Data Mining and Warehouse

Experiment 3

Name: Jigar Siddhpura

SAP: 60004210155

Batch: B2

Branch: Computer Engineering

Jigar Siddhpura
60004210155

DMW - Experiment 3

Aim : Implementation of classification algo using
1. Decision Tree
2. Naive Bayes algorithm.

Theory : Decision tree ID3 :

1. Decision tree is a structure that contains nodes & edges & is built from a dataset (table of columns representing features & rows corresponding to records).
2. Each node is either used to make a decision (known as decision node) or represent an outcome (known as leaf node).
3. ID3 stands for 'Iterative Dichotomiser 3' & is named because algorithm iteratively dichotomizes (divides) feature into 2 or more groups at each step.
4. ID3 uses a top-down greedy approach to build a decision tree.
5. Top-down means that we start building the tree from top & greedy approach means that at each iteration we select the best feature at the present moment to create a node.

Naive Bayes: 1. Naive Bayes classifier is a collection of classification algorithm based on Bayes theorem.

2. It is not a single algorithm but a family of algorithms where all of them share a common principle i.e. every pair of feature being classified is independent of each other.

3. Consider a fictional dataset that describes weather conditions for playing golf. Given the weather conditions, each tuple classifies the conditions as fit ("Yes") or unfit ("No"). for playing golf.

Initialisation :

```
from google.colab import drive
drive.mount("/content/gdrive")

!pip install scikit-plot
import pandas as pd
import numpy as np
import seaborn as sns
import re
import matplotlib.pyplot as plt
from scikitplot.metrics import plot_confusion_matrix
from sklearn.multiclass import OneVsRestClassifier
from sklearn.metrics import roc_curve, roc_auc_score, accuracy_score, classification_report, confusion_matrix
titanic_train = "/content/gdrive/MyDrive/Synapse-Task/synapse_w1/train.csv"
titanic_test = "/content/gdrive/MyDrive/Synapse-Task/synapse_w1/test.csv"
penguin_df = sns.load_dataset("penguins")
iris_df = pd.read_csv("https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv")
spam_df = pd.read_csv("/content/gdrive/MyDrive/DMW/datasets/spam.csv")
wine_df = pd.read_csv("/content/gdrive/MyDrive/DMW/datasets/WineQT.csv")
gaussian = []
decision = []
```

Part A:

Dataset(Titanic) :

```
"""### Titanic"""
titanic_train_df = pd.read_csv(titanic_train)
titanic_test_df = pd.read_csv(titanic_test)
import re
titles = []
for nm in titanic_train_df.Name:
  title_search = re.search("(\w+)\.", nm)
  title = title_search.group(1)
  titles.append(title)
titanic_train_df['Title'] = titles
titanic_train_df.columns
titanic_train_df.drop(['PassengerId', 'Ticket', 'Name"], axis=1, inplace=True)
nullPercent = {}
for i in titanic_train_df:
  null_count_i =  titanic_train_df.isnull().sum()[i]
  per = null_count_i*100/titanic_train_df.shape[0]
  nullPercent[i] = per
for i in nullPercent:
  if(nullPercent[i] > 50) : titanic_train_df.drop([i], axis=1, inplace=True)
titanic_train_df.info()
mean = np.mean(titanic_train_df.Age)
titanic_train_df["Age"].fillna(value=mean,       inplace=True)
train_df = titanic_train_df.assign(Family=lambda x: x.SibSp + x.Parch)
def zscore_norm(x):
 mean = np.mean(x)
 std = np.std(x)
 return (x-mean)/std
train_df = train_df.assign(Age=lambda x: zscore_norm(x.Age))
train_df = train_df.assign(Fare=lambda x: zscore_norm(x.Fare))
train_df = train_df.assign(Family=lambda x: zscore_norm(x.Family))
train_df = pd.get_dummies(train_df , columns=["Pclass", 'Sex', 'Title', "Embarked"])
train_df
y = train_df.pop("Survived")
```

```
x = train_df
from sklearn.model_selection import train_test_split
x_train , x_valid , y_train , y_valid = train_test_split(x ,y, random_state=10, stratify=y, test_size=0.25 )
y_train.value_counts(normalize=True)
y_valid.value_counts(normalize=True)
```

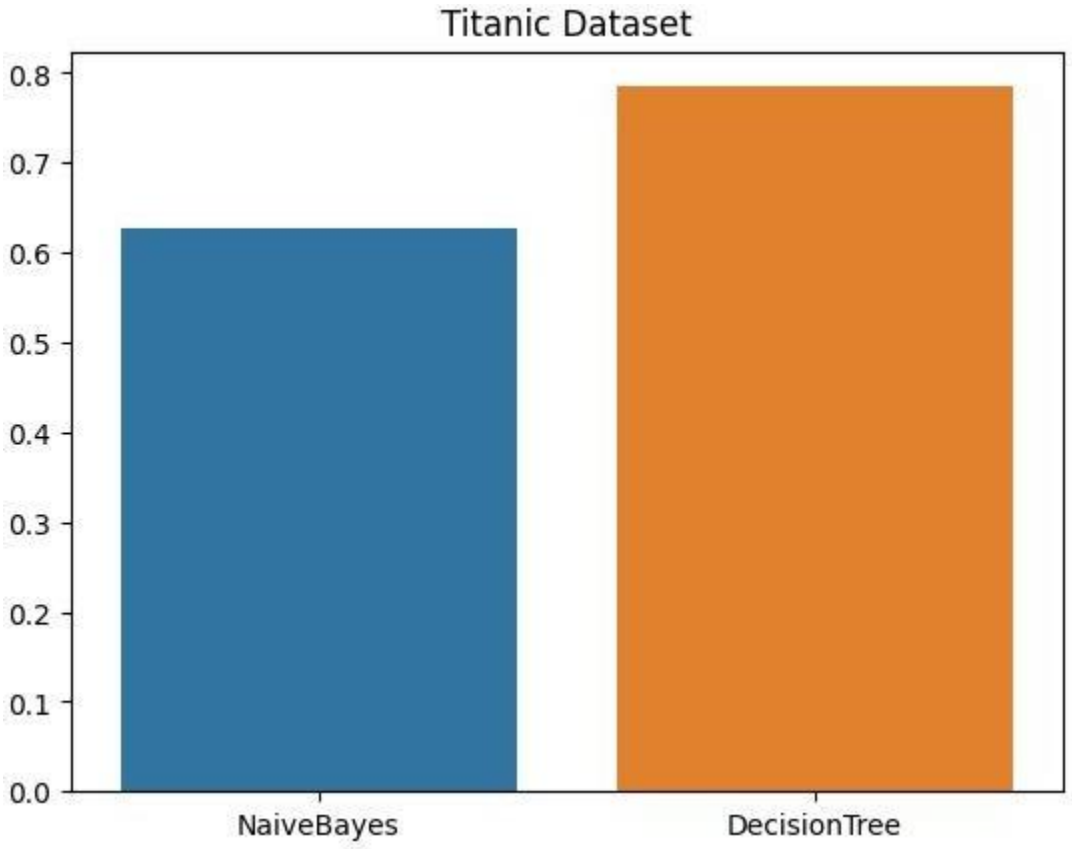
```
# using naive bayes
from sklearn.naive_bayes import GaussianNB
nb_model = GaussianNB()
nb_model.fit(x_train, y_train)
nb_accuracy = nb_model.score(x_valid, y_valid)
print(nb_accuracy)
```

```
# using decision tree
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier()
dt_model.fit(x_train, y_train)
dt_accuracy = dt_model.score(x_valid, y_valid)
gaussian.append(nb_accuracy)
decision.append(dt_accuracy)

accuracy = [nb_accuracy, dt_accuracy]
Models = ['NaiveBayes','DecisionTree']
sns.barplot(x=Models,y=accuracy).set(title="Titanic Dataset")
y_score_gnb = nb_model.predict_proba(x_valid)[:, 1]
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid, y_score_gnb)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
y_score_dtc = dt_model.predict_proba(x_valid)[:, 1]
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid, y_score_dtc)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})".format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})".format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()

q = y_valid
pred_test = dt_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title='DecisionTree Confusion Matrix", cmap="BuGn")
y_valid = q

q = y_valid
pred_test = nb_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title="GaussianNB Confusion Matrix", cmap="BuGn")
y_test = q

from sklearn.model_selection import KFold, cross_val_score
kf = KFold(n_splits=7,shuffle=True,random_state=10)
cv_score = cross_val_score(estimator=nb_model,X=x_train,y=y_train,cv=kf,scoring="accuracy")
mean_cv_score = np.mean(cv_score)
print(mean_cv_score)
```

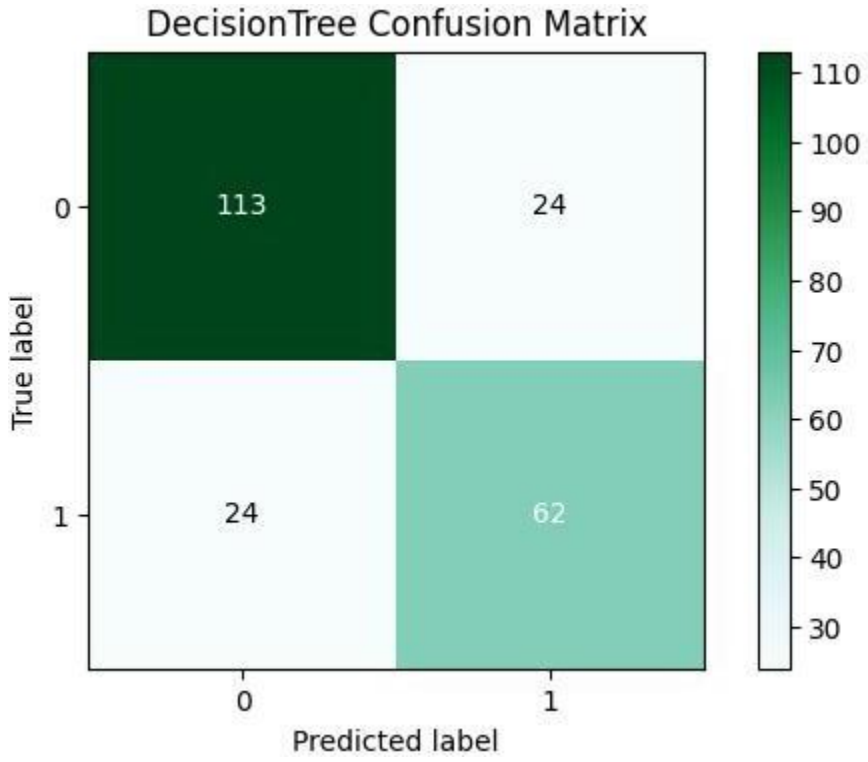
```
# ensemble tech - RandomForest
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier()
rf_model.fit(x_train, y_train)
rf_accuracy = rf_model.score(x_valid, y_valid)
print(rf_accuracy)
```

