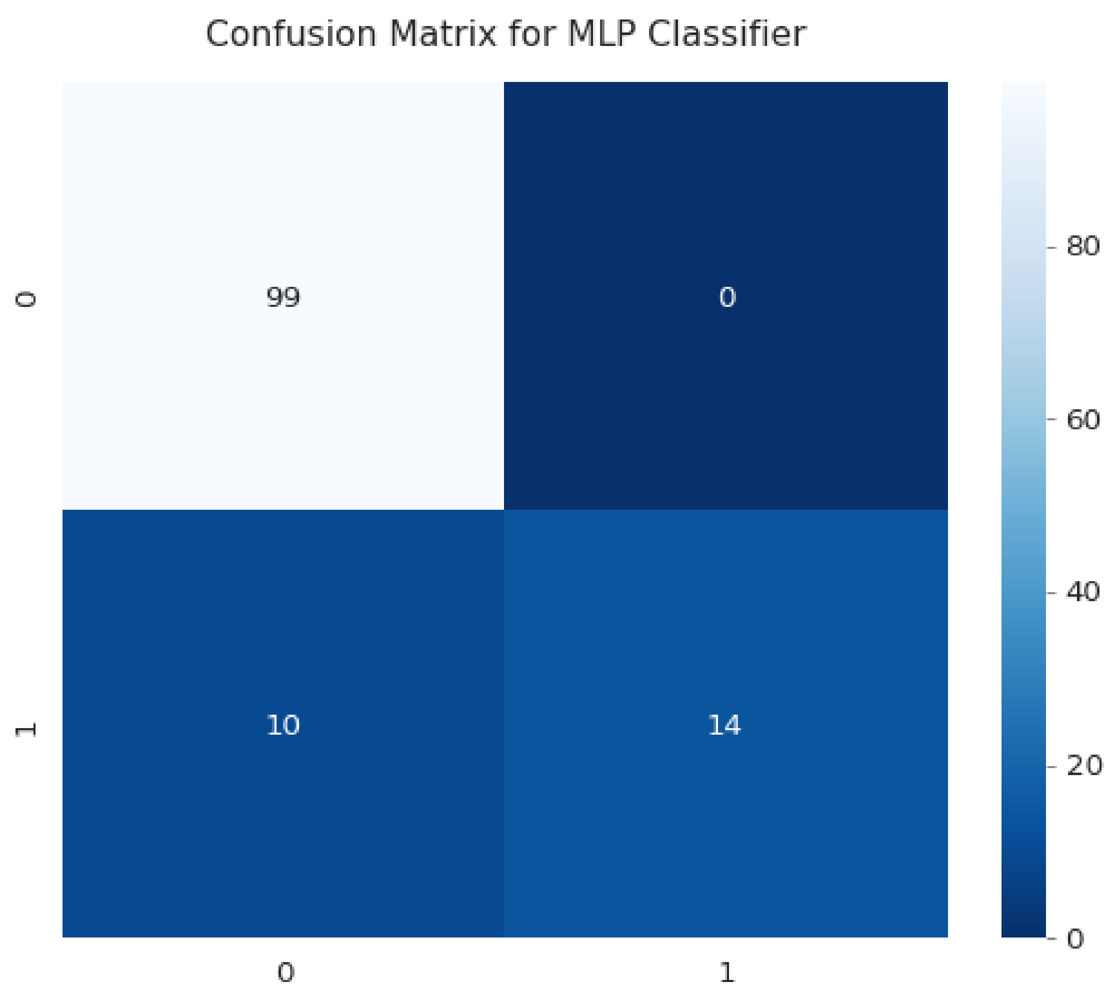
[ ]:
```
from sklearn.neural_network import MLPClassifier
MultiLayerPerceptronClassifier= MLPClassifier(hidden_layer_sizes=(100,),
 ↪max_iter=1000, random_state=42)
MultiLayerPerceptronClassifier.fit(X_train, y_train)
```

[ ]:
```
MLPClassifier(max_iter=1000, random_state=42)
```

[ ]:
```
MLPscore = MultiLayerPerceptronClassifier.score(X_test, y_test)
print("Accuracy obtained by MLP Classifier:", MLPscore*100)
```

```
Accuracy obtained by MLP Classifier: 91.869918699187
```

[ ]:
```
# Confusion matrix for Neural Network
y_pred_MLPClassifier = MultiLayerPerceptronClassifier.predict(X_test)
cf_matrix = confusion_matrix(y_test, y_pred_MLPClassifier)
sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")
plt.title("Confusion Matrix for MLP Classifier", fontsize=14, y=1.03);
```



[ ]:
```
# Classification Report for Neural Network
print(metrics.classification_report(y_test, y_pred_MLPClassifier))
```

```
              precision    recall  f1-score   support

           0       0.91      1.00      0.95        99
           1       1.00      0.58      0.74        24

    accuracy                           0.92       123
   macro avg       0.95      0.79      0.84       123
weighted avg       0.93      0.92      0.91       123
```

[ ]:
```
import pandas as pd
from tabulate import tabulate

# Models and their respective metrics
models = [
    "Logistic Regression",
    "Decision Tree ",
    "Random Forest ",
    "K Neighbors ",
    "CatBoost ",
    "Gradient Boosting ",
    "Gaussian Naive Bayes ",
    "Support Vector Machine ",
    "MultiLayer Perceptron "
]

precision = [0.89,0.93,0.92,0.85,0.91,0.93,0.90,0.92,0.91]
recall = [0.98,0.97,0.99,1.00,1.00,1.00,0.96,0.97,1.00]
f1_score = [0.93,0.95,0.95,0.92,0.95,0.97,0.93,0.95,0.95]
support = [99,99,99,99,99,99,99,99,99]
accuracy = [88.62,91.87,91.87,85.37,91.87,94.31,87.80,91.06,91.87]

# Create DataFrame with index starting from 1
df_metrics = pd.DataFrame({
    "Model": models,
    "Precision": precision,
    "Recall": recall,
    "F1-Score": f1_score,
    "Support": support,
    "Accuracy": accuracy
}, index=range(1, len(models) + 1))
```

