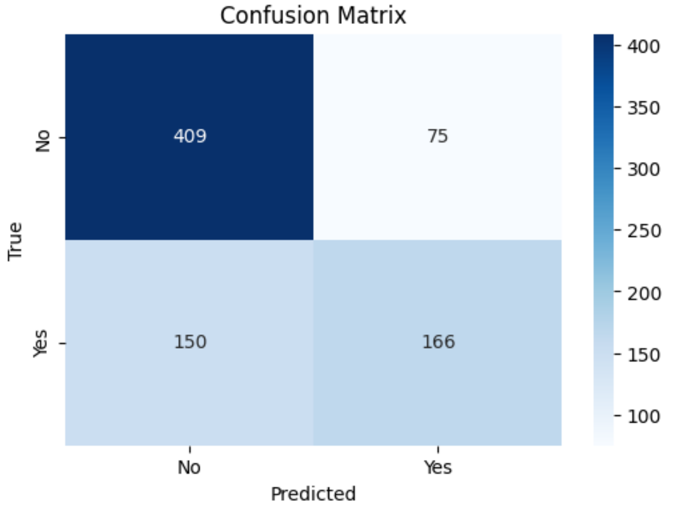
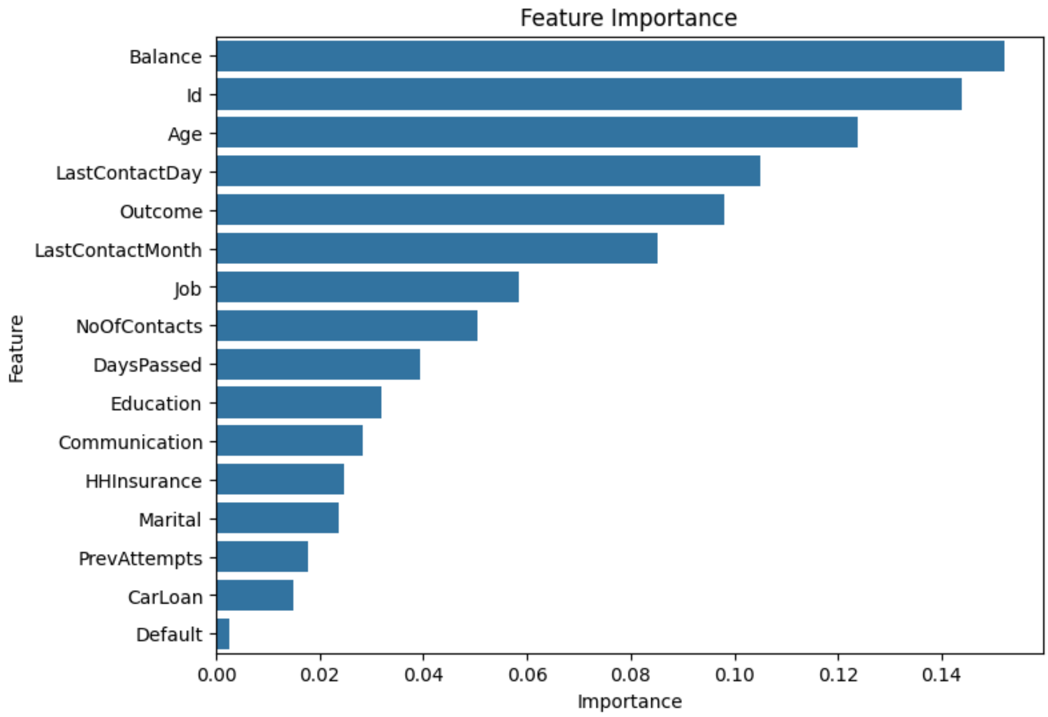
```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import BaggingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# Load training and test data
train_data = pd.read_csv("Train.csv")
test_data = pd.read_csv("Test.csv")

# Step 1: Data Preprocessing
# Handle categorical features with Label Encoding
categorical_columns = ['Job', 'Marital', 'Education', 'Default', 'Communication', 'LastContactMonth', 'Outcome']
le = LabelEncoder()

for col in categorical_columns:
    train_data[col] = le.fit_transform(train_data[col].astype(str))
    test_data[col] = le.transform(test_data[col].astype(str))

# Fill missing values for numerical columns, such as Balance, with the median value
train_data['Balance'].fillna(train_data['Balance'].median(), inplace=True)
test_data['Balance'].fillna(test_data['Balance'].median(), inplace=True)

# Step 2: Drop time-based columns (or convert them if needed)
train_data.drop(columns=['CallStart', 'CallEnd'], inplace=True)
test_data.drop(columns=['CallStart', 'CallEnd'], inplace=True)

# Step 3: Feature Scaling
scaler = StandardScaler()
train_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']] = scaler.fit_transform(
    train_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']])
test_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']] = scaler.transform(
    test_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']])

# Step 4: Splitting the training data into train and validation sets
X = train_data.drop('CarInsurance', axis=1)
y = train_data['CarInsurance']

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 5: Bagging Classifier without base_estimator parameter
bagging_model = BaggingClassifier(n_estimators=50, random_state=42)

# Train the model
bagging_model.fit(X_train, y_train)

# Step 6: Evaluate the model
y_pred = bagging_model.predict(X_val)

# Accuracy
accuracy = accuracy_score(y_val, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# Classification report
print("Classification Report:")
print(classification_report(y_val, y_pred))

# Confusion Matrix
conf_matrix = confusion_matrix(y_val, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# Step 7: Feature Importance Visualization from Base Estimators