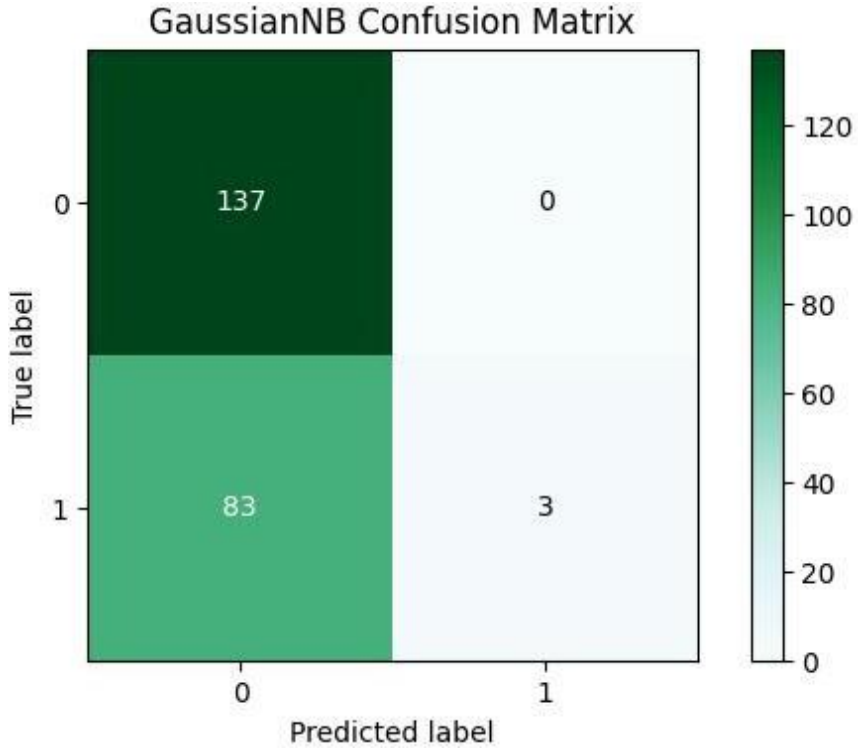
```
accuracies=[nb_accuracy,dt_accuracy,rf_accuracy,mean_cv_score]
plt.figure(figsize=(10,5))
models=[' Naive Bayes','Decision Tree','Random Forest',' aNve Bayes + Cross validation']
sns.barplot(x=models,y=accuracies,).set(title='Part C')
plt.xlabel("Models")
plt.ylabel('Accuracy')
plt.title('Accuracy of Different Models')
```

Accuracies of both models :

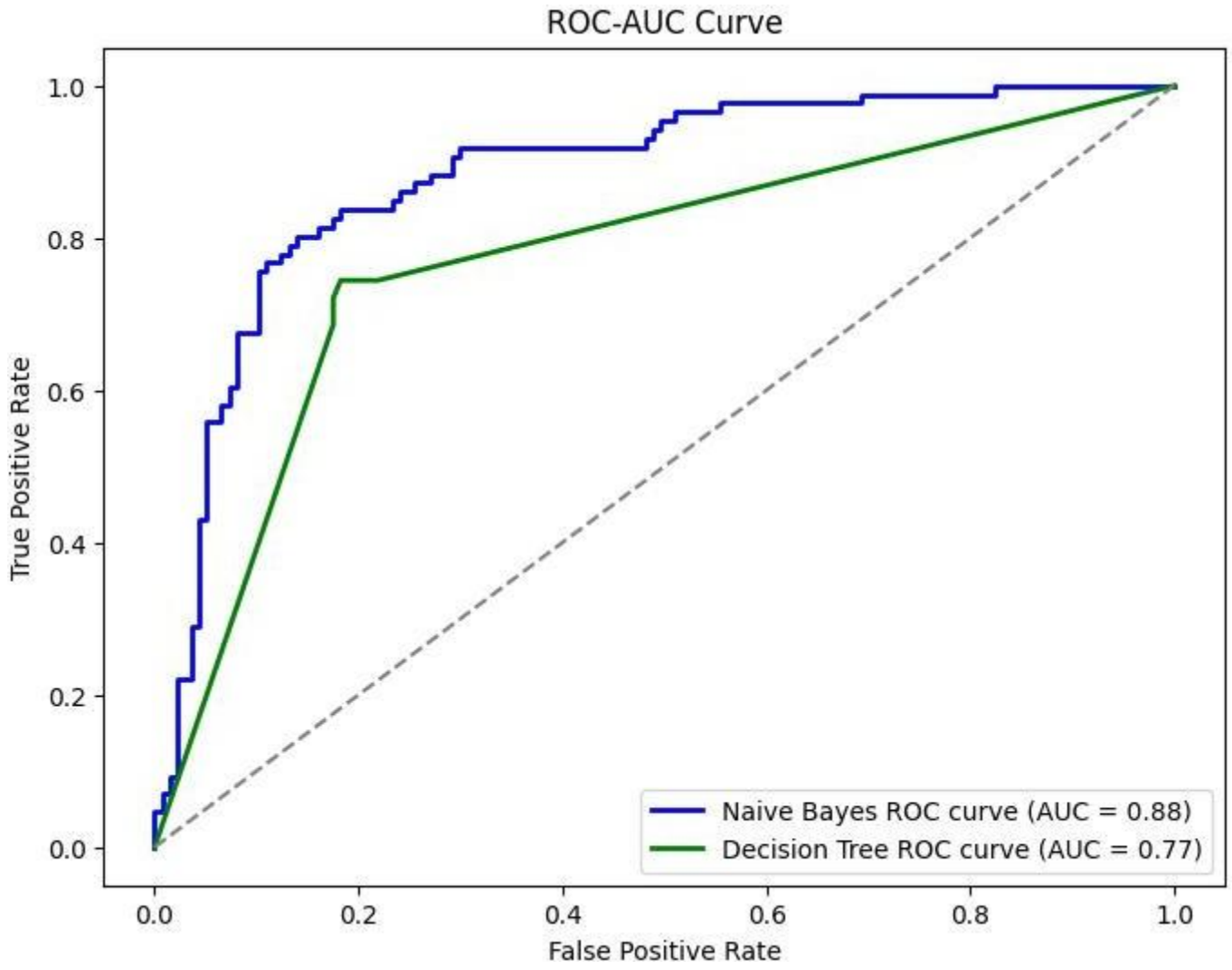


Confusion Matrix :





AUROC:


ROC-AUC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Naive Bayes ROC curve (AUC = 0.88)
Decision Tree ROC curve (AUC = 0.77)

Dataset 2 (penguins):

```
""" ### Penguin"""

pg_df = penguin_df
pg_df.head()
pg_df.shape
pg_df.species.unique()
pg_df.island.unique()
pg_df.dropna(inplace=True)
pg_df = pd.get_dummies(pg_df, columns=["island","sex"])
y = pg_df.pop('species')
X = pg_df
x_train, x_valid, y_train, y_valid = train_test_split(X,y,random_state=10,stratify=y, test_size=0.25)
y_train.value_counts(normalize=True)
y_valid.value_counts(normalize=True)
```

```
# using naive bayes
from sklearn.naive_bayes import GaussianNB
nb_model = OneVsRestClassifier(GaussianNB())
nb_model.fit(x_train, y_train)
nb_accuracy = nb_model.score(x_valid, y_valid)
print(nb_accuracy)
```

```
# using decision tree
from sklearn.tree import DecisionTreeClassifier
dt_model = OneVsRestClassifier(DecisionTreeClassifier())
dt_model.fit(x_train, y_train)
dt_accuracy = dt_model.score(x_valid, y_valid)
print(dt_accuracy)
gaussian.append(nb_accuracy)
decision.append(dt_accuracy)
```

```
accuracy = [nb_accuracy, dt_accuracy]
Models = ['NaiveBayes','DecisionTree']
sns.barplot(x=Models,y=accuracy).set(title="Penguin  Dataset")
```

```
y_score_gnb = nb_model.predict_proba(x_valid)
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid.values, y_score_gnb.values)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
```

```
y_score_dtc = dt_model.predict_proba(x_valid)
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid.values, y_score_dtc.values)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
```

```
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})".format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})".format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()
```