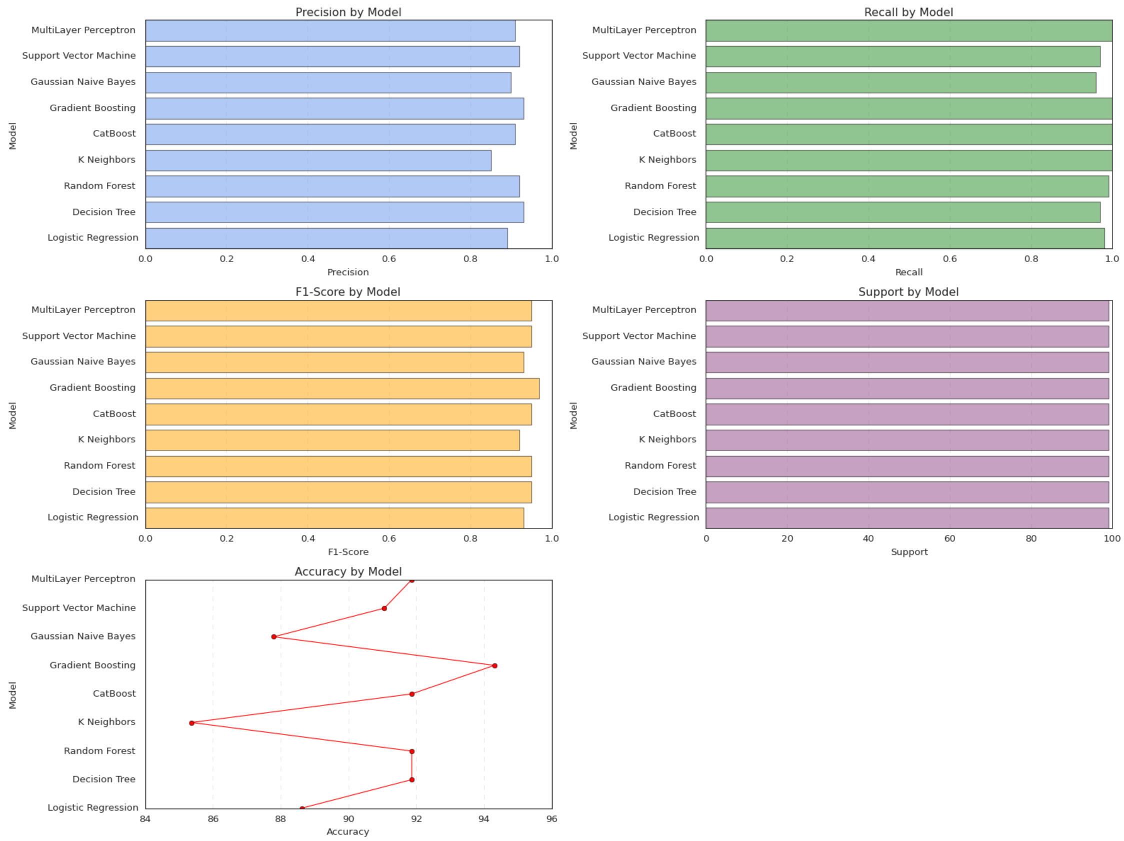
```python
# Print DataFrame using tabulate
print(tabulate(df_metrics, headers='keys', tablefmt='fancy_grid'))
```

	Model	Precision	Recall	F1-Score	Support	Accuracy
1	Logistic Regression	0.89	0.98	0.93	99	88.62
2	Decision Tree	0.93	0.97	0.95	99	91.87
3	Random Forest	0.92	0.99	0.95	99	91.87
4	K Neighbors	0.85	1	0.92	99	85.37
5	CatBoost	0.91	1	0.95	99	91.87
6	Gradient Boosting	0.93	1	0.97	99	94.31
7	Gaussian Naive Bayes	0.9	0.96	0.93	99	87.8
8	Support Vector Machine	0.92	0.97	0.95	99	91.06
9	MultiLayer Perceptron	0.91	1	0.95	99	91.87

[ ]:

