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IT464 Lab Assignment 2

(i) Apply Decision tree, Naive Bayes classifiers and Random Forest to detect the target as yes or no (for bank data) and to detect the diabetes as yes or no (for diabetes data) using the following data sets. (40M)
https://www.kaggle.com/datasets/krantiswalke/bankfullcsv
https://www.kaggle.com/datasets/shashankvichare/diabetes-prediction (ii) Test the algorithm's performance on the following test datasets. Test Datasets: (a) bank-test.xls (b) diabetes-test.xls

Bank

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix,roc_curve,auc
import matplotlib.pyplot as plt
df = pd.read_csv("bank-full.csv")

categorical_cols = ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome', 'Target']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

X = df.drop(columns=['Target'])
y = df['Target']


scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# ------------------------------
# Decision Tree Classifier
# ------------------------------
dt = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=10,
                            max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0,
                            min_samples_leaf=2, min_samples_split=5, min_weight_fraction_leaf=0.0,
                            random_state=None, splitter='best')
dt.fit(X_train, y_train)
dt_pred = dt.predict(X_test)

print("=== Decision Tree ===")
print("Accuracy:", accuracy_score(y_test, dt_pred))
print("Classification Report:\n", classification_report(y_test, dt_pred))
cm = confusion_matrix(y_test, dt_pred)
print("\nConfusion Matrix:")
print(cm)
```

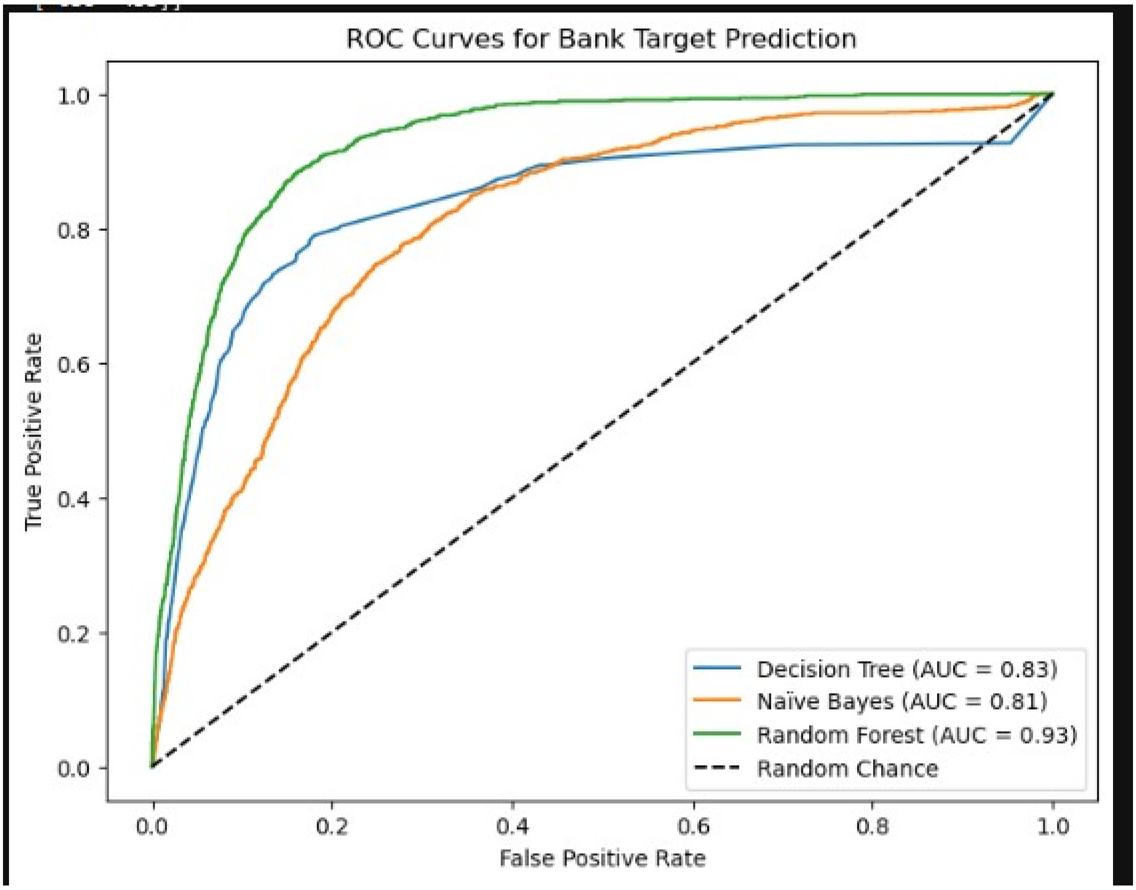
```python
# -----------------------------
# Naïve Bayes Classifier
# -----------------------------
nb = GaussianNB()
nb.fit(X_train, y_train)
nb_pred = nb.predict(X_test)

print("=== Naïve Bayes ===")
print("Accuracy:", accuracy_score(y_test, nb_pred))
print("Classification Report:\n", classification_report(y_test, nb_pred))
cm = confusion_matrix(y_test, nb_pred)
print("\nConfusion Matrix:")
print(cm)
# -----------------------------
# Random Forest Classifier
# -----------------------------
rf = RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None, criterion='gini',
                            max_depth=20, max_features='sqrt', max_leaf_nodes=None, max_samples=None,
                            min_impurity_decrease=0.0, min_samples_leaf=1, min_samples_split=2,
                            min_weight_fraction_leaf=0.0, n_estimators=200, random_state=42)
rf.fit(X_train, y_train)
rf_pred = rf.predict(X_test)

print("=== Random Forest ===")
print("Accuracy:", accuracy_score(y_test, rf_pred))
print("Classification Report:\n", classification_report(y_test, rf_pred))
cm = confusion_matrix(y_test, rf_pred)
print("\nConfusion Matrix:")
print(cm)

# -----------------------------
# Compute ROC Curves and AUC for Each Model
# -----------------------------

dt_probs = dt.predict_proba(X_test)[:, 1]
dt_fpr, dt_tpr, _ = roc_curve(y_test, dt_probs)
dt_auc = auc(dt_fpr, dt_tpr)

nb_probs = nb.predict_proba(X_test)[:, 1]
nb_fpr, nb_tpr, _ = roc_curve(y_test, nb_probs)
nb_auc = auc(nb_fpr, nb_tpr)

rf_probs = rf.predict_proba(X_test)[:, 1]
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_probs)
rf_auc = auc(rf_fpr, rf_tpr)
```