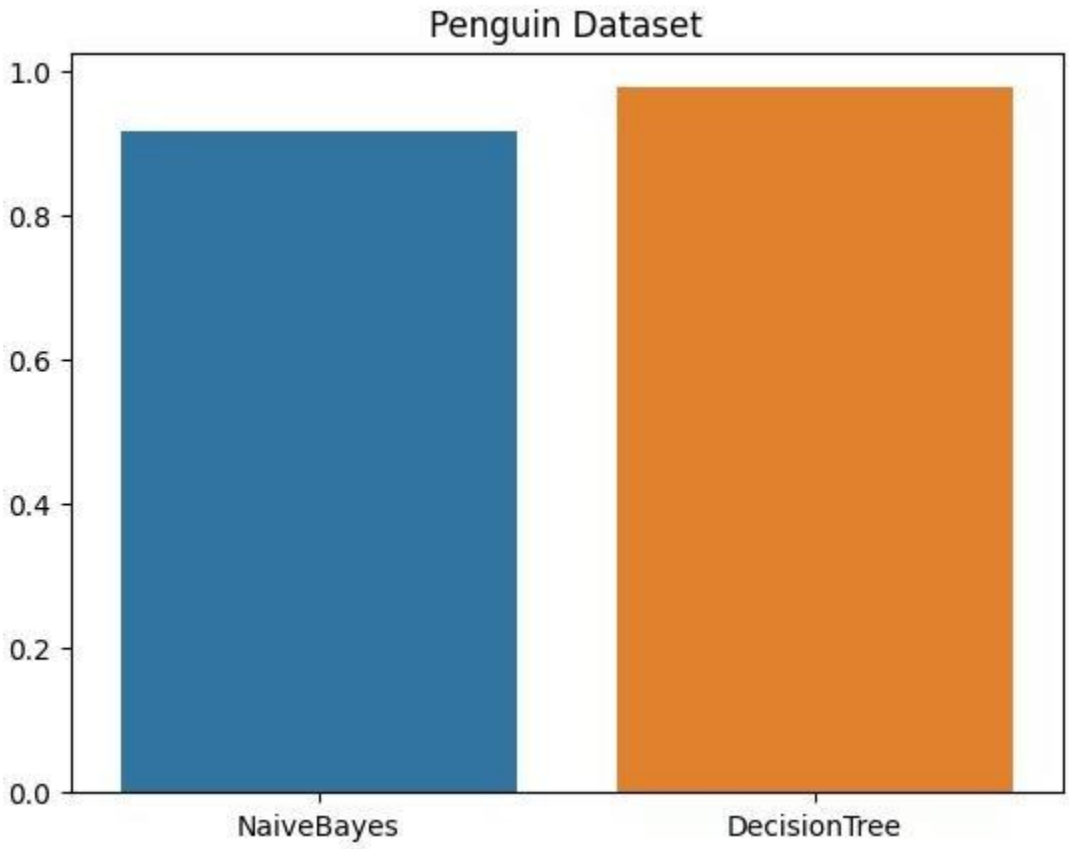
```
#  confiusion matrix
q = y_valid
pred_test = dt_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title='DecisionTree Confusion Matrix", cmap="BuGn")
```

```
y_test = q
```

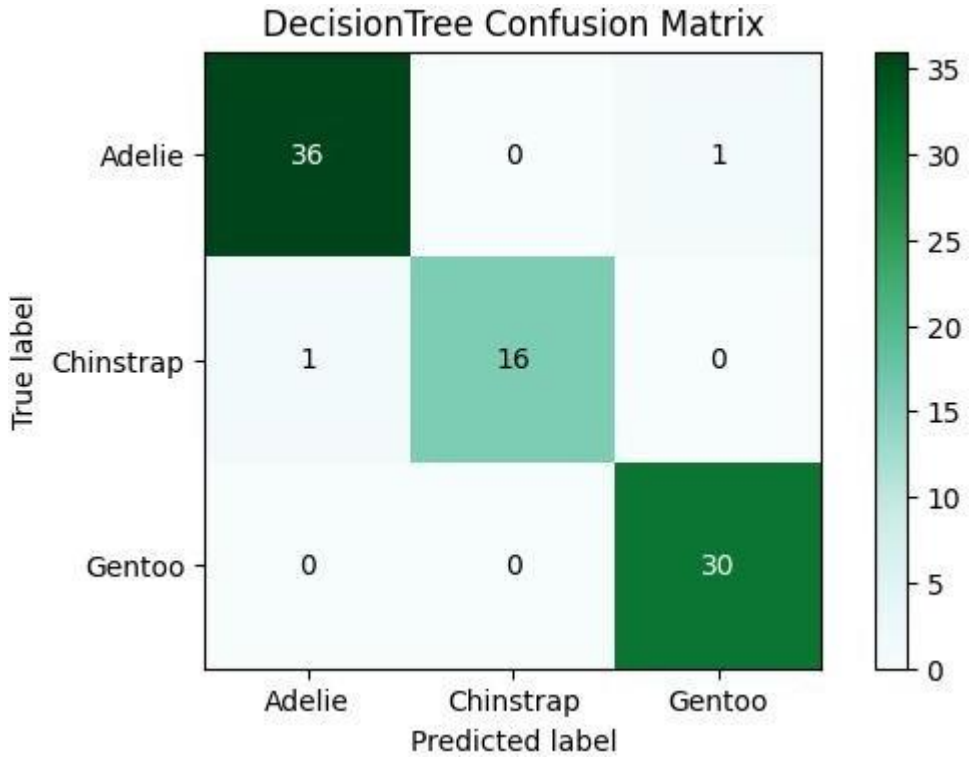
```
q = y_valid
pred_test = nb_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title="GaussianNB Confusion Matrix", cmap="BuGn")
y_test = q
```

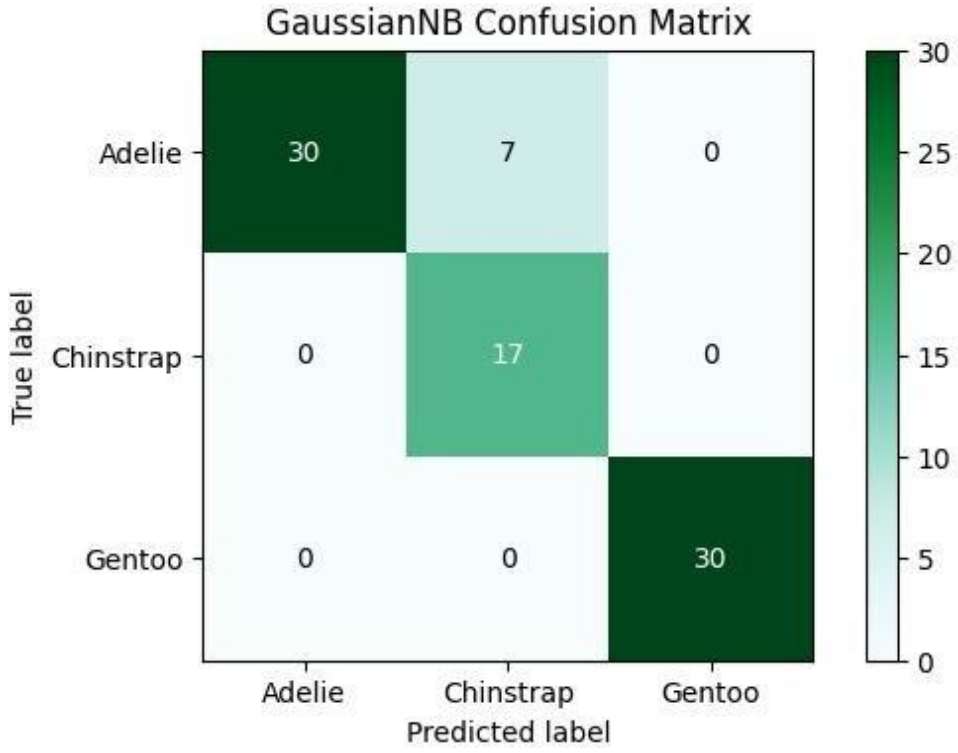
```
# auc - roc
y_score_gnb = nb_model.predict_proba(x_valid)
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid.values, y_score_gnb.values)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
y_score_dtc = dt_model.predict_proba(x_valid)
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid.values, y_score_dtc.values)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})'.format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})'.format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()
```

Accuracies of both models :