importances = np.mean([tree.feature_importances_ for tree in bagging_model.estimators_], axis=0)

# Create a DataFrame with feature names and their importances
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
})

# Sort the features by importance
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
```

```
# Plotting feature importances
plt.figure(figsize=(8, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance')
plt.show()

# Step 8: Predicting on the test data
X_test = test_data.drop('CarInsurance', axis=1)

# Save the 'Id' column separately before dropping it
test_ids = test_data['Id']

# Predict on the test set
y_test_pred = bagging_model.predict(X_test)

# Add predictions to the test data (including the preserved 'Id' column)
test_data['PredictedCarInsurance'] = y_test_pred

# Save predictions along with 'Id' to a CSV file
test_data[['Id', 'PredictedCarInsurance']].to_csv('predictions.csv', index=False)

# Output some predictions (including the 'Id' column)
print(test_data[['Id', 'PredictedCarInsurance']].head())
```

```
/var/folders/vg/sx4xytfs3d7259x53nqmn0s80000gn/T/ipykernel_7066/1139527043.py:25: FutureWarning: A value is trying to be set on a
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setti

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[


  train_data['Balance'].fillna(train_data['Balance'].median(), inplace=True)
/var/folders/vg/sx4xytfs3d7259x53nqmn0s80000gn/T/ipykernel_7066/1139527043.py:26: FutureWarning: A value is trying to be set on a
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setti

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[


  test_data['Balance'].fillna(test_data['Balance'].median(), inplace=True)
Accuracy: 0.7188
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.85      0.78       484
           1       0.69      0.53      0.60       316

    accuracy                           0.72       800
   macro avg       0.71      0.69      0.69       800
weighted avg       0.71      0.72      0.71       800
```






```
     Id  PredictedCarInsurance
0  4001                      0
1  4002                      1
2  4003                      1
3  4004                      0
```

```
# Import necessary libraries
import pandas as pd
```