```python
plt.figure(figsize=(8, 6))
plt.plot(dt_fpr, dt_tpr, label=f'Decision Tree (AUC = {dt_auc:.2f})')
plt.plot(nb_fpr, nb_tpr, label=f'Naïve Bayes (AUC = {nb_auc:.2f})')
plt.plot(rf_fpr, rf_tpr, label=f'Random Forest (AUC = {rf_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Chance')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Bank Target Prediction')
plt.legend(loc='lower right')
plt.show()
```

```python
test_df=pd.read_excel("bank-test.xlsx",header=4);
test_df=test_df.iloc[1:]
test_df=test_df.drop(test_df.columns[0],axis=1)
test_df
for col in test_df.columns:
    test_df[col] = test_df[col].astype(str).str.lower()

month_map = {
    "january": "jan", "february": "feb", "march": "mar", "april": "apr",
    "may": "may", "june": "jun", "july": "jul", "august": "aug",
    "september": "sep", "october": "oct", "november": "nov", "december": "dec"
}

test_df["month"] = test_df["month"].str.strip().str.lower().replace(month_map)

for col in categorical_cols[:-1]:
    if col in test_df.columns:
        test_df[col] = label_encoders[col].transform(test_df[col])

test_X_scaled = scaler.transform(test_df)

test_predictions = {
    "Decision Tree": dt.predict(test_X_scaled),
    "Naïve Bayes": nb.predict(test_X_scaled),
    "Random Forest": rf.predict(test_X_scaled)
}

for model_name, predictions in test_predictions.items():
    print(f"=== {model_name} Predictions ===")
    print(predictions)
```

Output

```
=== Decision Tree ===
Accuracy: 0.8912971359062258
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.96      0.94      7952
           1       0.57      0.40      0.47      1091

    accuracy                           0.89      9043
   macro avg       0.75      0.68      0.70      9043
weighted avg       0.88      0.89      0.88      9043


Confusion Matrix:
[[7624  328]
 [ 655  436]]
=== Naive Bayes ===
Accuracy: 0.8248368904124738
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.87      0.90      7952
           1       0.34      0.49      0.40      1091

    accuracy                           0.82      9043
   macro avg       0.63      0.68      0.65      9043
weighted avg       0.86      0.82      0.84      9043


Confusion Matrix:
[[6922 1030]
 [ 554  537]]
=== Random Forest ===
Accuracy: 0.9020236647130377
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.97      0.95      7952
           1       0.65      0.42      0.51      1091

    accuracy                           0.90      9043
   macro avg       0.78      0.69      0.73      9043
weighted avg       0.89      0.90      0.89      9043


Confusion Matrix:
[[7704  248]
 [ 638  453]]
```



Predictions

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	Decision Tree Prediction	Naïve Bayes Prediction	Random Forest Prediction
1	40.0	0	2	1	0	1303.0	1	1	0	6.0	4	1585.0	8.0	405.0	405.0	2	No	Yes	Yes
2	66.0	1	1	2	1	50775.0	0	0	2	21.0	9	646.0	22.0	94.0	94.0	0	No	Yes	No
3	50.0	2	2	0	0	24161.0	1	0	1	25.0	2	1395.0	49.0	414.0	414.0	1	Yes	Yes	Yes
4	72.0	3	0	3	1	-134.0	1	1	2	20.0	9	381.0	30.0	576.0	576.0	2	Yes	Yes	Yes
5	61.0	4	1	2	0	-1382.0	0	0	0	23.0	6	1096.0	52.0	257.0	257.0	0	Yes	Yes	No
6	77.0	5	1	1	1	68792.0	0	1	0	28.0	8	653.0	54.0	498.0	498.0	2	No	Yes	Yes
7	44.0	6	0	1	1	864.0	1	1	1	2.0	9	590.0	45.0	30.0	30.0	0	No	No	No
8	38.0	7	1	2	0	23208.0	0	1	2	2.0	4	924.0	40.0	84.0	84.0	3	No	No	No
9	26.0	8	2	3	0	2263.0	1	0	0	27.0	2	1379.0	50.0	69.0	69.0	1	Yes	No	Yes
10	84.0	9	0	2	0	28385.0	0	0	1	5.0	5	633.0	8.0	488.0	488.0	2	Yes	Yes	Yes
11	43.0	10	1	1	1	28813.0	0	1	0	22.0	8	928.0	7.0	237.0	237.0	0	Yes	Yes	Yes
12	27.0	4	0	2	0	31857.0	0	1	1	1.0	1	1427.0	35.0	597.0	597.0	2	No	Yes	No
13	32.0	7	2	3	0	33084.0	1	0	1	10.0	2	1883.0	55.0	27.0	27.0	0	Yes	No	No
14	31.0	5	1	0	1	44960.0	0	1	0	19.0	4	1795.0	38.0	595.0	595.0	1	Yes	Yes	No
15	40.0	10	2	2	1	42639.0	1	0	1	16.0	9	1178.0	29.0	24.0	24.0	2	Yes	No	No

Diabetes

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (classification_report, accuracy_score, confusion_matrix,
                             roc_curve, auc)
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt

df = pd.read_csv("Diabetespred.csv")
df.fillna(df.median(), inplace=True)

X = df.drop("Outcome", axis=1)
y = df["Outcome"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled  = scaler.transform(X_test)

sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train_scaled, y_train)

# ------------------------------
# Decision Tree Classifier
# ------------------------------
dt_model = DecisionTreeClassifier(
    criterion='entropy',
    max_depth=None,
    min_samples_split=5,
    min_samples_leaf=2,
    random_state=42
)
dt_model.fit(X_train_res, y_train_res)
y_pred_dt = dt_model.predict(X_test_scaled)

print("----- Decision Tree Classifier -----")
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))

#
```