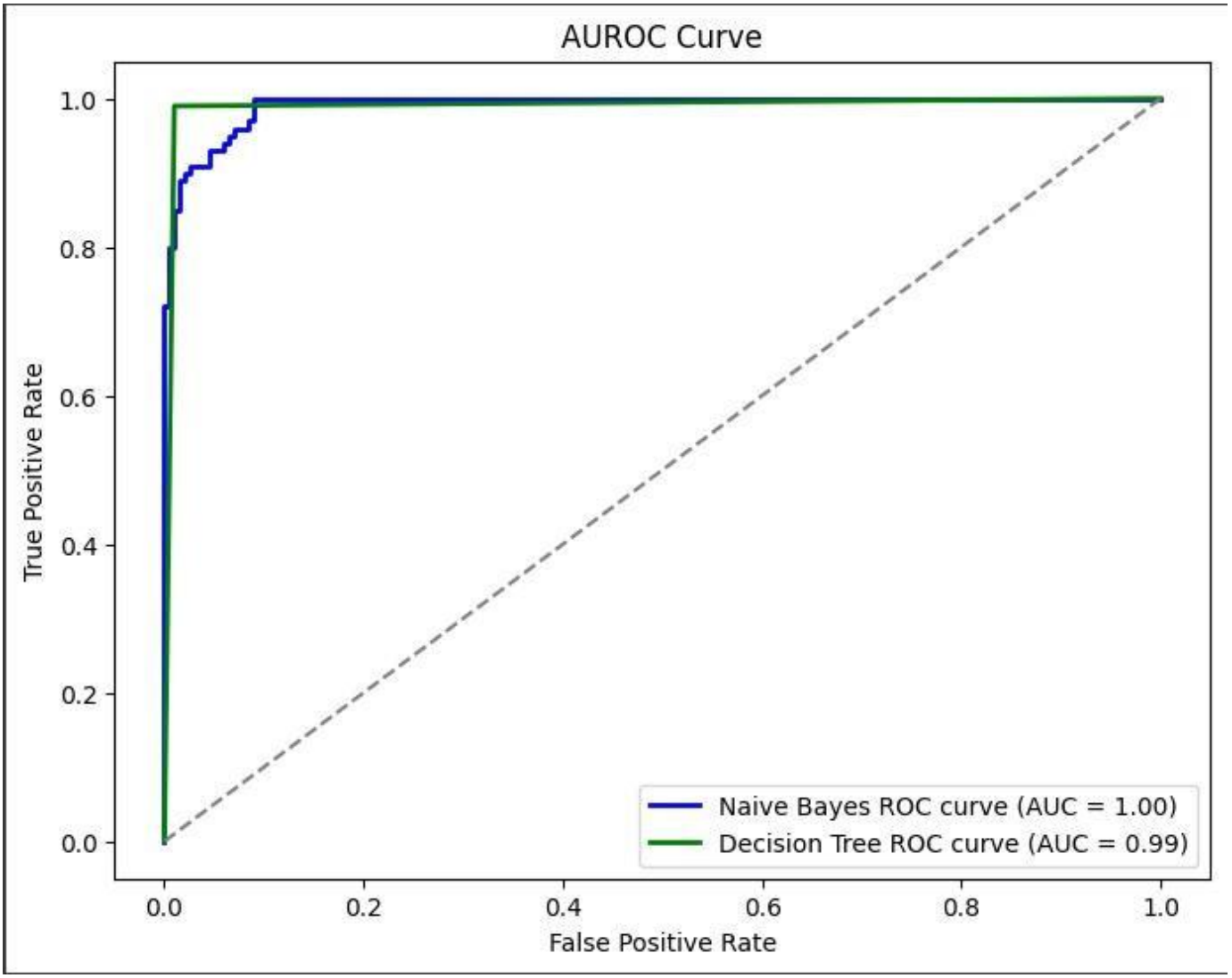


Confusion Matrix :





AUROC:


AUROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Naive Bayes ROC curve (AUC = 1.00)
Decision Tree ROC curve (AUC = 0.99)

Dataset 3 (Iris):

```
""" ### Iris"""
iris_df.head()
iris_df.species.unique()
y = iris_df.pop('species')
X = iris_df
x_train, x_valid, y_train, y_valid = train_test_split(X,y,random_state=10,stratify=y, test_size=0.25)
y_train.value_counts(normalize=True)
```

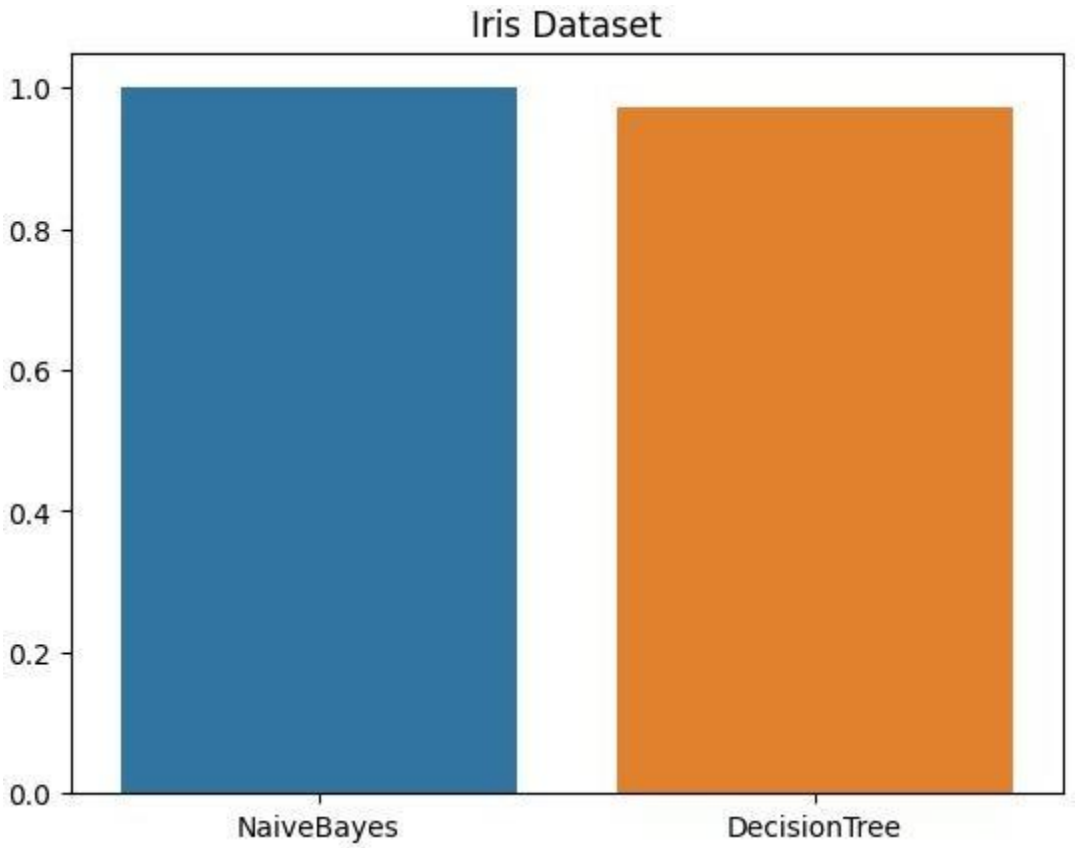
```
# using naive bayes
from sklearn.naive_bayes import GaussianNB
nb_model = GaussianNB()
nb_model.fit(x_train, y_train)
nb_accuracy = nb_model.score(x_valid, y_valid)
print(nb_accuracy)
```

```
# using decision tree
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier()
dt_model.fit(x_train, y_train)
dt_accuracy = dt_model.score(x_valid, y_valid)
print(dt_accuracy)
gaussian.append(nb_accuracy)
decision.append(dt_accuracy)
accuracy = [nb_accuracy, dt_accuracy]
Models = ['NaiveBayes','DecisionTree']
sns.barplot(x=Models,y=accuracy).set(title="Iris  Dataset")
```

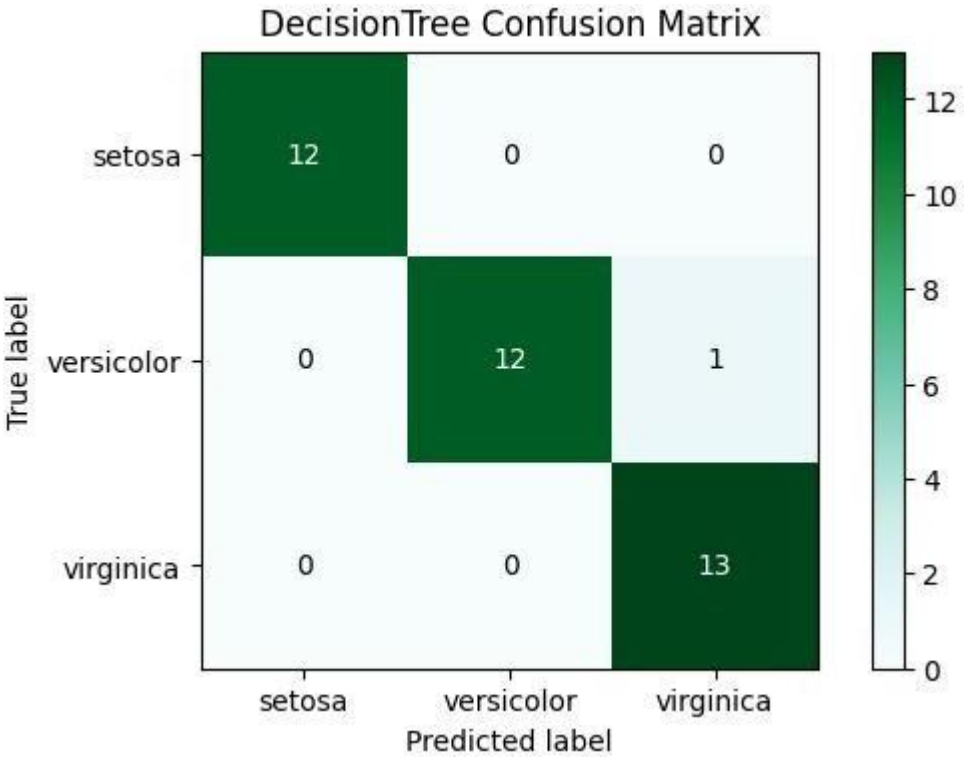
```
q = y_valid
pred_test = dt_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title='DecisionTree Confusion Matrix", cmap="BuGn")
y_test = q
q = y_valid
pred_test = nb_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title="GaussianNB Confusion Matrix", cmap="BuGn")
y_test = q
```

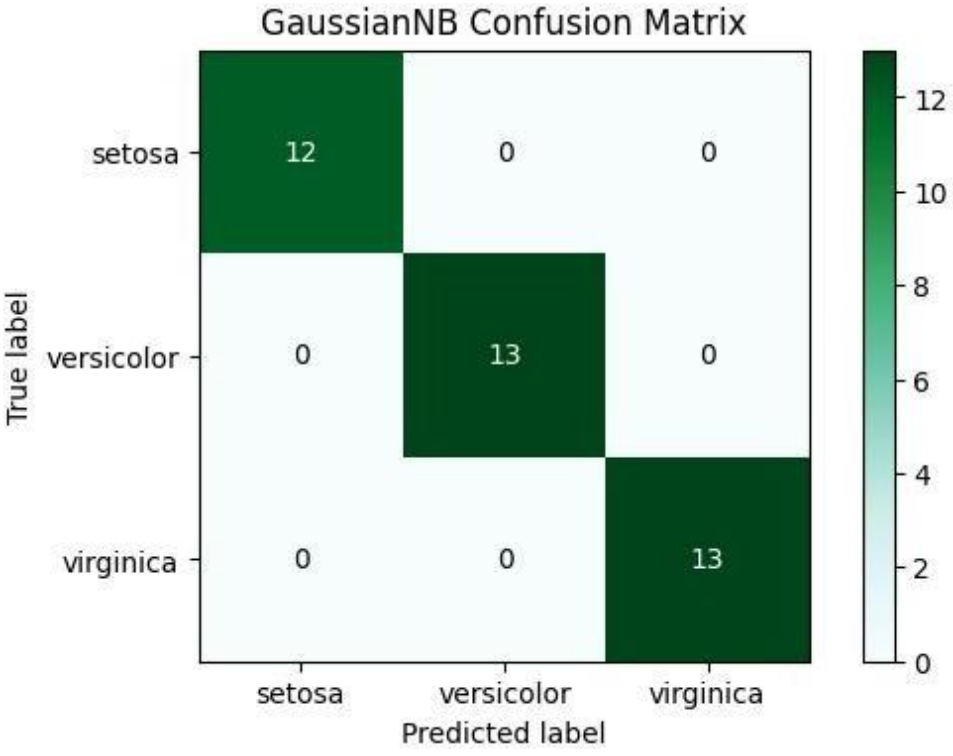
```
# auc - roc
y_score_gnb = nb_model.predict_proba(x_valid)
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid.values, y_score_gnb.values)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
y_score_dtc = dt_model.predict_proba(x_valid)
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid.values, y_score_dtc.values)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})".format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})".format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()
```