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
import xgboost as xgb
from sklearn.ensemble import GradientBoostingClassifier

# Load training and test data
train_data = pd.read_csv("Train.csv")
test_data = pd.read_csv("Test.csv")

# Step 1: Data Preprocessing (same as before)
categorical_columns = ['Job', 'Marital', 'Education', 'Default', 'Communication', 'LastContactMonth', 'Outcome']
le = LabelEncoder()

for col in categorical_columns:
    train_data[col] = le.fit_transform(train_data[col].astype(str))
    test_data[col] = le.transform(test_data[col].astype(str))

# Fill missing values for numerical columns, such as Balance, with the median value
train_data['Balance'].fillna(train_data['Balance'].median(), inplace=True)
test_data['Balance'].fillna(test_data['Balance'].median(), inplace=True)

# Step 2: Drop time-based columns (or convert them if needed)
train_data.drop(columns=['CallStart', 'CallEnd'], inplace=True)
test_data.drop(columns=['CallStart', 'CallEnd'], inplace=True)

# Step 3: Feature Scaling
scaler = StandardScaler()
train_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']] = scaler.fit_transform(
    train_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']])
test_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']] = scaler.transform(
    test_data[['Balance', 'Age', 'NoOfContacts', 'DaysPassed', 'PrevAttempts']])

# Step 4: Splitting the training data into train and validation sets
X = train_data.drop('CarInsurance', axis=1)
y = train_data['CarInsurance']

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 5: Train XGBoost Model
xgb_model = xgb.XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)

# Train the XGBoost model
xgb_model.fit(X_train, y_train)

# Step 6: Evaluate XGBoost Model
y_pred_xgb = xgb_model.predict(X_val)

# Accuracy
accuracy_xgb = accuracy_score(y_val, y_pred_xgb)
print(f"XGBoost Accuracy: {accuracy_xgb:.4f}")

# Classification report
print("XGBoost Classification Report:")
print(classification_report(y_val, y_pred_xgb))

# Confusion Matrix for XGBoost
conf_matrix_xgb = confusion_matrix(y_val, y_pred_xgb)
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_xgb, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('XGBoost Confusion Matrix')
plt.show()

# Step 7: Train GBM Model
gbm_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)

# Train the GBM model
gbm_model.fit(X_train, y_train)

# Step 8: Evaluate GBM Model
y_pred_gbm = gbm_model.predict(X_val)

# Accuracy
accuracy_gbm = accuracy_score(y_val, y_pred_gbm)
print(f"GBM Accuracy: {accuracy_gbm:.4f}")

# Classification report
```

```
print("GBM Classification Report:")
print(classification_report(y_val, y_pred_gbm))

# Confusion Matrix for GBM
conf_matrix_gbm = confusion_matrix(y_val, y_pred_gbm)
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_gbm, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'], yticklabels=['No', 'Yes'])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('GBM Confusion Matrix')
plt.show()

# Step 9: Feature Importance Visualization (for XGBoost and GBM)
# XGBoost Feature Importance
xgb_importance = xgb_model.feature_importances_

# GBM Feature Importance
gbm_importance = gbm_model.feature_importances_

# Create DataFrame for XGBoost feature importances
xgb_feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': xgb_importance
})
xgb_feature_importance_df = xgb_feature_importance_df.sort_values(by='Importance', ascending=False)

# Create DataFrame for GBM feature importances
gbm_feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': gbm_importance
})
gbm_feature_importance_df = gbm_feature_importance_df.sort_values(by='Importance', ascending=False)

# Plotting Feature Importances for XGBoost
plt.figure(figsize=(8, 6))
sns.barplot(x='Importance', y='Feature', data=xgb_feature_importance_df)
plt.title('XGBoost Feature Importance')
plt.show()

# Plotting Feature Importances for GBM
plt.figure(figsize=(8, 6))
sns.barplot(x='Importance', y='Feature', data=gbm_feature_importance_df)
plt.title('GBM Feature Importance')
plt.show()

# Step 10: Predicting on the test data (same as before)
X_test = test_data.drop('CarInsurance', axis=1)
test_ids = test_data['Id']

# Predict on the test set using XGBoost
y_test_pred_xgb = xgb_model.predict(X_test)

# Predict on the test set using GBM
y_test_pred_gbm = gbm_model.predict(X_test)

# Add predictions to the test data (including the preserved 'Id' column)
test_data['PredictedCarInsurance_XGB'] = y_test_pred_xgb
test_data['PredictedCarInsurance_GBM'] = y_test_pred_gbm

# Save predictions for XGBoost and GBM to a CSV file
test_data[['Id', 'PredictedCarInsurance_XGB', 'PredictedCarInsurance_GBM']].to_csv('predictions_boosting.csv', index=False)

# Output some predictions (including the 'Id' column)
print(test_data[['Id', 'PredictedCarInsurance_XGB', 'PredictedCarInsurance_GBM']].head())
```

```
XGBoost Accuracy: 0.7375
XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.91      0.81       484
           1       0.77      0.48      0.59       316

    accuracy                           0.74       800
   macro avg       0.75      0.69      0.70       800
weighted avg       0.74      0.74      0.72       800