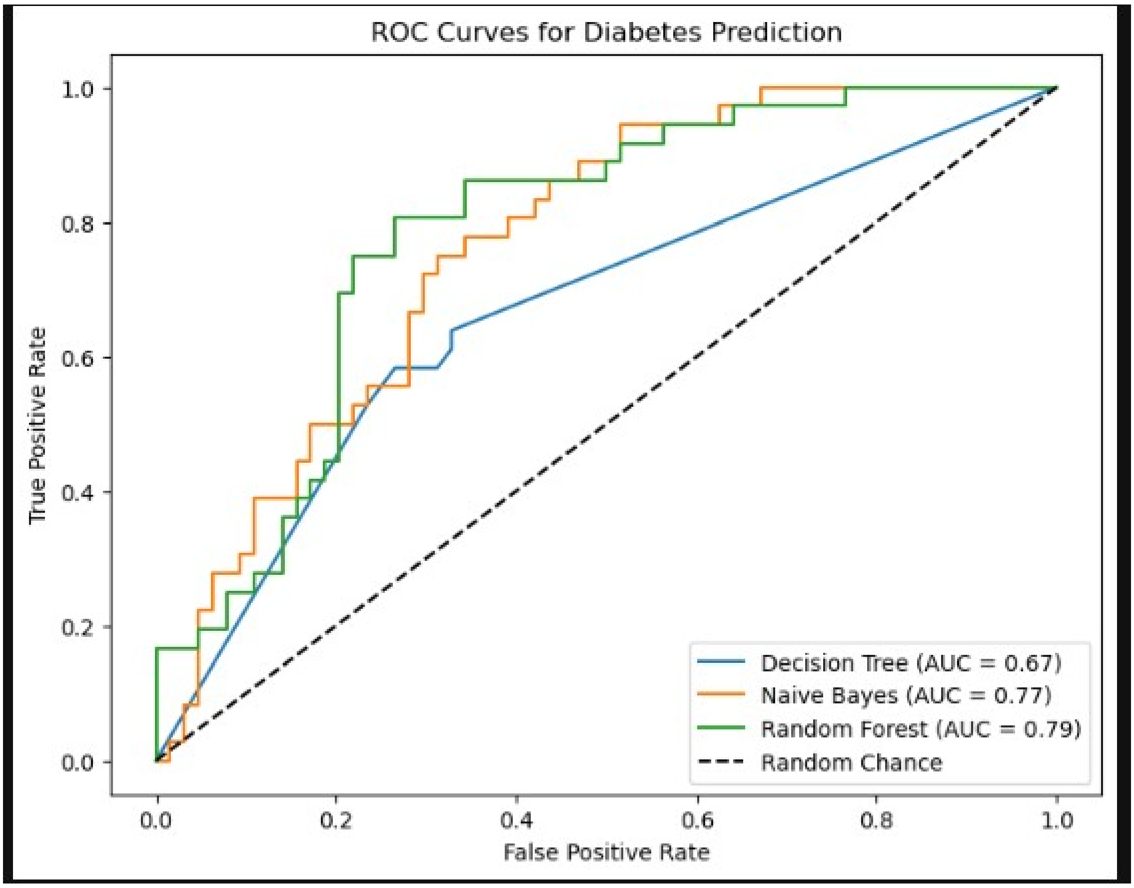
```python
# ------------------------------
# Gaussian Naive Bayes Classifier
# ------------------------------
nb_model = GaussianNB(var_smoothing=1e-09)
nb_model.fit(X_train_res, y_train_res)
y_pred_nb = nb_model.predict(X_test_scaled)

print("\n----- Gaussian Naive Bayes Classifier -----")
print("Accuracy:", accuracy_score(y_test, y_pred_nb))
print("Classification Report:\n", classification_report(y_test, y_pred_nb))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_nb))

# ------------------------------
# Random Forest Classifier
# ------------------------------
rf_model = RandomForestClassifier(
    criterion='gini',
    max_depth=10,
    min_samples_split=5,
    min_samples_leaf=1,
    n_estimators=200,
    random_state=42
)
rf_model.fit(X_train_res, y_train_res)
y_pred_rf = rf_model.predict(X_test_scaled)

print("\n----- Random Forest Classifier -----")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))

# ------------------------------
# ROC Curve and AUC for Each Classifier
# ------------------------------

dt_probs = dt_model.predict_proba(X_test_scaled)[:, 1]  # probabilities for class 1
dt_fpr, dt_tpr, _ = roc_curve(y_test, dt_probs)
dt_auc = auc(dt_fpr, dt_tpr)

nb_probs = nb_model.predict_proba(X_test_scaled)[:, 1]
nb_fpr, nb_tpr, _ = roc_curve(y_test, nb_probs)
nb_auc = auc(nb_fpr, nb_tpr)

rf_probs = rf_model.predict_proba(X_test_scaled)[:, 1]
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_probs)
rf_auc = auc(rf_fpr, rf_tpr)
```

```python
plt.figure(figsize=(8, 6))
plt.plot(dt_fpr, dt_tpr, label=f'Decision Tree (AUC = {dt_auc:.2f})')
plt.plot(nb_fpr, nb_tpr, label=f'Naive Bayes (AUC = {nb_auc:.2f})')
plt.plot(rf_fpr, rf_tpr, label=f'Random Forest (AUC = {rf_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Chance')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Diabetes Prediction')
plt.legend(loc='lower right')
plt.show()
```

```python
test_df=pd.read_excel("diabetes-test.xlsx",header=5)
test_df=test_df.iloc[1:]
test_df=test_df.drop(test_df.columns[0],axis=1)
test_df
test_X_scaled = scaler.transform(test_df)
test_predictions = {
    "Decision Tree": dt_model.predict(test_X_scaled),
    "Naïve Bayes": nb_model.predict(test_X_scaled),
    "Random Forest": rf_model.predict(test_X_scaled)
}

for model_name, predictions in test_predictions.items():
    print(f"=== {model_name} Predictions ===")
    print(predictions)
```

Output

```
----- Decision Tree Classifier -----
Accuracy: 0.65
Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.69      0.72        64
           1       0.51      0.58      0.55        36

    accuracy                           0.65       100
   macro avg       0.63      0.64      0.63       100
weighted avg       0.66      0.65      0.65       100

Confusion Matrix:
 [[44 20]
 [15 21]]

----- Gaussian Naive Bayes Classifier -----
Accuracy: 0.69
Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.72      0.75        64
           1       0.56      0.64      0.60        36

    accuracy                           0.69       100
   macro avg       0.67      0.68      0.67       100
weighted avg       0.70      0.69      0.69       100

Confusion Matrix:
 [[46 18]
 [13 23]]

----- Random Forest Classifier -----
Accuracy: 0.76
Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.78      0.81        64
           1       0.65      0.72      0.68        36

    accuracy                           0.76       100
   macro avg       0.74      0.75      0.75       100
weighted avg       0.77      0.76      0.76       100

Confusion Matrix:
 [[50 14]
 [10 26]]
```