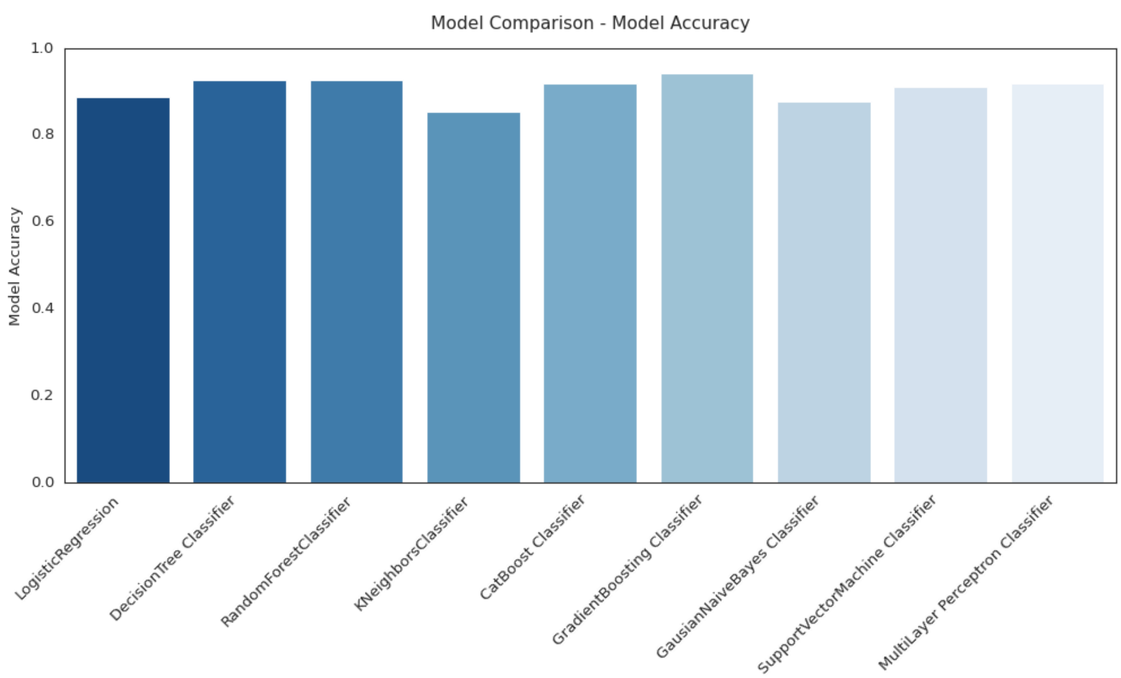
```python
import matplotlib.pyplot as plt

# Set figure size and create subplots
fig, ax = plt.subplots(3, 2, figsize=(20, 15))

# Plotting precision
ax[0, 0].barh(df_metrics['Model'], df_metrics['Precision'],␣
 ↪color='#6495ED',edgecolor='black', alpha=0.5)
ax[0, 0].set_xlabel('Precision')
ax[0, 0].set_ylabel('Model')
ax[0, 0].set_title('Precision by Model')
ax[0, 0].grid(axis='x', linestyle='--', alpha=0.7)

# Plotting recall
ax[0, 1].barh(df_metrics['Model'], df_metrics['Recall'],␣
 ↪color='#228B22',edgecolor='black', alpha=0.5)
ax[0, 1].set_xlabel('Recall')
ax[0, 1].set_ylabel('Model')
ax[0, 1].set_title('Recall by Model')
ax[0, 1].grid(axis='x', linestyle='--', alpha=0.7)

# Plotting F1-score
ax[1, 0].barh(df_metrics['Model'], df_metrics['F1-Score'],␣
 ↪color='#FFA500',edgecolor='black', alpha=0.5)
ax[1, 0].set_xlabel('F1-Score')
ax[1, 0].set_ylabel('Model')
ax[1, 0].set_title('F1-Score by Model')
ax[1, 0].grid(axis='x', linestyle='--', alpha=0.7)

# Plotting support
ax[1, 1].barh(df_metrics['Model'], df_metrics['Support'],␣
 ↪color='#8E4585',edgecolor='black', alpha=0.5)
ax[1, 1].set_xlabel('Support')
ax[1, 1].set_ylabel('Model')
ax[1, 1].set_title('Support by Model')
ax[1, 1].grid(axis='x', linestyle='--', alpha=0.7)

# Plotting accuracy
ax[2, 0].plot(df_metrics['Accuracy'], df_metrics['Model'], color='#FF0000',␣
 ↪marker='o', linestyle='-')
ax[2, 0].set_xlabel('Accuracy')
ax[2, 0].set_ylabel('Model')
ax[2, 0].set_title('Accuracy by Model')
ax[2, 0].grid(axis='x', linestyle='--', alpha=0.7)

# Remove empty subplot
fig.delaxes(ax[2, 1])
```

```python
# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```



[ ]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
#plt.style.use("seaborn")

x = ["LogisticRegression",
     "DecisionTree Classifier",
     "RandomForestClassifier",
     "KNeighborsClassifier",
     "CatBoost Classifier",
     "GradientBoosting Classifier",
     "GausianNaiveBayes Classifier",
     "SupportVectorMachine Classifier",
     "MultiLayer Perceptron Classifier"]
```

```
y = [LogisticRegressionScore,
     DecisionTreeClassifierScore,
     RandomForestClassifierScore,
     KNeighborsClassifierScore,
     CatBoostClassifierScore,
     GradientBoostingClassifierScore,
     nb_score,
     SVMScore,
     MLPscore]

colors = sns.color_palette("viridis", len(x))

fig, ax = plt.subplots(figsize=(15,6))
sns.barplot(x=x,y=y, palette="Blues_r");
plt.ylabel("Model Accuracy")
plt.xticks(rotation=45,ha='right')
plt.title("Model Comparison - Model Accuracy", fontsize=14, y=1.03);
```



- `Gradient Boosting Classifier` and `Random Forest Regression` perform best on the test set.