Accuracies of both models :

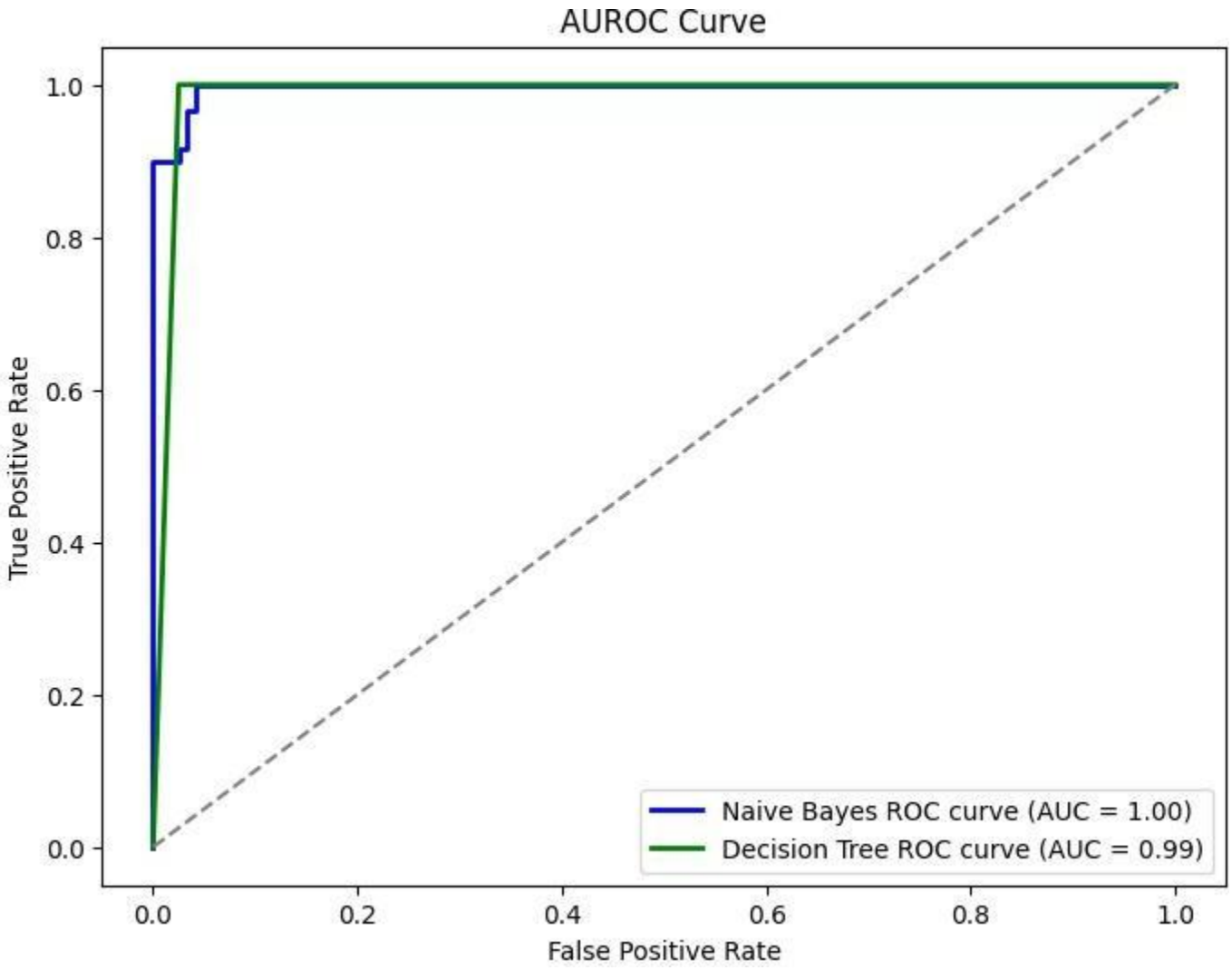


Confusion Matrix :





AUROC:


AUROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Naive Bayes ROC curve (AUC = 1.00)
Decision Tree ROC curve (AUC = 0.99)

Dataset 4 (Email spam-ham dataset):

```
""" ### spam """
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
import string
from nltk.tokenize import word_tokenize
import re
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import lightgbm as ltb
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
import nltk
nltk.download("punkt")
nltk.download("stopwords")
nltk.download("wordnet")
```

```
spam_df.head()

def cleaning (text):
    # text = text.lower()
    text =  re.sub(r'@\S+', '',text)
    text =  re.sub(r'http\S+', '',text) # remove urls
    text =  re.sub(r'pic.\S+', '',text)
    text =  re.sub(r"[^a-zA-ZáéíóúÁÉÍÓÚ']", ' ',text) # only keeps characters
    text =  re.sub(r'\s+[a-zA-ZáéíóúÁÉÍÓÚ]\s+', ' ', text+' ')  # keep words with length>1 only
    text = "".join([i for i in text if i not in string.punctuation])
    words = word_tokenize(text)
    stopwords = nltk.corpus.stopwords.words('english')   # remove stopwords
    text = " ".join([i for i in words if i not in stopwords])
    text= re.sub("\s[\s]+", " ",text).strip()
    text= re.sub("\s[\s]+", " ",text).strip() # remove repeated/leading/trailing spaces
    return text
```

```
def lemmatize(data):
    wordnet = WordNetLemmatizer()
    lemmanized = []
    for i in range(len(data)):
        lemmed = []
        words = word_tokenize(data['Message'].iloc[i])
        for w in words:
            lemmed.append(wordnet.lemmatize(w))
        lemmanized.append(lemmed)

    data['lemmanized'] = lemmanized
    data['text'] = data['lemmanized'].apply(' '.join)
    data=data.drop("lemmanized",axis=1)
    data=data.drop("Message",axis=1)
    return data
spam_df = lemmatize(spam_df)
```

```
obj = {"ham":0,"spam":1}
spam_df["Category"]=spam_df["Category"].map(obj)
X = spam_df["text"]
y = spam_df["Category"]
x_train, x_valid, y_train, y_valid = train_test_split(X,y,random_state=10,stratify=y, test_size=0.25)
y_train.value_counts(normalize=True)
from sklearn.feature_extraction.text import TfidfVectorizer
x_train.shape
tfidf = TfidfVectorizer()
X_train = tfidf.fit_transform(x_train)
x_valid = tfidf.transform(x_valid)
```

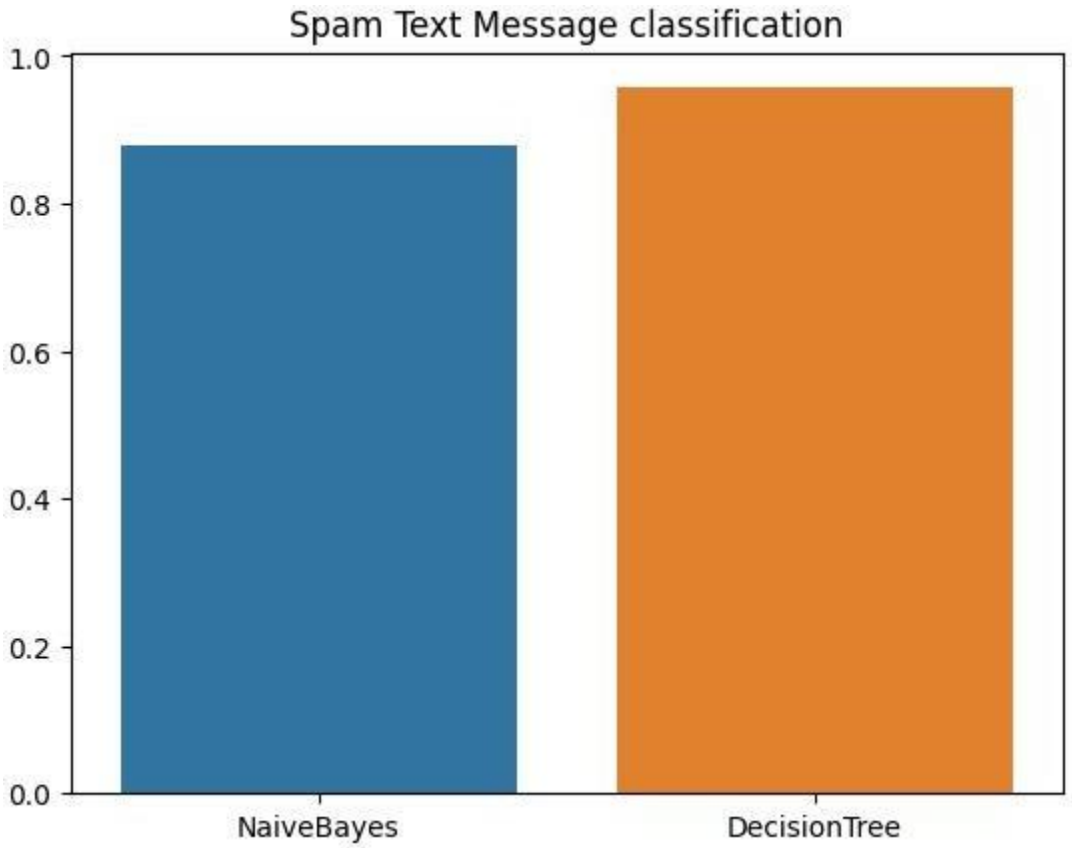
```
dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
pred = dt_model.predict(x_valid)
dt_accuracy = accuracy_score(pred, y_valid)
print(dt_accuracy)
```

```
nb_model = GaussianNB()
nb_model.fit(X_train.toarray(), y_train)
pred = nb_model.predict(x_valid.toarray())
nb_accuracy = accuracy_score(pred, y_valid)
print(nb_accuracy)
gaussian.append(nb_accuracy)
decision.append(dt_accuracy)
accuracy = [nb_accuracy, dt_accuracy]
Models = ['NaiveBayes','DecisionTree']
sns.barplot(x=Models,y=accuracy).set(title="Spam Text Message classification")
```