Predictions

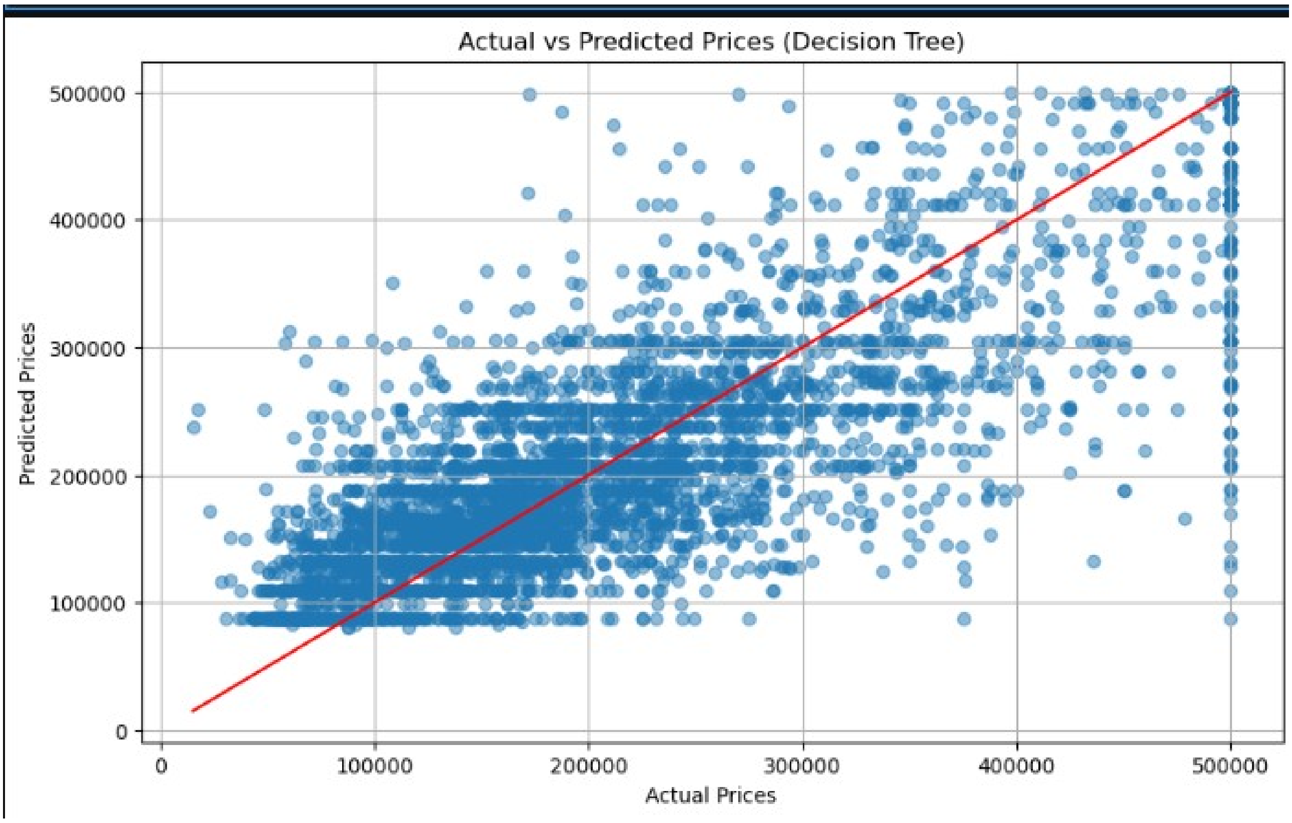
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Decision Tree Prediction	Naïve Bayes Prediction	Random Forest Prediction
1	12.0	49.0	56.0	18.0	331.0	50.0	0.192313	21.0	No	Yes	No
2	4.0	128.0	39.0	53.0	367.0	22.0	0.411382	21.0	Yes	Yes	No
3	15.0	95.0	113.0	40.0	494.0	27.0	0.780781	48.0	Yes	Yes	Yes
4	12.0	77.0	37.0	9.0	193.0	23.0	0.392337	55.0	No	No	No
5	9.0	53.0	83.0	6.0	481.0	24.0	0.861166	63.0	No	Yes	No
6	1.0	96.0	30.0	37.0	473.0	18.0	1.438416	32.0	No	Yes	No
7	4.0	148.0	103.0	49.0	405.0	40.0	1.251075	42.0	Yes	Yes	Yes
8	11.0	120.0	86.0	47.0	450.0	24.0	1.217705	37.0	Yes	Yes	Yes
9	12.0	143.0	88.0	15.0	266.0	29.0	0.833595	60.0	No	Yes	Yes
10	3.0	102.0	114.0	27.0	453.0	28.0	1.709989	70.0	No	Yes	No

Q2. Apply Decision tree for the California Housing Dataset to predict the house price and show it. (10M) https://www.geeksforgeeks.org/dataset-for-linear-regression/ Note: Exclude “longitude, latitude and ocean proximity” parameters/variables. Compute the price for the “housing2” test data using the trained Decision tree.

```python
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
import numpy as np

housing_data = pd.read_csv('housing.csv')
housing_data = housing_data.drop(['longitude', 'latitude', 'ocean_proximity'], axis=1)

housing_data['total_bedrooms'].fillna(housing_data['total_bedrooms'].median(), inplace=True)
housing_data['rooms_per_household'] = housing_data['total_rooms'] / housing_data['households']
housing_data['bedrooms_per_room'] = housing_data['total_bedrooms'] / housing_data['total_rooms']
housing_data['population_per_household'] = housing_data['population'] / housing_data['households']

housing_data['median_income'] = np.log1p(housing_data['median_income'])
housing_data['total_rooms'] = np.log1p(housing_data['total_rooms'])

X = housing_data.drop('median_house_value', axis=1)
y = housing_data['median_house_value']

poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_poly)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

dt_model = DecisionTreeRegressor(max_depth=8, min_samples_split=10, min_samples_leaf=4, random_state=42)
dt_model.fit(X_train, y_train)

y_pred = dt_model.predict(X_test)

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices (Decision Tree)')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
plt.grid(True)
plt.show()

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

```python
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R-squared Score (R²): {r2:.4f}")

housing_test_data = pd.read_csv("housing2.csv", skiprows=2)
housing_test_data = housing_test_data.drop(housing_test_data.columns[0], axis=1)
housing_test_data = housing_test_data.drop(index=housing_test_data.index[0]).reset_index(drop=True)
expected_columns = ['housing_median_age', 'total_rooms', 'total_bedrooms', 'population', 'households', 'median_income']
housing_test_data = housing_test_data[expected_columns]

housing_test_data['total_bedrooms'].fillna(housing_test_data['total_bedrooms'].median(), inplace=True)

housing_test_data['rooms_per_household'] = housing_test_data['total_rooms'] / housing_test_data['households']
housing_test_data['bedrooms_per_room'] = housing_test_data['total_bedrooms'] / housing_test_data['total_rooms']
housing_test_data['population_per_household'] = housing_test_data['population'] / housing_test_data['households']


housing_test_data['median_income'] = np.log1p(housing_test_data['median_income'])
housing_test_data['total_rooms'] = np.log1p(housing_test_data['total_rooms'])

housing_test_data_poly = poly.transform(housing_test_data)

housing_test_data_scaled = scaler.transform(housing_test_data_poly)