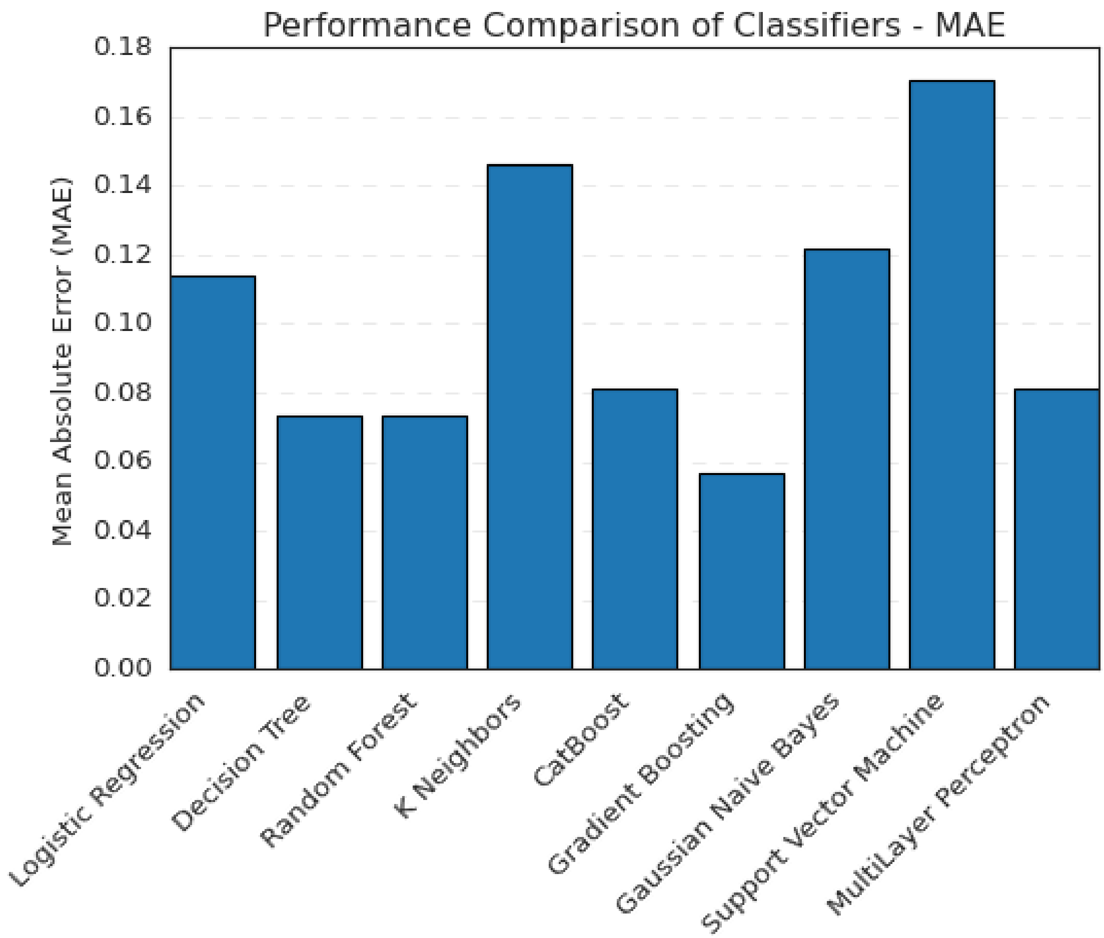
[ ]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
 ↪mean_squared_log_error
import numpy as np
from tabulate import tabulate
```

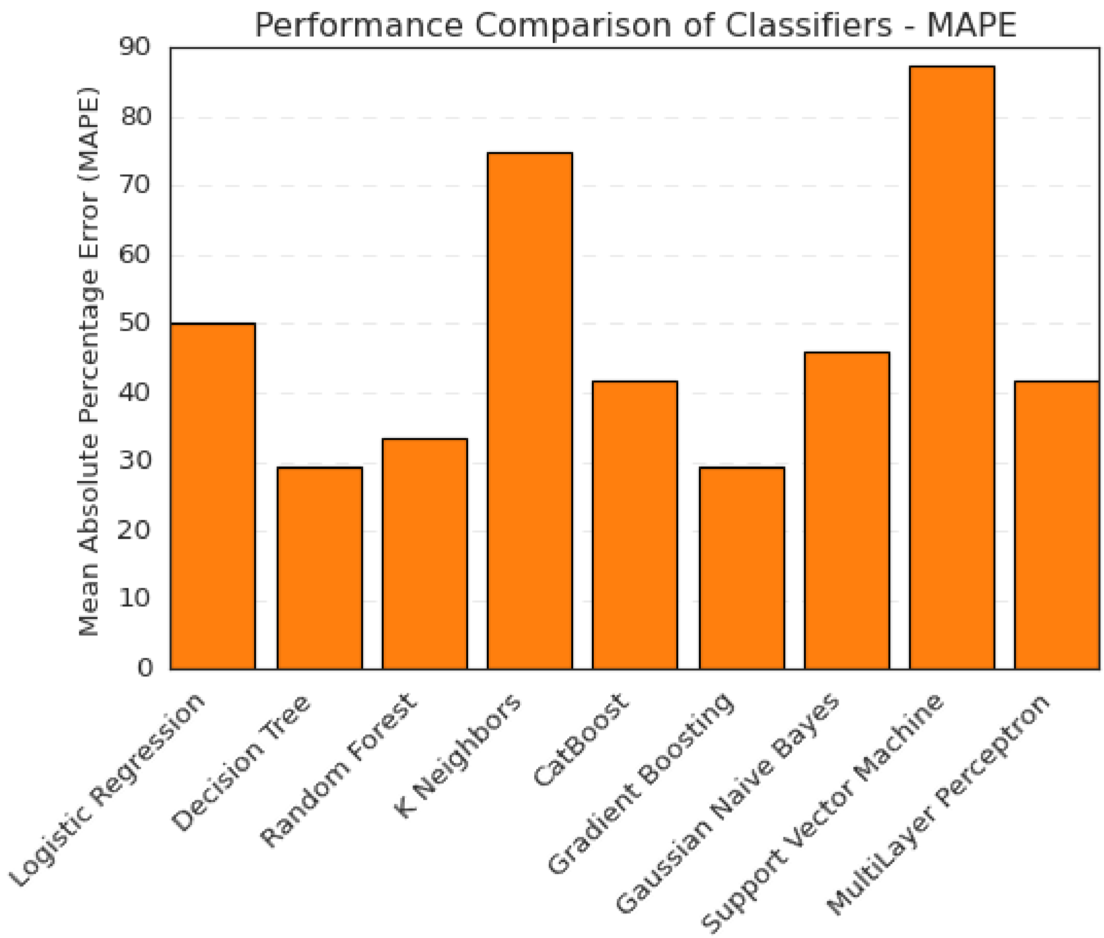
```python
classifiers = [("Logistic Regression", lr), ("Decision Tree", tree), ("Random Forest", rfc), ("K Neighbors", knn),
               ("CatBoost", cat), ("Gradient Boosting", gb), ("Gaussian Naive Bayes", nb),
               ("Support Vector Machine", SupportVectorClassifier), ("MultiLayer Perceptron", MultiLayerPerceptronClassifier)]

metrics_results = {}

for name, clf in classifiers:
    y_pred_score = clf.decision_function(X_test) if name == "Support Vector Machine" else clf.predict_proba(X_test)[:, 1]
    y_pred_binary = (y_pred_score > 0.5).astype(int)
    mae = mean_absolute_error(y_test, y_pred_binary)
    mse = mean_squared_error(y_test, y_pred_binary)
    rmse = np.sqrt(mse)
    male = mean_squared_log_error(y_test, y_pred_binary)
    non_zero_indices = np.where(y_test != 0)[0]
    y_test_filtered = y_test.iloc[non_zero_indices]
    y_pred_binary_filtered = y_pred_binary[non_zero_indices]
    absolute_percentage_errors = np.abs((y_test_filtered - y_pred_binary_filtered) / y_test_filtered)
    mape = np.mean(absolute_percentage_errors) * 100 if len(absolute_percentage_errors) > 0 else np.nan
    metrics_results[name] = {"MAE": mae, "MAPE": mape, "MSE": mse, "RMSE": rmse, "MALE": male}

table_data = [["Classifier", "MAE", "MAPE (%)", "MSE", "RMSE", "MALE"]]

for name, metrics in metrics_results.items():
    table_data.append([name, f"{metrics['MAE']:.4f}", f"{metrics['MAPE']:.2f}%",
                       f"{metrics['MSE']:.4f}", f"{metrics['RMSE']:.4f}", f"{metrics['MALE']:.4f}"])