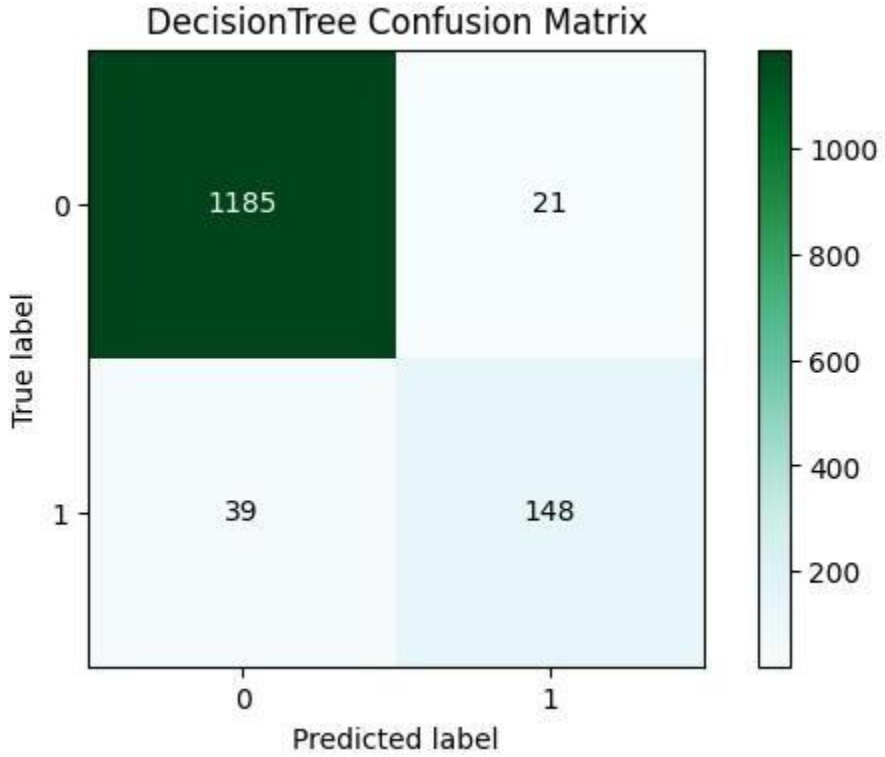
```
# auc - roc
y_score_gnb = nb_model.predict_proba(x_valid.toarray())[:, 1]
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid, y_score_gnb)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
y_score_dtc = dt_model.predict_proba(x_valid)[:, 1]
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid, y_score_dtc)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})".format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})".format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()
```

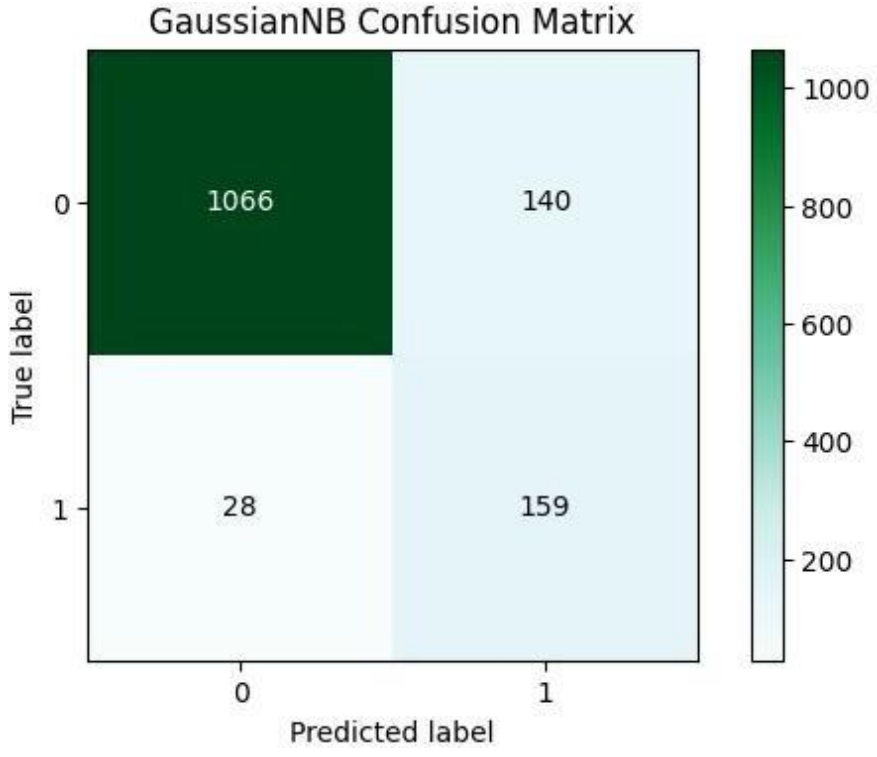
```
# confiusion matrix
q = y_valid
pred_test = dt_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title='DecisionTree Confusion Matrix", cmap="BuGn")
y_valid = q
q = y_valid
pred_test = nb_model.predict(x_valid.toarray())
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title="GaussianNB Confusion Matrix", cmap="BuGn")
y_valid = q
```

Accuracies of both models :

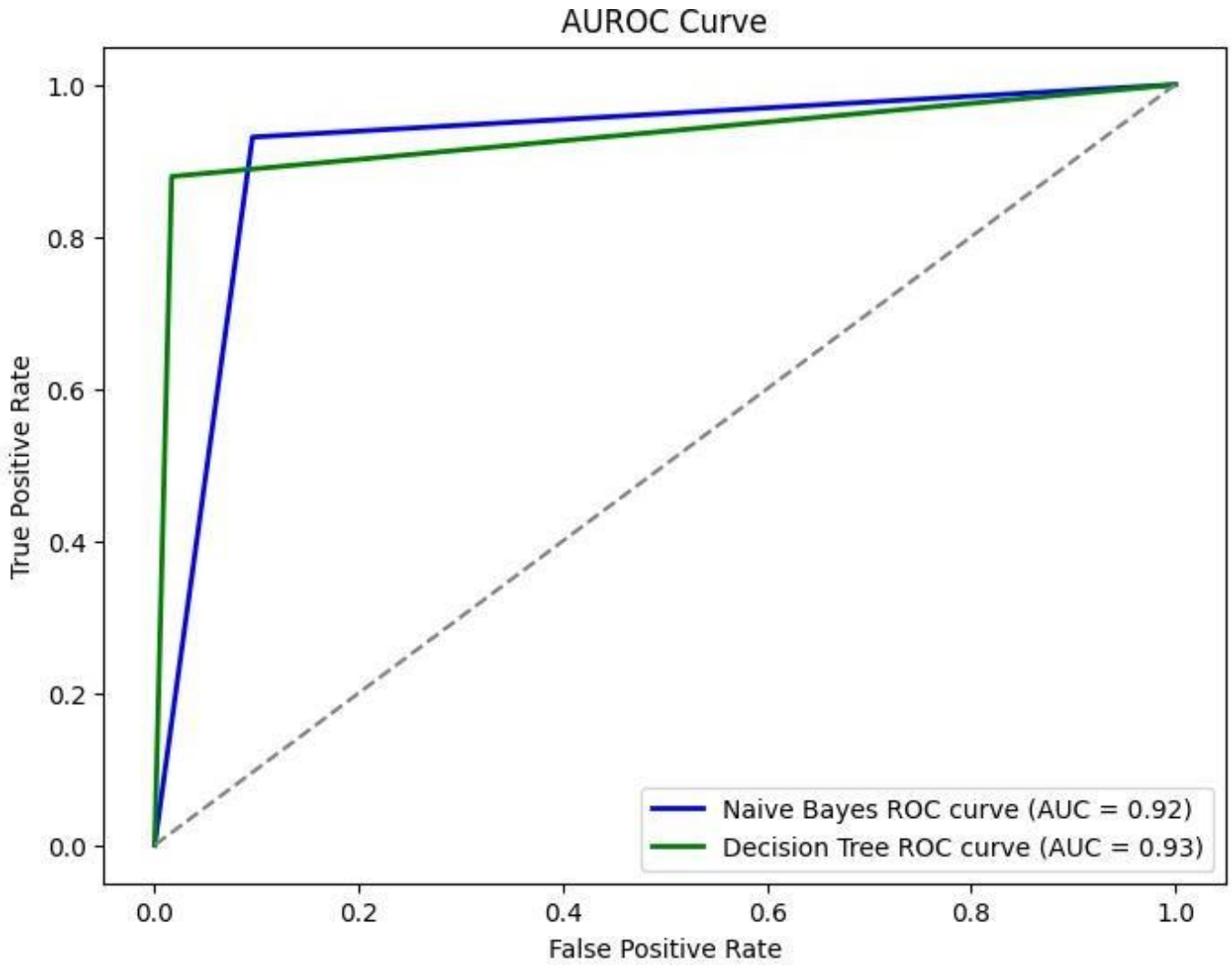


Confusion Matrix :