housing_test_predictions = dt_model.predict(housing_test_data_scaled)
housing_test_data['Predicted_Price'] = housing_test_predictions

print("\nTest Data with Predictions:")
housing_test_data
```

Output



```
Mean Absolute Error (MAE): 50022.68
Mean Squared Error (MSE): 4857231631.10
Root Mean Squared Error (RMSE): 69693.84
R-squared Score (R²): 0.6293
```

Predictions

Test Data with Predictions:

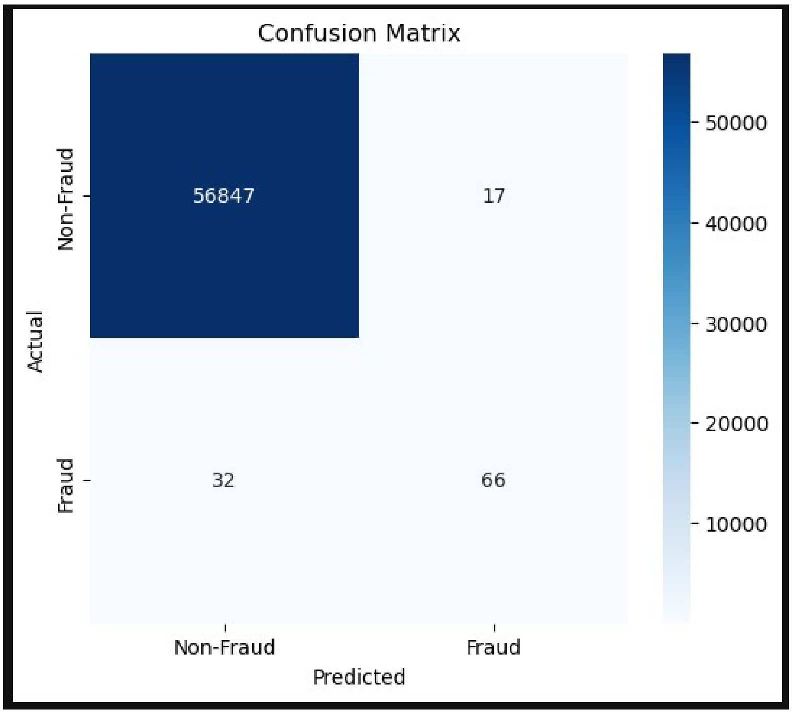
	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	rooms_per_household	bedrooms_per_room	population_per_household	Predicted_Price
0	20.0	8.322151	302.0	999.0	302.0	2.052905	13.619205	0.073426	3.307947	296684.210526
1	10.0	8.966739	645.0	2307.0	265.0	1.113829	29.573585	0.082302	8.705660	245533.444444
2	63.0	9.068546	619.0	1659.0	227.0	2.254161	38.224670	0.071338	7.308370	438157.285714
3	46.0	8.230844	984.0	607.0	334.0	2.034758	11.239521	0.262120	1.817365	479654.915663
4	10.0	8.366835	578.0	653.0	391.0	1.886660	11.000000	0.134387	1.670077	314410.100000
5	23.0	8.307213	458.0	1458.0	285.0	2.047719	14.217544	0.113031	5.115789	296684.210526
6	9.0	9.179159	791.0	1472.0	369.0	1.840661	26.265583	0.081614	3.989160	192886.440678
7	42.0	8.434464	916.0	657.0	353.0	2.180508	13.036827	0.199044	1.861190	491122.459459
8	5.0	8.865594	101.0	1289.0	383.0	2.241029	18.493473	0.014259	3.365535	472050.500000
9	33.0	8.603554	404.0	980.0	481.0	1.550325	11.330561	0.074128	2.037422	480200.250000

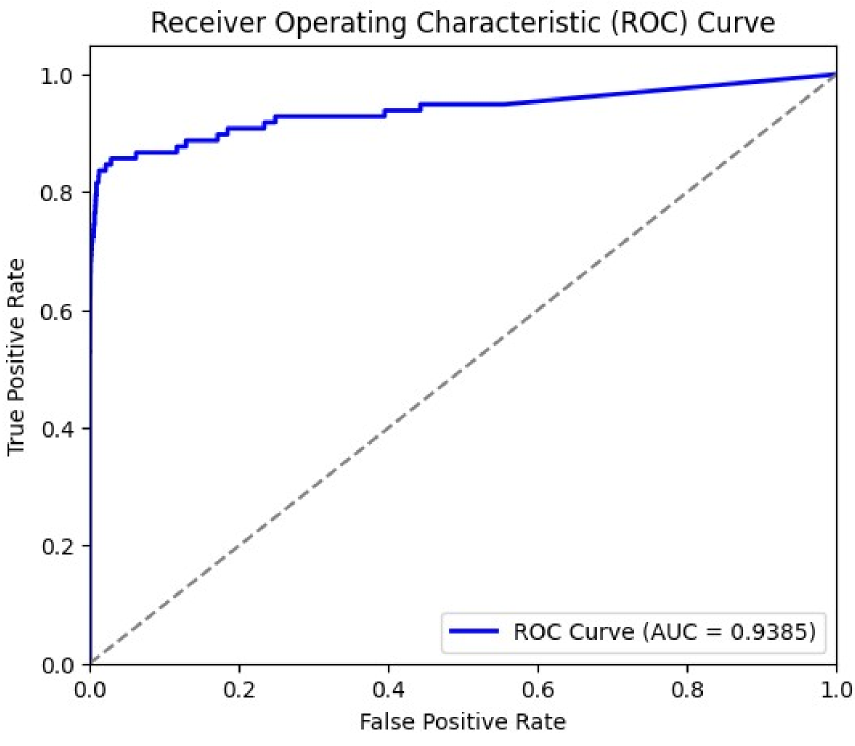
Q3. Perform SVM and Bayes classifiers on the following data to predict credit card fraud. (20M) https://www.kaggle.com/datasets/nishipatkar/credit-card-details (a) Predict credit card fraud for the test data: creditcard-test.xls

SVM

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix

from imblearn.over_sampling import SMOTE

df = pd.read_csv("creditcard.csv")
print("Class distribution in dataset before SMOTE:")
print(df['Class'].value_counts())

X = df.drop(columns=['Class'])
y = df['Class']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

smote = SMOTE(sampling_strategy=0.1,random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

svm_model = SVC(kernel='rbf', C=10, gamma='auto', random_state=42)
svm_model.fit(X_train_resampled, y_train_resampled)

y_pred = svm_model.predict(X_test)

print("Updated Classification Report:")
print(classification_report(y_test, y_pred))

plt.figure(figsize=(6, 5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues',
            xticklabels=['Non-Fraud', 'Fraud'], yticklabels=['Non-Fraud', 'Fraud'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```
Class distribution in dataset before SMOTE:
Class
0    284315
1       492
Name: count, dtype: int64
Updated Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56864
           1       0.80      0.67      0.73        98

    accuracy                           1.00     56962
   macro avg       0.90      0.84      0.86     56962
weighted avg       1.00      1.00      1.00     56962
```