/var/folders/vg/sx4xytfs3d7259x53nqmn0s80000gn/T/ipykernel_7066/757702331.py:25: FutureWarning: A value is trying to be set on a
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  train_data['Balance'].fillna(train_data['Balance'].median(), inplace=True)
/var/folders/vg/sx4xytfs3d7259x53nqmn0s80000gn/T/ipykernel_7066/757702331.py:26: FutureWarning: A value is trying to be set on a
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setti

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[


  test_data['Balance'].fillna(test_data['Balance'].median(), inplace=True)
```
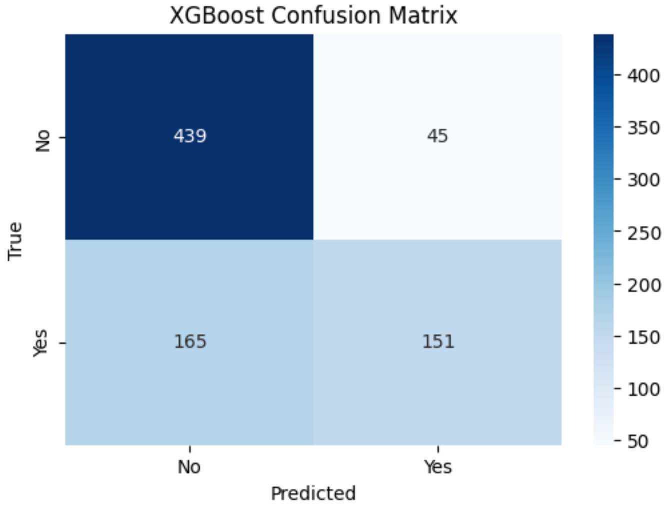
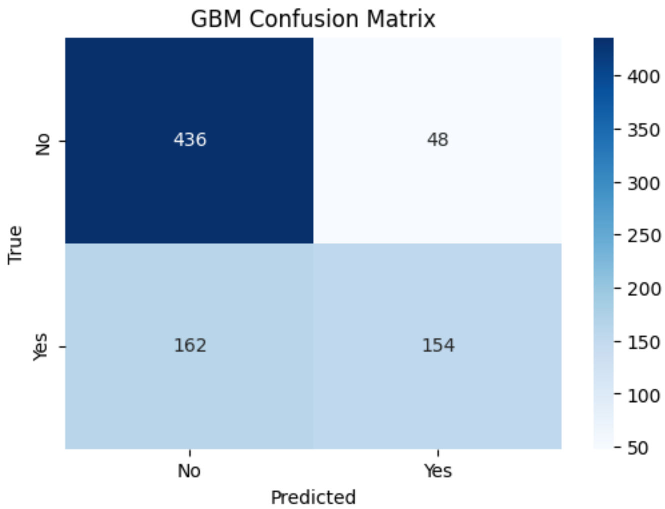
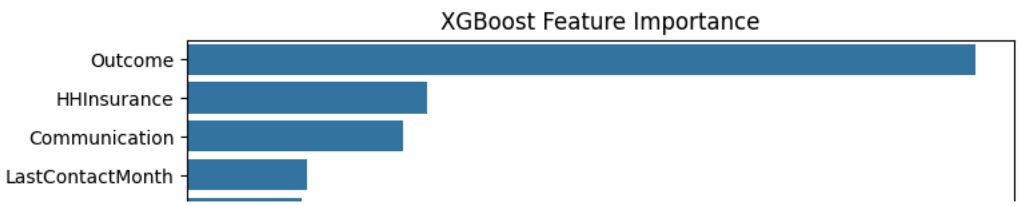