print(tabulate(table_data, headers="firstrow", tablefmt="fancy_grid"))
```

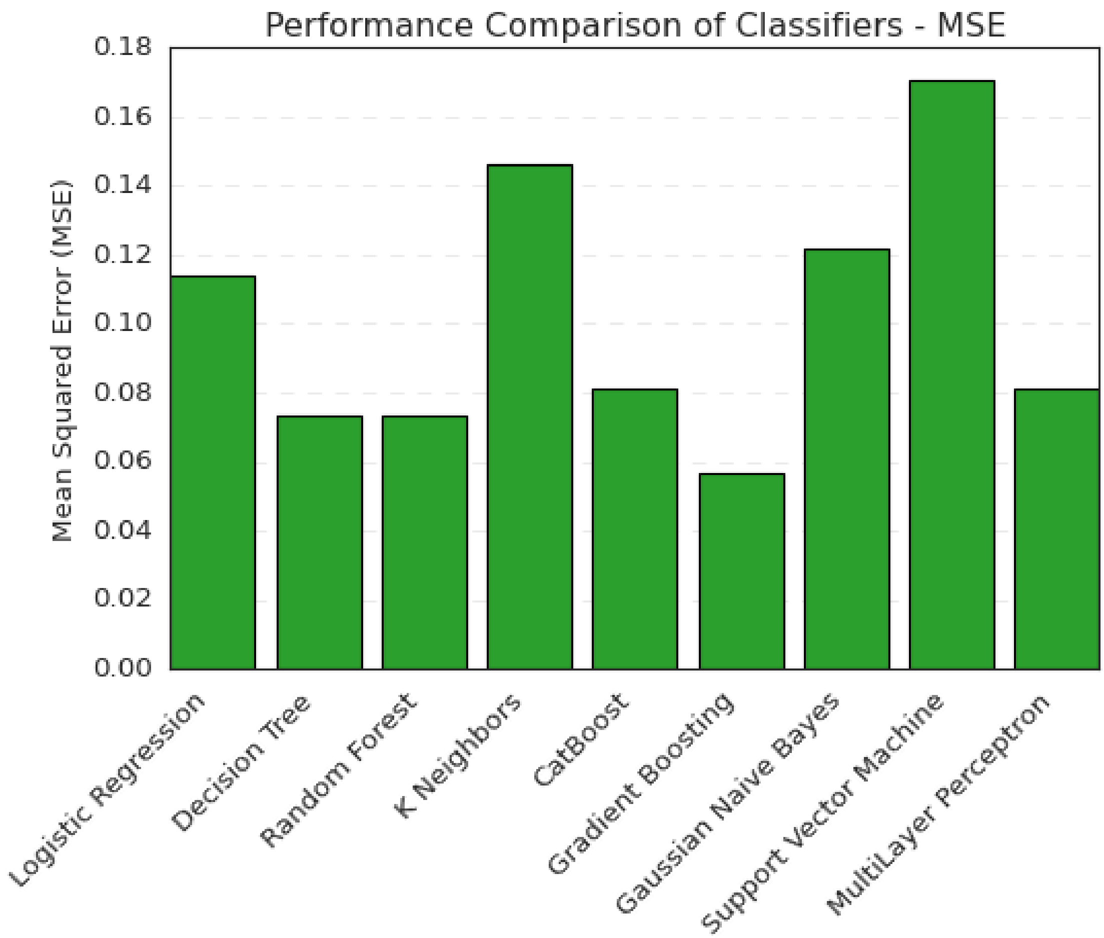
Classifier	MAE	MAPE (%)	MSE	RMSE	MALE
Logistic Regression	0.1138	50.00%	0.1138	0.3374	0.0547
Decision Tree	0.0732	29.17%	0.0732	0.2705	0.0352
Random Forest	0.0732	33.33%	0.0732	0.2705	0.0352
K Neighbors	0.1463	75.00%	0.1463	0.3825	0.0703