Predictions

```
test_df = pd.read_excel("creditcard-test.xlsx", header=3)
test_df = test_df.iloc[1:].reset_index(drop=True)
test_df = test_df.drop(test_df.columns[0], axis=1)
test_df = test_df.apply(pd.to_numeric, errors='coerce')

X_test_new = scaler.transform(test_df)
y_test_pred = svm_model.predict(X_test_new)
test_df['Predicted Class'] = y_test_pred

test_df
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Predicted Class
0	11707.0	7.28	-0.53	8.17	9.32	1.11	0.53	-0.43	9.69	9.72	...	6.07	1.13	0.46	9.82	3.30	5.07	-0.71	-0.91	958.184120	0
1	75775.0	0.76	5.92	-0.69	-0.49	7.88	1.13	6.90	3.62	0.00	...	3.35	0.10	5.18	1.85	4.39	-0.24	8.38	8.82	822.209306	0
2	50010.0	-0.92	7.57	6.30	2.68	2.93	0.32	5.06	0.15	5.29	...	6.11	5.35	7.84	7.02	-0.73	2.97	2.22	5.75	61.662134	0
3	11996.0	4.00	1.22	0.65	4.29	7.33	-0.45	1.19	1.57	7.58	...	4.94	0.20	3.60	2.41	3.28	8.67	6.05	5.99	956.869145	0
4	3360.0	8.60	6.43	-0.34	10.00	0.36	7.91	4.96	8.80	3.94	...	4.96	6.72	9.73	8.07	0.11	8.31	9.96	7.78	159.284273	0
5	71278.0	2.63	-0.31	3.91	1.75	-0.12	0.89	8.17	1.13	5.53	...	7.10	8.75	5.97	-0.26	9.98	5.18	2.07	1.04	282.008097	0
6	15904.0	8.27	4.01	6.60	8.61	6.04	9.74	6.60	3.67	9.28	...	8.75	6.50	9.99	3.69	3.92	8.26	-0.66	6.67	109.150863	0
7	47645.0	7.86	2.27	0.87	9.47	6.45	-0.12	1.41	0.68	8.83	...	2.65	5.60	2.94	4.44	4.70	9.25	2.96	-0.68	839.448067	0
8	40430.0	0.27	1.17	5.53	4.90	9.94	7.12	6.69	6.89	3.64	...	5.44	5.75	-0.20	9.61	7.96	-0.52	-0.71	3.52	120.055819	0
9	14347.0	1.85	9.79	0.96	0.00	8.24	2.39	0.28	8.34	9.68	...	1.87	4.88	9.15	2.60	2.51	-0.89	3.61	-0.93	201.238715	0

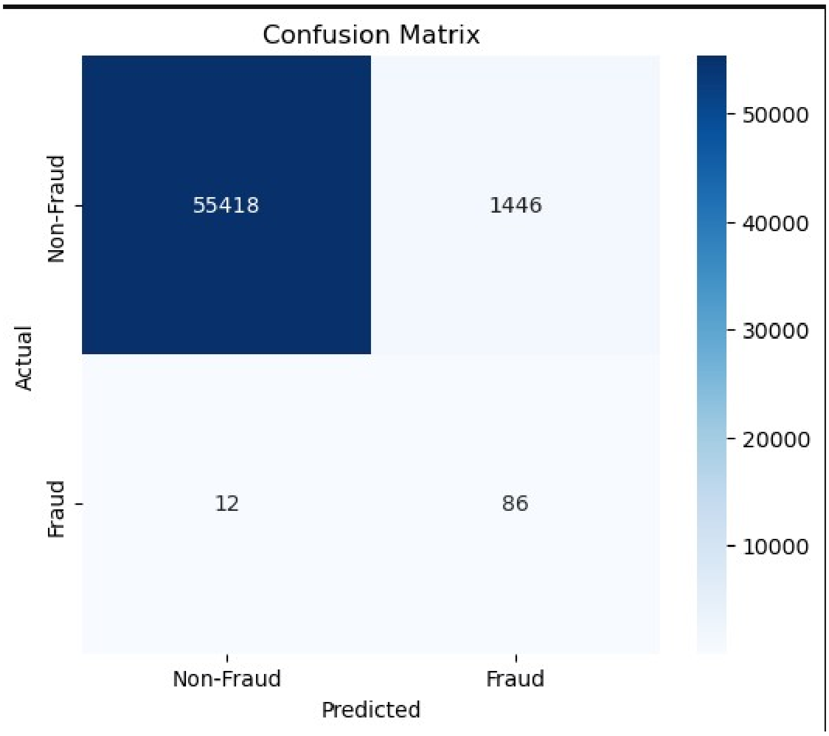
10 rows × 31 columns

Naive Bayes

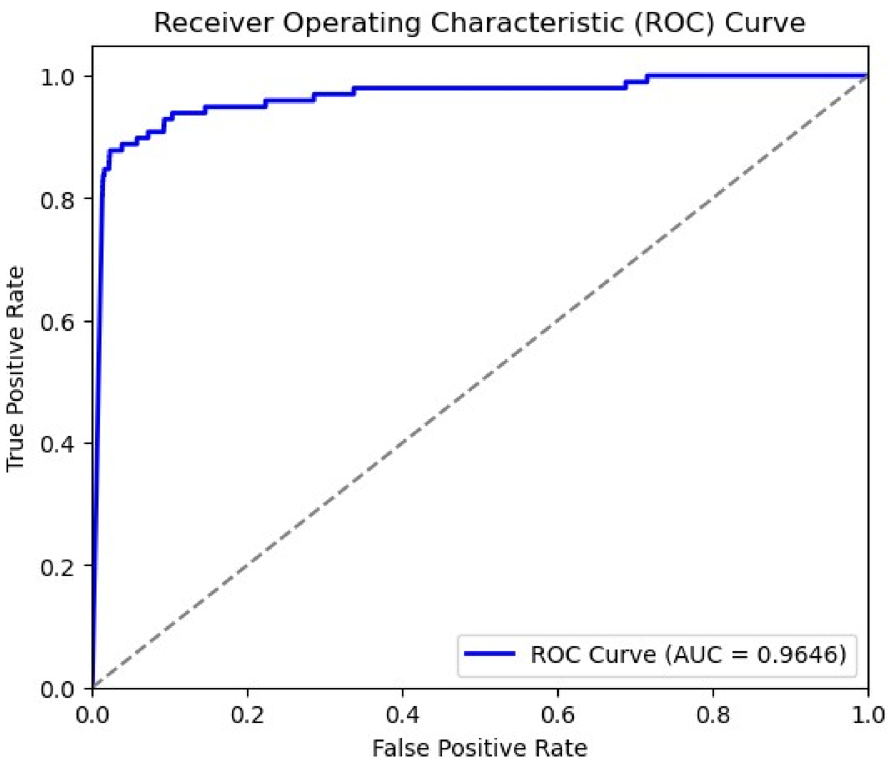
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from imblearn.over_sampling import SMOTE


df = pd.read_csv("creditcard.csv")
print("Class distribution in dataset before SMOTE:")
print(df['Class'].value_counts())

X = df.drop(columns=['Class'])
y = df['Class']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42, stratify=y)

smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

nb_model = GaussianNB()
nb_model.fit(X_train_resampled, y_train_resampled)

y_pred = nb_model.predict(X_test)
y_pred_prob = nb_model.predict_proba(X_test)[:, 1]

print("Updated Classification Report:")
print(classification_report(y_test, y_pred))

plt.figure(figsize=(6, 5))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues',
            xticklabels=['Non-Fraud', 'Fraud'], yticklabels=['Non-Fraud', 'Fraud'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```python
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

test_df = pd.read_excel("creditcard-test.xlsx", header=3)
test_df = test_df.iloc[1:].reset_index(drop=True)
test_df = test_df.drop(test_df.columns[0], axis=1)
test_df = test_df.apply(pd.to_numeric, errors='coerce')

X_test_new = scaler.transform(test_df)
y_test_pred = nb_model.predict(X_test_new)
test_df['Predicted Class'] = y_test_pred

test_df
```

```
Class distribution in dataset before SMOTE:
Class
0    284315
1       492
Name: count, dtype: int64
Updated Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.99     56864
           1       0.06      0.88      0.11        98

    accuracy                           0.97     56962
   macro avg       0.53      0.93      0.55     56962
weighted avg       1.00      0.97      0.99     56962
```



