```
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from \ sklearn. ensemble \ import \ Random Forest Classifier, \ Gradient Boosting Classifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
# Load the dataset from a file in Google Colab
from google.colab import files
uploaded = files.upload()
# Assuming the file is named 'Dataset.csv'
dataset = pd.read_csv('Dataset.csv')
# Dropping unnecessary columns
dataset = dataset.drop(columns=['RowNumber', 'CustomerId', 'Surname'])
# Encoding categorical variables
label_encoders = {}
for column in ['Geography', 'Gender', 'Card Type']:
    le = LabelEncoder()
    dataset[column] = le.fit_transform(dataset[column])
    label_encoders[column] = le
# Splitting the data into features and target
X = dataset.drop(columns=['Exited'])
y = dataset['Exited']
# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Standardizing the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
    Choose Files Dataset.csv
     Dataset.csv(text/csv) - 837415 bytes, last modified: 4/28/2023 - 100% done
     Saving Dataset.csv to Dataset (1).csv
# Dictionary to store the models
models = {
    "Logistic Regression": LogisticRegression(max_iter=10000),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(n_estimators=100, max_depth=10),
    "Support Vector Machine": SVC(),
    "K-Nearest Neighbors": KNeighborsClassifier(),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss', n_estimators=100),
    "Naive Bayes": GaussianNB()
}
# Dictionary to store the evaluation metrics for each model
results = {}
# Training and evaluating each model
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    results[model_name] = {
        "Accuracy": accuracy_score(y_test, y_pred),
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1-Score": f1_score(y_test, y_pred)
# Display the results
results_df = pd.DataFrame(results).T
print(results_df)
                                                     Recall F1-Score
                                      Precision
                             Accuracy
     Logistic Regression
                                0.999
                                        0.997455 0.997455 0.997455
```

```
      Decision Tree
      0.998
      0.992405
      0.997455
      0.994924

      Random Forest
      0.999
      0.997455
      0.997455
      0.997455

      Support Vector Machine
      0.999
      0.997455
      0.997455
      0.997455

      K-Nearest Neighbors
      0.997
      0.997429
      0.987277
      0.992324

      Gradient Boosting
      0.998
      0.992405
      0.997455
      0.997455

      XGBoost
      0.999
      0.997455
      0.997455
      0.997455

      Naive Bayes
      0.999
      0.997455
      0.997455
      0.997455
```

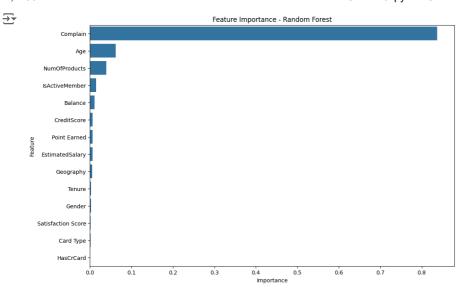
Double-click (or enter) to edit

Print the results in a sorted manner by F1-Score
print(results_df.sort_values(by="F1-Score", ascending=False))

```
Accuracy Precision Recall F1-Score Logistic Regression 0.999 0.997455 0.997455 0.997455 Random Forest 0.999 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.997455 0.9
```

Feature Importance Analysis

```
import matplotlib.pyplot as plt
import seaborn as sns
# Feature importance from Random Forest
model = models["Random Forest"]
importances = model.feature_importances_
feature_names = X.columns
# Create a DataFrame for visualization
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)
# Plot feature importances
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance - Random Forest')
plt.show()
```

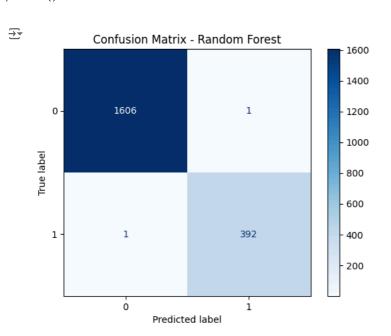


Confusion Matrix

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
# Compute confusion matrix for the best model (assuming Random Forest here)
best_model = models["Random Forest"]
y_pred = best_model.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

# Plot confusion matrix
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix - Random Forest')
plt.show()
```



Hyperparameter Tuning (using GridSearchCV for Random Forest as an example)

```
from sklearn.model_selection import GridSearchCV
# Define parameter grid for Random Forest
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```