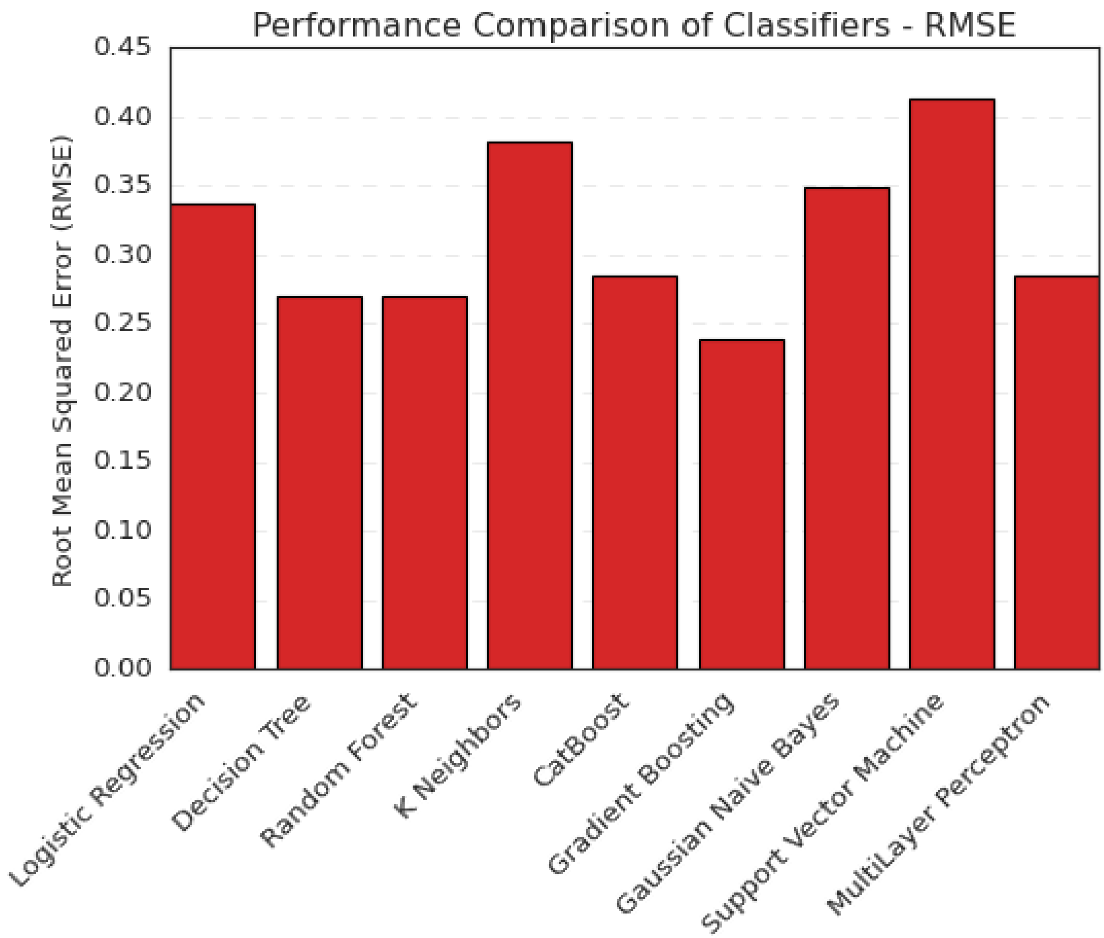
CatBoost	0.0813	41.67%	0.0813	0.2851	0.0391
Gradient Boosting	0.0569	29.17%	0.0569	0.2386	0.0273
Gaussian Naive Bayes	0.122	45.83%	0.122	0.3492	0.0586
Support Vector Machine	0.1707	87.50%	0.1707	0.4132	0.082
MultiLayer Perceptron	0.0813	41.67%	0.0813	0.2851	0.0391

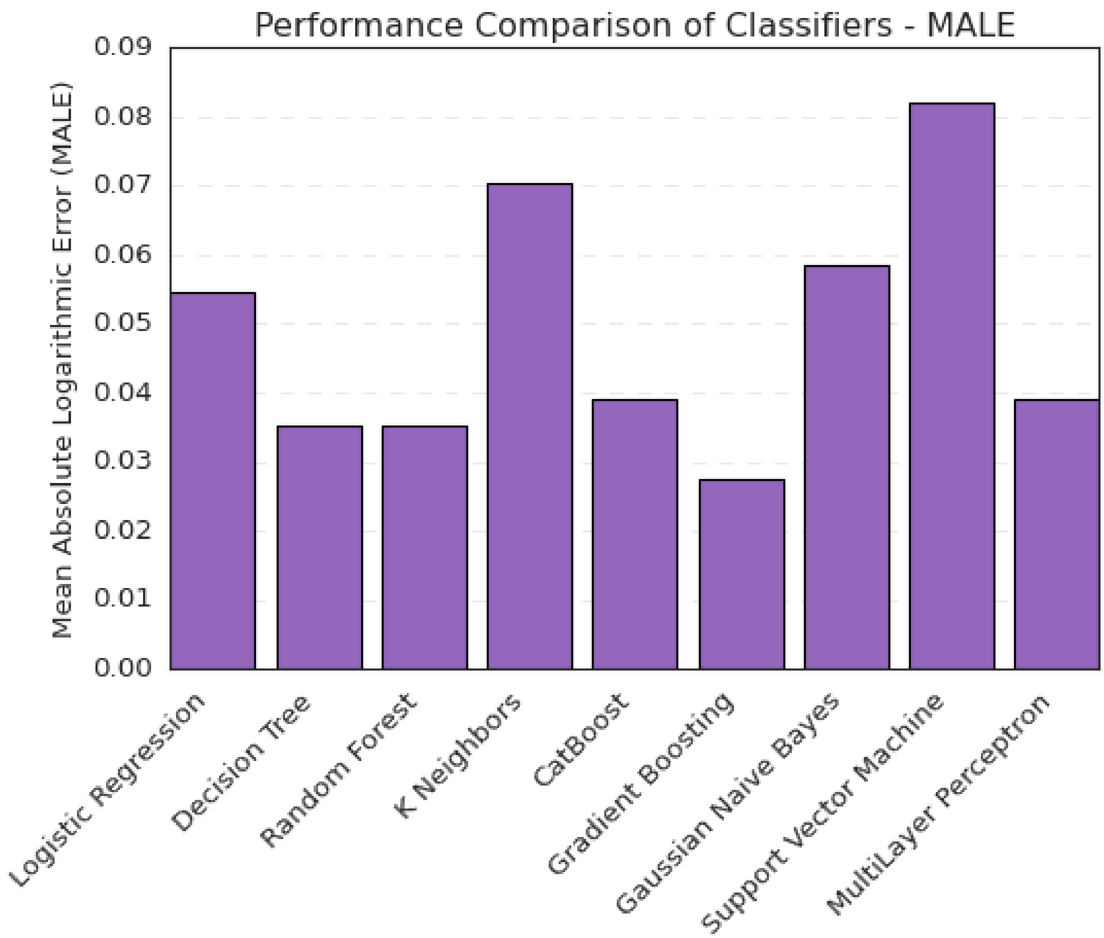
[ ]:
```
import matplotlib.pyplot as plt