AUROC:


AUROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Naive Bayes ROC curve (AUC = 0.92)
Decision Tree ROC curve (AUC = 0.93)

Dataset 5 (Wine Quality Dataset):

```
""" ### wine dataset"""
wine_df.head()
y  =  wine_df.pop("quality")
X = wine_df
x_train, x_valid, y_train, y_valid = train_test_split(X,y,random_state=10,stratify=y, test_size=0.25)
y_train.value_counts(normalize=True)
```

```
# using naive bayes
nb_model = GaussianNB()
nb_model.fit(x_train, y_train)
nb_accuracy = nb_model.score(x_valid, y_valid)
print(nb_accuracy)
```

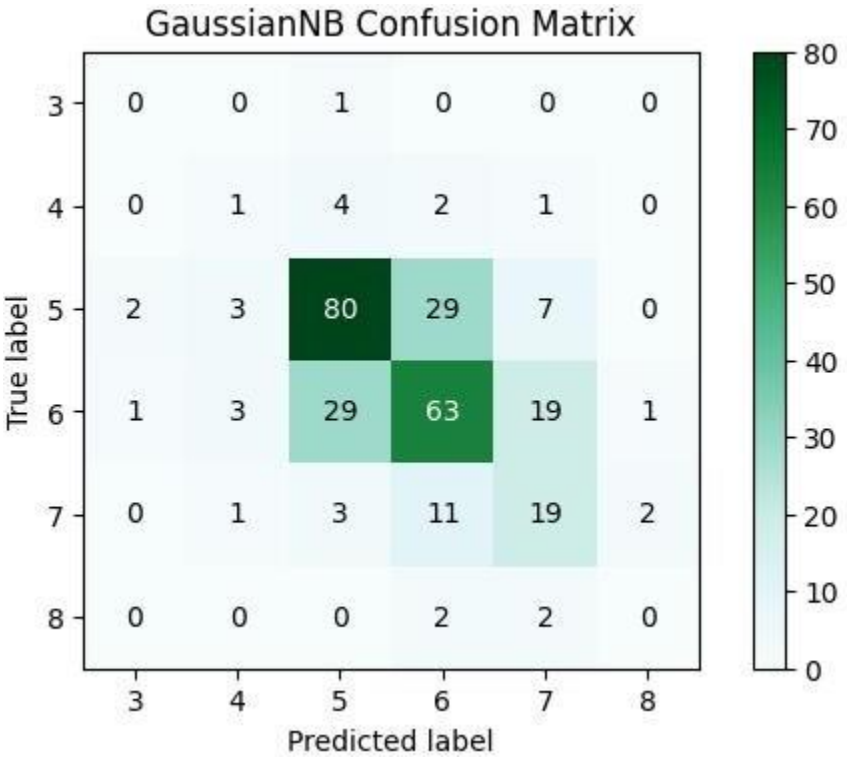
```
# using decision tree
dt_model = DecisionTreeClassifier()
dt_model.fit(x_train, y_train)
dt_accuracy = dt_model.score(x_valid, y_valid)
print(dt_accuracy)
gaussian.append(nb_accuracy)
decision.append(dt_accuracy)
accuracy = [nb_accuracy, dt_accuracy]
Models = ['NaiveBayes','DecisionTree']
sns.barplot(x=Models,y=accuracy).set(title="Wine  Quality  Classifier")
```

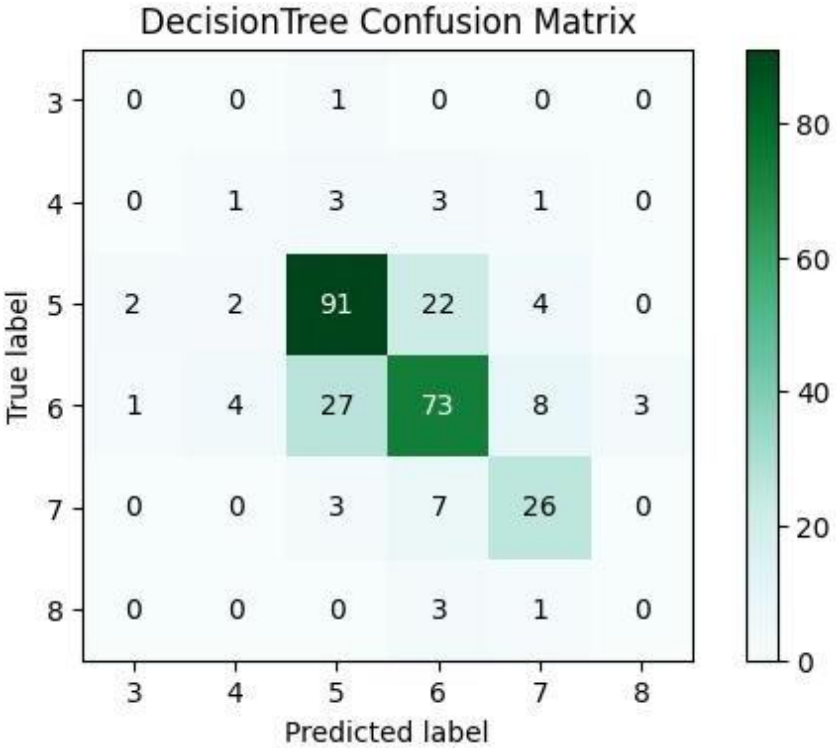
```
# roc - auc
y_score_gnb = nb_model.predict_proba(x_valid)
fpr_gnb, tpr_gnb, thresholds_gnb = roc_curve(y_valid.values, y_score_gnb.values)
roc_auc_gnb = roc_auc_score(y_valid, y_score_gnb)
y_score_dtc = dt_model.predict_proba(x_valid)
fpr_dtc, tpr_dtc, thresholds_dtc = roc_curve(y_valid.values, y_score_dtc.values)
roc_auc_dtc = roc_auc_score(y_valid, y_score_dtc)
plt.figure(figsize=(8, 6))
plt.plot(fpr_gnb, tpr_gnb, color='blue', lw=2, label='Naive Bayes ROC curve (AUC = {:.2f})".format(roc_auc_gnb))
plt.plot(fpr_dtc, tpr_dtc, color='green', lw=2, label='Decision Tree ROC curve (AUC =
{:.2f})".format(roc_auc_dtc))
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title("ROC-AUC Curve')
plt.legend(loc="lower right')
plt.show()
```

```
#  confiusion matrix
q = y_valid
pred_test = nb_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title="GaussianNB Confusion Matrix", cmap="BuGn")
y_test= q
q = y_valid
pred_test = dt_model.predict(x_valid)
pred_test = pd.DataFrame(pred_test)
y_valid = pd.DataFrame(y_valid)
plot_confusion_matrix(y_valid, pred_test, figsize=(7,4), title='DecisionTree Confusion Matrix", cmap="BuGn")
ytest = q
```

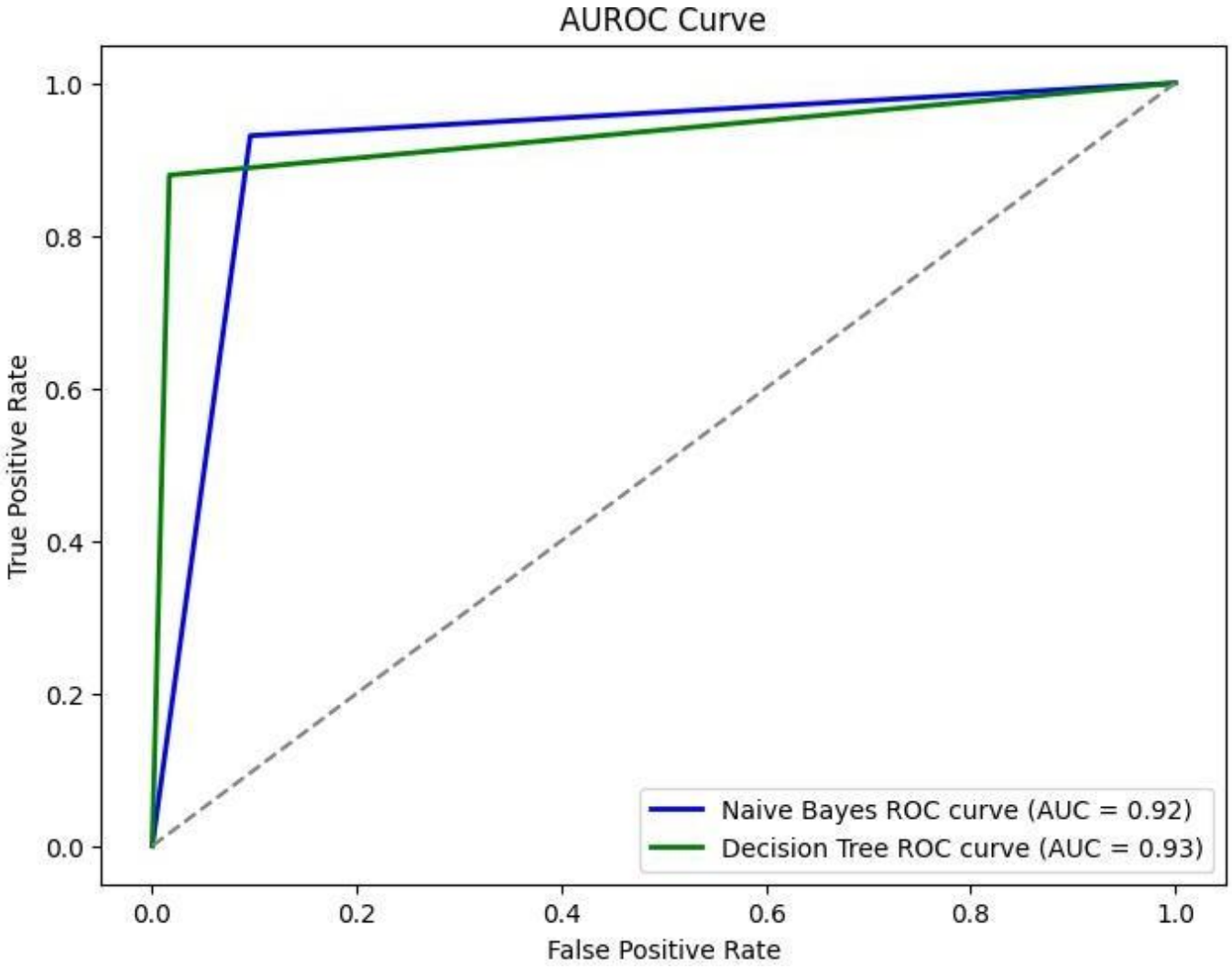
Accuracies of both models :