Confusion Matrix
Non-Fraud
Fraud
Actual
55418
1446
12
86
Non-Fraud
Fraud
Predicted
50000
40000
30000
20000
10000



Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
ROC Curve (AUC = 0.9646)
0.0
0.2
0.4
0.6
0.8
1.0

Predictions

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Predicted Class
0	11707.0	7.28	-0.53	8.17	9.32	1.11	0.53	-0.43	9.69	9.72	...	6.07	1.13	0.46	9.82	3.30	5.07	-0.71	-0.91	958.184120	1
1	75775.0	0.76	5.92	-0.69	-0.49	7.88	1.13	6.90	3.62	0.00	...	3.35	0.10	5.18	1.85	4.39	-0.24	8.38	8.82	822.209306	1
2	50010.0	-0.92	7.57	6.30	2.68	2.93	0.32	5.06	0.15	5.29	...	6.11	5.35	7.84	7.02	-0.73	2.97	2.22	5.75	61.662134	1
3	11996.0	4.00	1.22	0.65	4.29	7.33	-0.45	1.19	1.57	7.58	...	4.94	0.20	3.60	2.41	3.28	8.67	6.05	5.99	956.869145	1
4	3360.0	8.60	6.43	-0.34	10.00	0.36	7.91	4.96	8.80	3.94	...	4.96	6.72	9.73	8.07	0.11	8.31	9.96	7.78	159.284273	1
5	71278.0	2.63	-0.31	3.91	1.75	-0.12	0.89	8.17	1.13	5.53	...	7.10	8.75	5.97	-0.26	9.98	5.18	2.07	1.04	282.008097	1
6	15904.0	8.27	4.01	6.60	8.61	6.04	9.74	6.60	3.67	9.28	...	8.75	6.50	9.99	3.69	3.92	8.26	-0.66	6.67	109.150863	1
7	47645.0	7.86	2.27	0.87	9.47	6.45	-0.12	1.41	0.68	8.83	...	2.65	5.60	2.94	4.44	4.70	9.25	2.96	-0.68	839.448067	1
8	40430.0	0.27	1.17	5.53	4.90	9.94	7.12	6.69	6.89	3.64	...	5.44	5.75	-0.20	9.61	7.96	-0.52	-0.71	3.52	120.055819	1
9	14347.0	1.85	9.79	0.96	0.00	8.24	2.39	0.28	8.34	9.68	...	1.87	4.88	9.15	2.60	2.51	-0.89	3.61	-0.93	201.238715	1

Q4. Perform KNN Classification to detect the diabetes as yes or no (for diabetes data) and to classify the flower type (for flower data) using the following data sets. (30M) https://www.kaggle.com/datasets/shashankvichare/diabetes-prediction https://www.kaggle.com/datasets/arshid/iris-flower-dataset (a) diabetes-test.xls (b) flower-test.xls

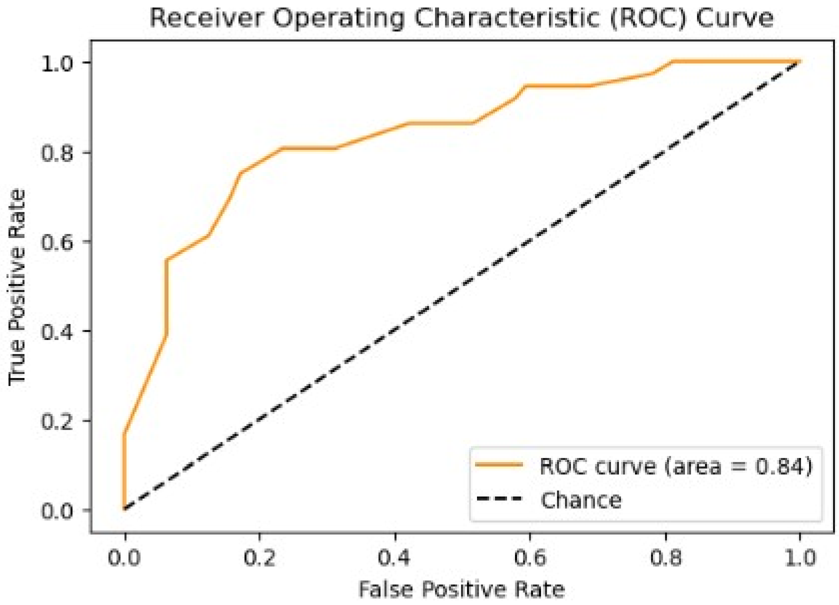
Diabetes

```python
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.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (accuracy_score, confusion_matrix, classification_report,
                             roc_auc_score, roc_curve)
from imblearn.over_sampling import SMOTE

diabetes_df = pd.read_csv("Diabetespred.csv")

X = diabetes_df.drop('Outcome', axis=1)
y = diabetes_df['Outcome']


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)


smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)


scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_smote)
X_test_scaled = scaler.transform(X_test)


knn = KNeighborsClassifier(n_neighbors=25, p=2, weights='uniform')
knn.fit(X_train_scaled, y_train_smote)


y_pred = knn.predict(X_test_scaled)


accuracy = accuracy_score(y_test, y_pred)
print("\nTest Set Accuracy: {:.2f}%".format(accuracy * 100))

cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap='Blues',
            xticklabels=["No Diabetes", "Diabetes"],
            yticklabels=["No Diabetes", "Diabetes"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