def plot_metric(classifiers_names, metric_values, title, ylabel, color,␣
 ↪filename):
    plt.figure(figsize=(7, 6))
    plt.bar(classifiers_names, metric_values, color=color, edgecolor='black')
    plt.ylabel(ylabel)
    plt.title(title)
    plt.xticks(rotation=45, ha='right')
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.savefig(filename)  # Saving the plot as an image
    plt.show()

# Define color schemes
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd']
titles = ['Performance Comparison of Classifiers - MAE',
          'Performance Comparison of Classifiers - MAPE',
          'Performance Comparison of Classifiers - MSE',
          'Performance Comparison of Classifiers - RMSE',
          'Performance Comparison of Classifiers - MALE']
ylabls = ['Mean Absolute Error (MAE)',
          'Mean Absolute Percentage Error (MAPE)',
          'Mean Squared Error (MSE)',
          'Root Mean Squared Error (RMSE)',
          'Mean Absolute Logarithmic Error (MALE)']
filenames = ['mae_plot.png', 'mape_plot.png', 'mse_plot.png', 'rmse_plot.png',␣
 ↪'male_plot.png']

for i, (title, ylabel, filename) in enumerate(zip(titles, ylabls, filenames)):
    metric_values = [metrics_results[classifier][" ".join(title.split(' -␣
 ↪')[-1].split()[-2:])] for classifier, _ in classifiers]
    plot_metric([classifier for classifier, _ in classifiers], metric_values,␣
 ↪title, ylabel, colors[i], filename)
```


Performance Comparison of Classifiers - MAE
Mean Absolute Error (MAE)
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Logistic Regression
Decision Tree
Random Forest
K Neighbors
CatBoost
Gradient Boosting
Gaussian Naive Bayes
Support Vector Machine
MultiLayer Perceptron


Performance Comparison of Classifiers - MAPE
Mean Absolute Percentage Error (MAPE)
0
10
20
30
40
50
60
70
80
90
Logistic Regression
Decision Tree
Random Forest
K Neighbors
CatBoost
Gradient Boosting
Gaussian Naive Bayes
Support Vector Machine
MultiLayer Perceptron


Performance Comparison of Classifiers - MSE
Mean Squared Error (MSE)
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Logistic Regression
Decision Tree
Random Forest
K Neighbors
CatBoost
Gradient Boosting
Gaussian Naive Bayes
Support Vector Machine
MultiLayer Perceptron


Performance Comparison of Classifiers - RMSE
Root Mean Squared Error (RMSE)
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Logistic Regression
Decision Tree
Random Forest
K Neighbors
CatBoost
Gradient Boosting
Gaussian Naive Bayes
Support Vector Machine
MultiLayer Perceptron



1.13 Hyperparameter Tuning on Random Forest Classifier

[ ]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'criterion' : ['gini', 'entropy'],
    'n_estimators': [100, 200, 300, 1000]
}

grid_search_rfc = GridSearchCV(estimator = rfc,
                           param_grid = param_grid,
                           cv = 3, n_jobs = -1, verbose = 2)
```

```
[ ]: grid_search_rfc.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 576 candidates, totalling 1728 fits
```

```
[ ]: GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
                  param_grid={'bootstrap': [True], 'criterion': ['gini', 'entropy'],
                              'max_depth': [80, 90, 100, 110],
                              'max_features': [2, 3], 'min_samples_leaf': [3, 4, 5],
                              'min_samples_split': [8, 10, 12],
                              'n_estimators': [100, 200, 300, 1000]},
                  verbose=2)
```

```
[ ]: grid_search_rfc.best_params_
```

```
[ ]: {'bootstrap': True,
      'criterion': 'gini',
      'max_depth': 110,
      'max_features': 3,
      'min_samples_leaf': 3,
      'min_samples_split': 12,
      'n_estimators': 200}
```

```
[ ]: grid_search_rfc.best_score_
```

```
[ ]: 0.9735772357723578
```

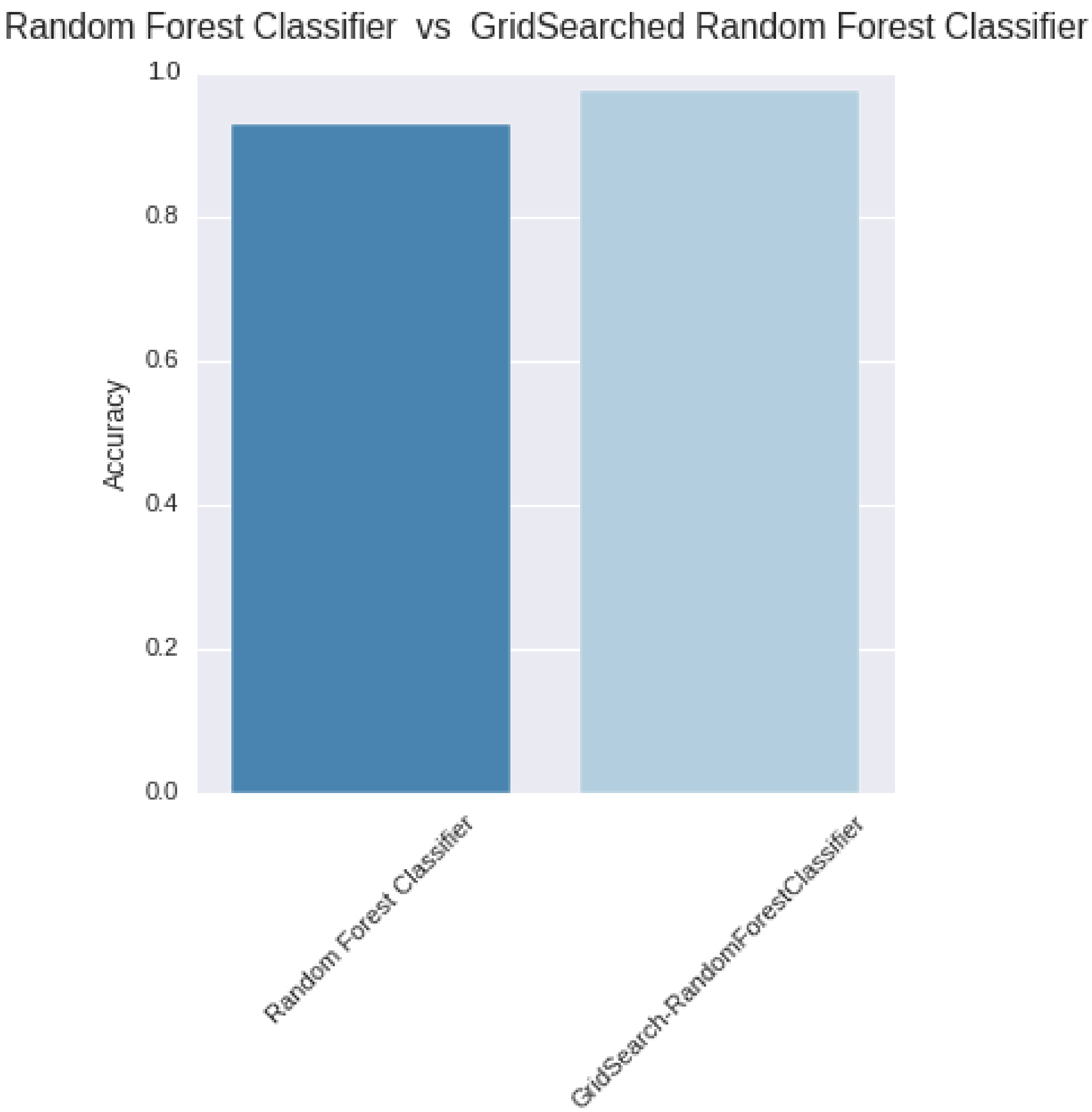
```
[ ]: grid_search_rfc_predict = grid_search_rfc.predict(X_test)
```

```
[ ]: print('Improvement in Random Forest Classifier after GridSearchCV: {:0.2f}%.'.
     ↪format(100 * (grid_search_rfc.best_score_ - RandomForestClassifierScore) /␣
     ↪RandomForestClassifierScore))
```

```
Improvement in Random Forest Classifier after GridSearchCV: 5.04%.
```