Confusion Matrix :





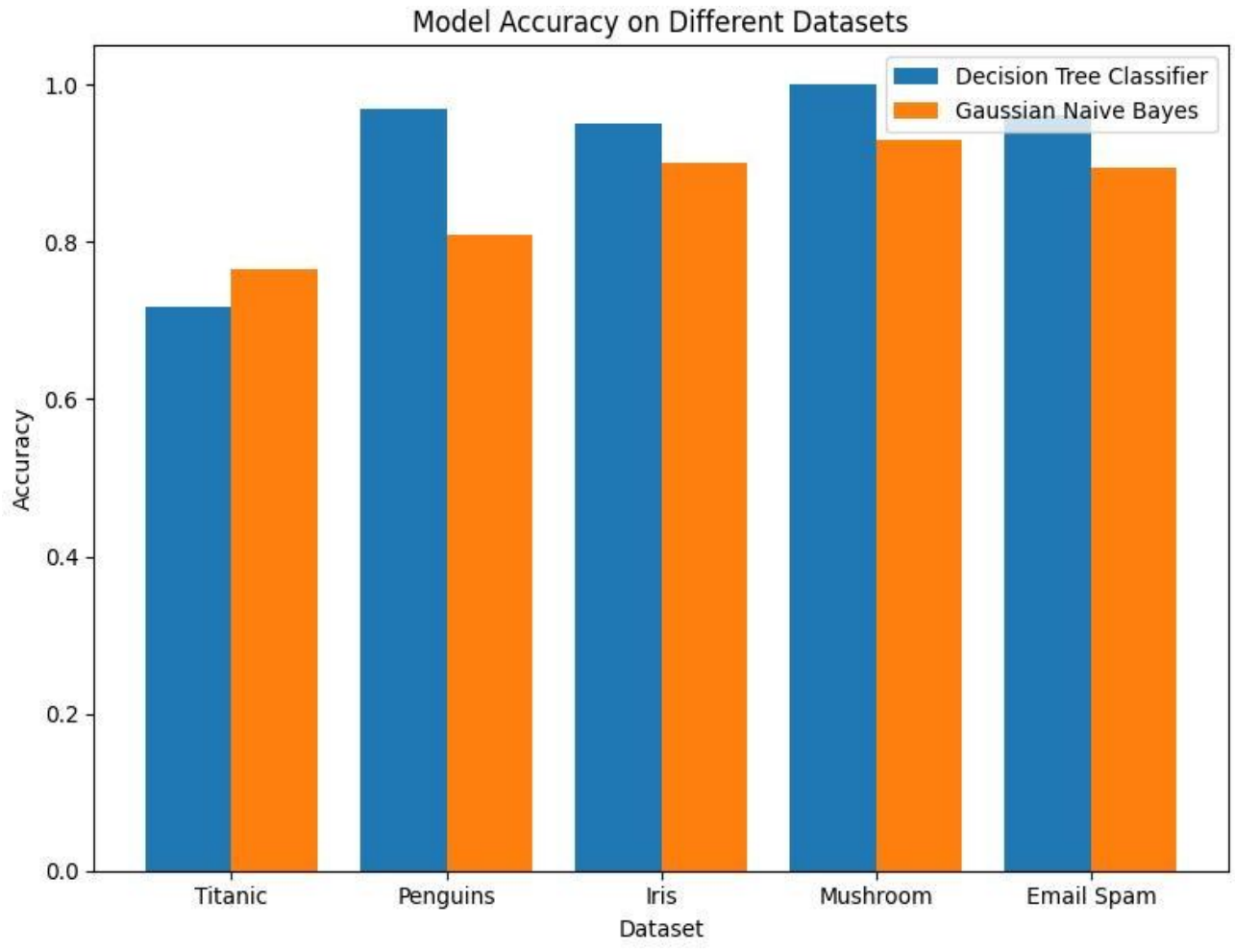
AUROC:


AUROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Naive Bayes ROC curve (AUC = 0.92)
Decision Tree ROC curve (AUC = 0.93)

Plot comparison graphs using the results of DT and NB

```
def grouped_barplot(data1, data2, labels, xticklabels=None, title="Grouped Barplot"):
    positions = np.arange(len(labels))
    width = 0.35
    # Create the grouped barplot
    plt.figure(figsize=(8, 6))
    plt.bar(positions - width/2, data1, width, label="Group 1")
    plt.bar(positions + width/2, data2, width, label="Group 2")
    plt.xlabel('Dataset')
    plt.ylabel('Acurracy')
    plt.title(title)
    # Set x-axis ticks and labels
    plt.xticks(positions,  labels)
    if xticklabels:
        plt.xticks(positions,  xticklabels)
    plt.legend()
    plt.show()
category_labels = ['Titanic', 'Penguin', 'Iris', "Email spam", "Wine"]
grouped_barplot(gaussian, decision, category_labels, title="Model Comparison")
```

comparison graphs:



Part C:

Modify DT/NB to use k-fold cross validation and ensemble models :Kfolds cross validation of 7 folds :

Modification Titanic Dataset :

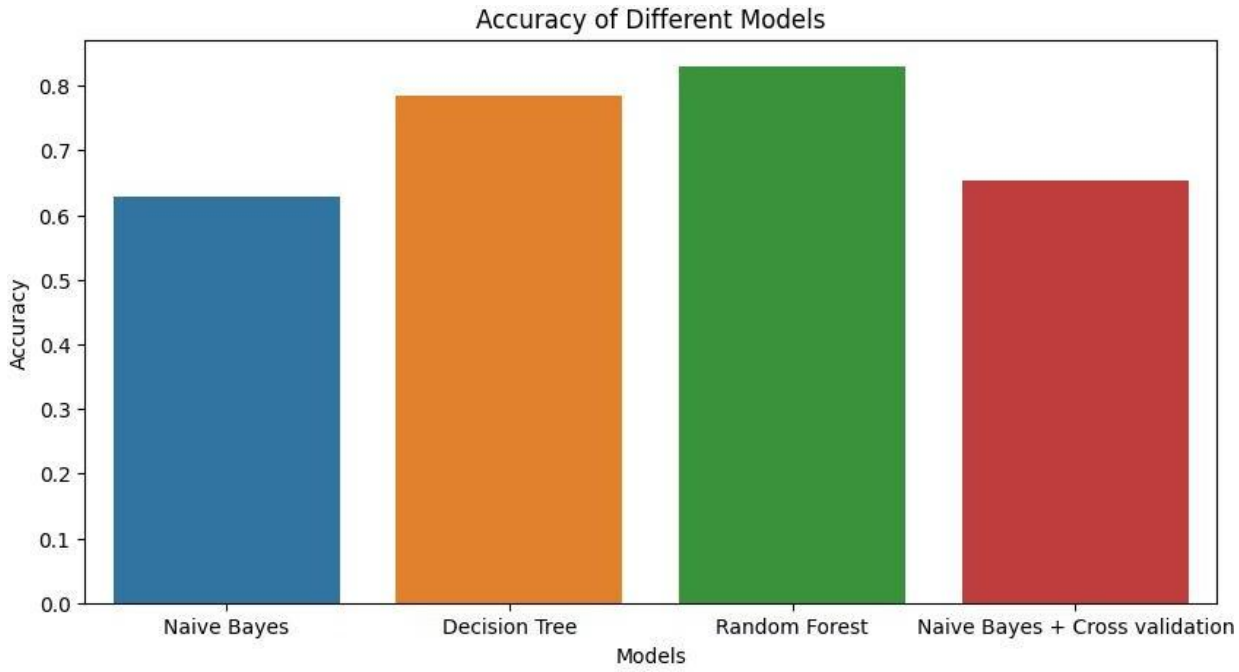
```
from sklearn.model_selection import KFold, cross_val_score
kf = KFold(n_splits=7,shuffle=True,random_state=10)
cv_score = cross_val_score(estimator=nb_model,X=x_train,y=y_train,cv=kf,scoring="accuracy")
mean_cv_score = np.mean(cv_score)
print(mean_cv_score)
```

```
# ensemble tech - RandomForest
from sklearn.ensemble import RandomForestClassifier
```

```
rf_model = RandomForestClassifier()
rf_model.fit(x_train, y_train)
rf_accuracy = rf_model.score(x_valid, y_valid)
print(rf_accuracy)
```

```
accuracies=[nb_accuracy,dt_accuracy,rf_accuracy,mean_cv_score]
plt.figure(figsize=(10,5))
models=[' Naive Bayes','Decision Tree','Random Forest',' Naive Bayes + Cross validation']
sns.barplot(x=models,y=accuracies,).set(title='Part C')
plt.xlabel("Models")
plt.ylabel('Accuracy')
plt.title('Accuracy of Different Models')
```

Comparison k-fold cross validation and ensemble models :



Conclusion:

Thus, we have successfully implemented Classification algorithm using Decision Tree ID3 and Naïve Bayes algorithm and performed all the parts