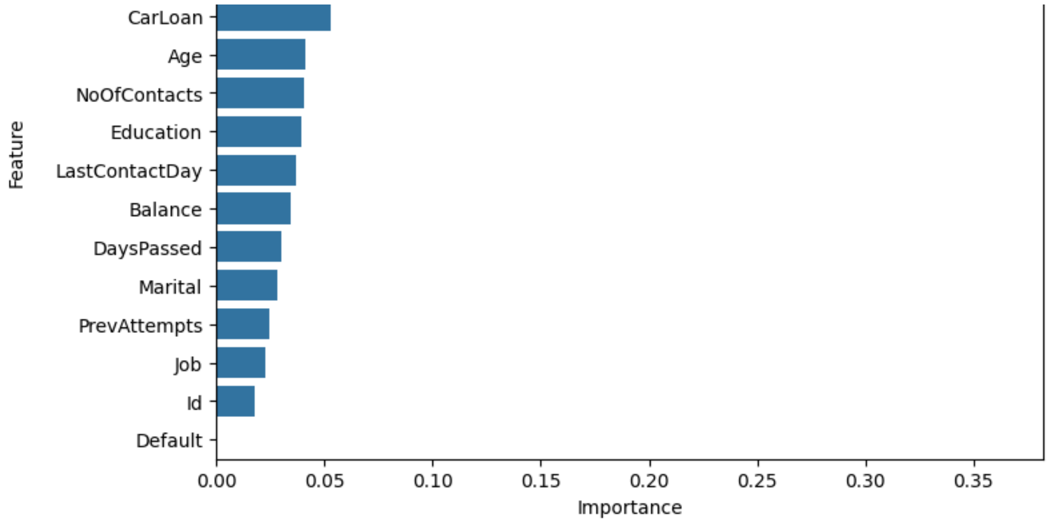
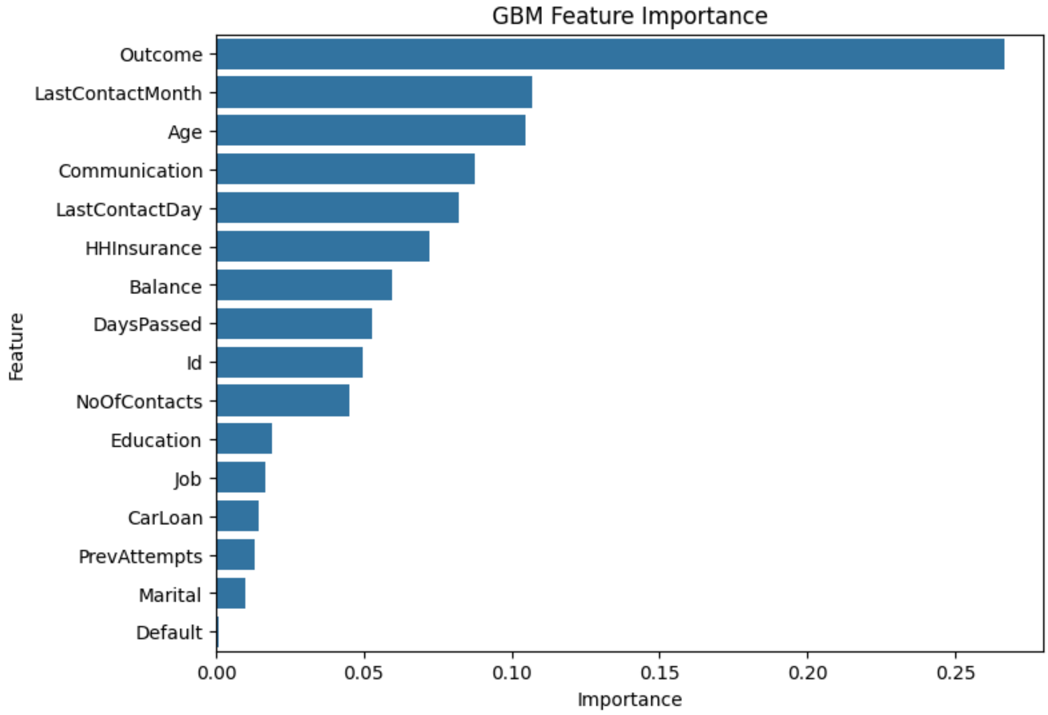




```
GBM Accuracy: 0.7375
GBM Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.90      0.81       484
           1       0.76      0.49      0.59       316

    accuracy                           0.74       800
   macro avg       0.75      0.69      0.70       800
weighted avg       0.74      0.74      0.72       800
```










```
     Id  PredictedCarInsurance_XGB  PredictedCarInsurance_GBM
0  4001                          0                          0
1  4002                          0                          0
2  4003                          0                          0
3  4004                          0                          0
```