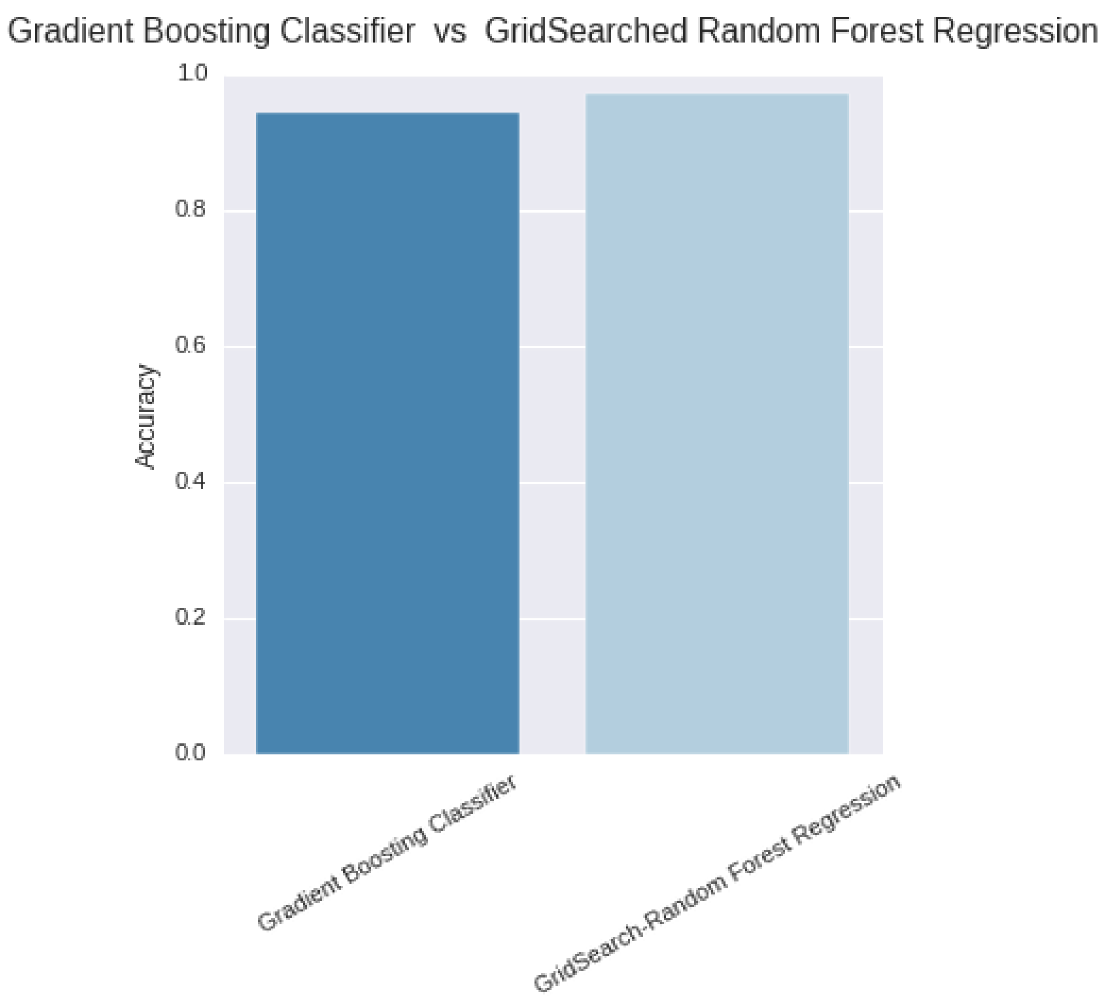
```
[ ]: # Comparing the results after the improvement in Random Forest Classifier

     plt.style.use("seaborn")

     x = ["Random Forest Classifier",
          "GridSearch-RandomForestClassifier"]

     y = [RandomForestClassifierScore,
          grid_search_rfc.best_score_]

     fig, ax = plt.subplots(figsize=(5,5))
     sns.barplot(x=x,y=y, palette="Blues_r");
     plt.ylabel("Accuracy")
```

```
plt.xticks(rotation=45)
plt.title("Random Forest Classifier  vs  GridSearched Random Forest␣
↪Classifier", fontsize=14, y=1.03);
```



[ ]:
```
# Comparing the GridSearch-Random Forest Regression and Gradient Boosting␣
↪Classifier

plt.style.use("seaborn")

x = ["Gradient Boosting Classifier",
     "GridSearch-Random Forest Regression"]
```

```
y = [GradientBoostingClassifierScore,
     grid_search_rfc.best_score_]

fig, ax = plt.subplots(figsize=(5,5))
sns.barplot(x=x,y=y, palette="Blues_r");
plt.ylabel("Accuracy")
plt.xticks(rotation=30)
plt.title("Gradient Boosting Classifier  vs  GridSearched Random Forest␣
 ↪Regression", fontsize=14, y=1.03);
```



1.13.1 After Hyperparameter tuning, the Random Forest Regression model performs better than the Gradient Boosting Classifier which was not the case before!

[ ]:
```python
# Classification Report of GridSearch-RandomForestRegression

print(classification_report(y_test, grid_search_rfc_predict))
```

```
              precision    recall  f1-score   support

           0       0.91      0.99      0.95        99
           1       0.93      0.58      0.72        24

    accuracy                           0.91       123
   macro avg       0.92      0.79      0.83       123
weighted avg       0.91      0.91      0.90       123
```