```python
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()

y_pred_proba = knn.predict_proba(X_test_scaled)[:, 1]
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("ROC AUC Score: {:.2f}".format(roc_auc))

fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc, color='darkorange')
plt.plot([0, 1], [0, 1], 'k--', label='Chance')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()


test_df = pd.read_excel("diabetes-test.xlsx", header=5)
test_df = test_df.iloc[1:]
test_df = test_df.drop(test_df.columns[0], axis=1)


test_df.columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
                   'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']


test_df_scaled = scaler.transform(test_df)

test_predictions = knn.predict(test_df_scaled)

test_df['Predicted_Outcome'] = test_predictions

print("\nPredicted Diabetes Outcomes:")
test_df[['Predicted_Outcome']]
```

Output

```
Test Set Accuracy: 80.00%

Confusion Matrix:
[[53 11]
 [ 9 27]]

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.83      0.84        64
           1       0.71      0.75      0.73        36

    accuracy                           0.80       100
   macro avg       0.78      0.79      0.79       100
weighted avg       0.80      0.80      0.80       100
```



Predictions

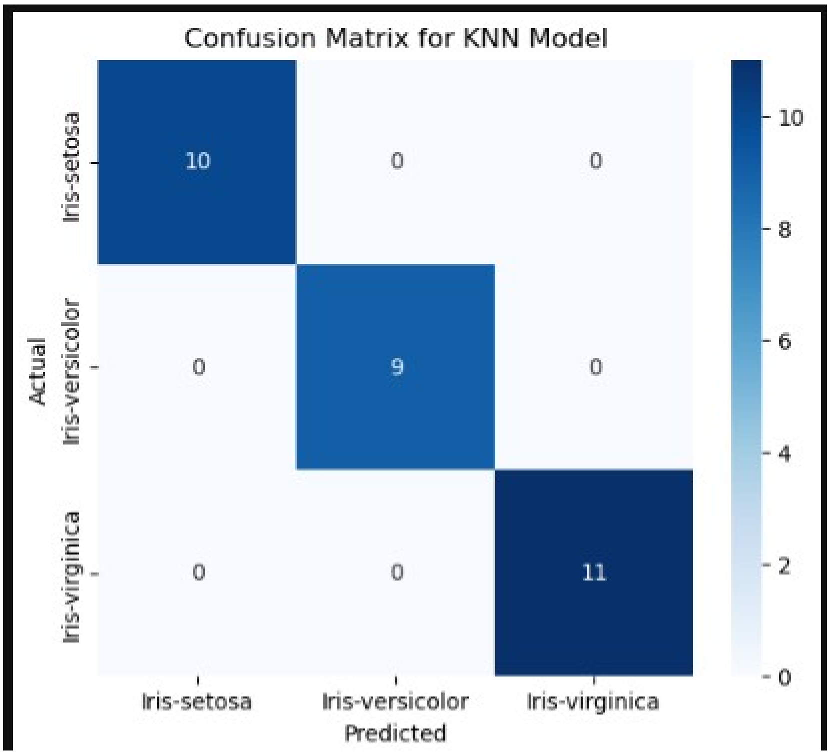
Predicted Diabetes Outcomes:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Predicted_Outcome
1	12.0	49.0	56.0	18.0	331.0	50.0	0.192313	21.0	No
2	4.0	128.0	39.0	53.0	367.0	22.0	0.411382	21.0	Yes
3	15.0	95.0	113.0	40.0	494.0	27.0	0.780781	48.0	Yes
4	12.0	77.0	37.0	9.0	193.0	23.0	0.392337	55.0	No
5	9.0	53.0	83.0	6.0	481.0	24.0	0.861166	63.0	Yes
6	1.0	96.0	30.0	37.0	473.0	18.0	1.438416	32.0	No
7	4.0	148.0	103.0	49.0	405.0	40.0	1.251075	42.0	Yes
8	11.0	120.0	86.0	47.0	450.0	24.0	1.217705	37.0	Yes
9	12.0	143.0	88.0	15.0	266.0	29.0	0.833595	60.0	Yes
10	3.0	102.0	114.0	27.0	453.0	28.0	1.709989	70.0	Yes

Flower

```
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.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

flower_df = pd.read_csv("IRIS.csv")
X = flower_df.drop(columns=["species"])
y = flower_df["species"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

knn = KNeighborsClassifier(n_neighbors=20, p=2, weights="distance")
knn.fit(X_train_scaled, y_train)

y_pred = knn.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
labels = y.unique()

plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=labels, yticklabels=labels)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix for KNN Model")
plt.show()
```

```
Accuracy: 1.0
Classification Report:
                  precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       1.00      1.00      1.00        11

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30
```



Predictions

```
print("======Predictions=====")
test_df=pd.read_excel("flower-test.xlsx",header=2)
test_df=test_df.iloc[1:]
test_df=test_df.drop(test_df.columns[0],axis=1)
test_df_scaled = scaler.transform(test_df)
predictions = knn.predict(test_df_scaled)
test_df["Predicted_Species"] = predictions
test_df
```

======Predictions=====

	sepal_length	sepal_width	petal_length	petal_width	Predicted_Species
1	6.4882	3.4127	6.1458	1.0739	Iris-versicolor
2	6.1154	3.2755	3.8060	0.2730	Iris-versicolor
3	6.7766	2.6693	2.9153	1.8620	Iris-versicolor
4	4.2439	3.7411	6.1605	2.0016	Iris-versicolor
5	5.7619	3.7088	2.2250	1.9717	Iris-versicolor
6	4.3800	3.2337	4.1747	0.5083	Iris-setosa
7	7.4658	3.2460	1.4442	0.9018	Iris-versicolor
8	4.7213	3.2989	6.4811	2.1413	Iris-virginica
9	6.4095	2.8048	5.9670	1.5241	Iris-virginica
10	7.1456	3.2493	1.4223	1.1015	Iris-versicolor