Census_income_prediction

April 2, 2025

1 Data Mining and Machine Learning (PMDS505L)

1.1 Digital Assignment-1

2 Problem Statement

The objective of this project is to apply multiple binary classification algorithms to a selected dataset to predict a target variable with two possible outcomes.

For this project, I have chosen a Census Income Dataset where the goal is to predict whether the annual income of an individual exceeds $50K/yr based on census data

2.1 Dataset Information

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
age	Feature	Integer	Age	N/A		no
workclass	Feature	Categorical	Income	Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.		yes
fnlwgt	Feature	Integer				no

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
education	Feature	Categorical	Education Level	Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.		no
education-num	Feature	Integer	Education Level			no
marital-status	Feature	Categorical	Other	Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.		no

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
occupation	Feature	Categorical	Other	Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.		yes
relationship	Feature	Categorical	Other	Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.		no
race	Feature	Categorical	Race	White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.		no
sex	Feature	Binary	Sex	Female, Male.		no
capital-gain	Feature	Integer				no
capital-loss	Feature	Integer				no

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
hours-per-week	Feature	Integer				no

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
native-country	Feature	Categorical	Other	United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.		yes

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
income	Target	Binary	Income	>50K, <=50K.		no

2.1.1 Loading the necessary libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, BaggingClassifier
from sklearn.metrics import accuracy_score, f1_score, precision_score,␣
↪recall_score, classification_report, roc_auc_score,␣
↪confusion_matrix,roc_curve, auc
from sklearn.decomposition import PCA
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings("ignore")
```

2.1.2 Loading the dataset

[2]:
```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.
↪data"
colnames = ['age', 'workclass', 'fnlwgt', 'education', 'education-num',␣
↪'marital-status', 'occupation',
            'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',␣
↪'hours-per-week', 'native-country', 'income']
data = pd.read_csv(url, header=None, names=colnames, na_values=' ?')
data.head()
```

[2]:
```
   age          workclass  fnlwgt   education  education-num  \
0   39          State-gov   77516   Bachelors             13
1   50   Self-emp-not-inc   83311   Bachelors             13
2   38            Private  215646     HS-grad              9
3   53            Private  234721        11th              7
4   28            Private  338409   Bachelors             13
```

```
       marital-status         occupation    relationship   race    sex  \
0       Never-married       Adm-clerical   Not-in-family  White   Male
1  Married-civ-spouse    Exec-managerial         Husband  White   Male
2            Divorced  Handlers-cleaners   Not-in-family  White   Male
3  Married-civ-spouse  Handlers-cleaners         Husband  Black   Male
4  Married-civ-spouse     Prof-specialty            Wife  Black Female

  capital-gain capital-loss hours-per-week native-country income
0         2174            0             40  United-States  <=50K
1            0            0             13  United-States  <=50K
2            0            0             40  United-States  <=50K
3            0            0             40  United-States  <=50K
4            0            0             40           Cuba  <=50K
```

[3]:
```python
print("Shape of the dataset is:", data.shape)
```

```
Shape of the dataset is: (32561, 15)
```

2.1.3 Checking for missing values

[4]:
```python
data.isnull().sum()
```

[4]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     583
income               0
dtype: int64
```

2.1.4 Dropping the missing values

[5]:
```python
data.dropna(inplace = True)
```

[6]:
```python
data.isna().sum().sum()
```

[6]:
```
0
```

2.1.5 Checking for duplicate values

[7]:
```
data.duplicated().sum()
```

[7]:
```
23
```

2.1.6 Dropping the duplicate values

[8]:
```
data.drop_duplicates(inplace = True)
```

[9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 30139 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30139 non-null  int64
 1   workclass       30139 non-null  object
 2   fnlwgt          30139 non-null  int64
 3   education       30139 non-null  object
 4   education-num   30139 non-null  int64
 5   marital-status  30139 non-null  object
 6   occupation      30139 non-null  object
 7   relationship    30139 non-null  object
 8   race            30139 non-null  object
 9   sex             30139 non-null  object
 10  capital-gain    30139 non-null  int64
 11  capital-loss    30139 non-null  int64
 12  hours-per-week  30139 non-null  int64
 13  native-country  30139 non-null  object
 14  income          30139 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

2.1.7 Setting the feature and target variables

[10]:
```
x = data.drop('income', axis=1)
y = (data['income'] == ' >50K').astype(int)  # 1 = >50K, 0 = <=50K
```

[11]:
```
y.value_counts(normalize=True)
```

[11]:
```
income
0    0.750954
1    0.249046
Name: proportion, dtype: float64
```

- Data is imbalanced

2.1.8 Encoding the Categorical Variables

[12]:
```
categorical_cols = ['workclass', 'education', 'marital-status', 'occupation',␣
 ↪'relationship', 'race', 'sex', 'native-country']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    x[col] = le.fit_transform(x[col])
    label_encoders[col] = le
```

[13]:
```
x
```

[13]:
```
       age  workclass  fnlwgt  education  education-num  marital-status  \
0       39          5   77516          9             13               4
1       50          4   83311          9             13               2
2       38          2  215646         11              9               0
3       53          2  234721          1              7               2
4       28          2  338409          9             13               2
…      …          …       …          …              …               …
32556   27          2  257302          7             12               2
32557   40          2  154374         11              9               2
32558   58          2  151910         11              9               6
32559   22          2  201490         11              9               4
32560   52          3  287927         11              9               2

       occupation  relationship  race  sex  capital-gain  capital-loss  \
0               0             1     4    1          2174             0
1               3             0     4    1             0             0
2               5             1     4    1             0             0
3               5             0     2    1             0             0
4               9             5     2    0             0             0
…             …             …   …   …            …            …
32556          12             5     4    0             0             0
32557           6             0     4    1             0             0
32558           0             4     4    0             0             0
32559           0             3     4    1             0             0
32560           3             5     4    0         15024             0

       hours-per-week  native-country
0                  40              38
1                  13              38
2                  40              38
3                  40              38
4                  40               4
…                …             …
32556              38              38
32557              40              38
```

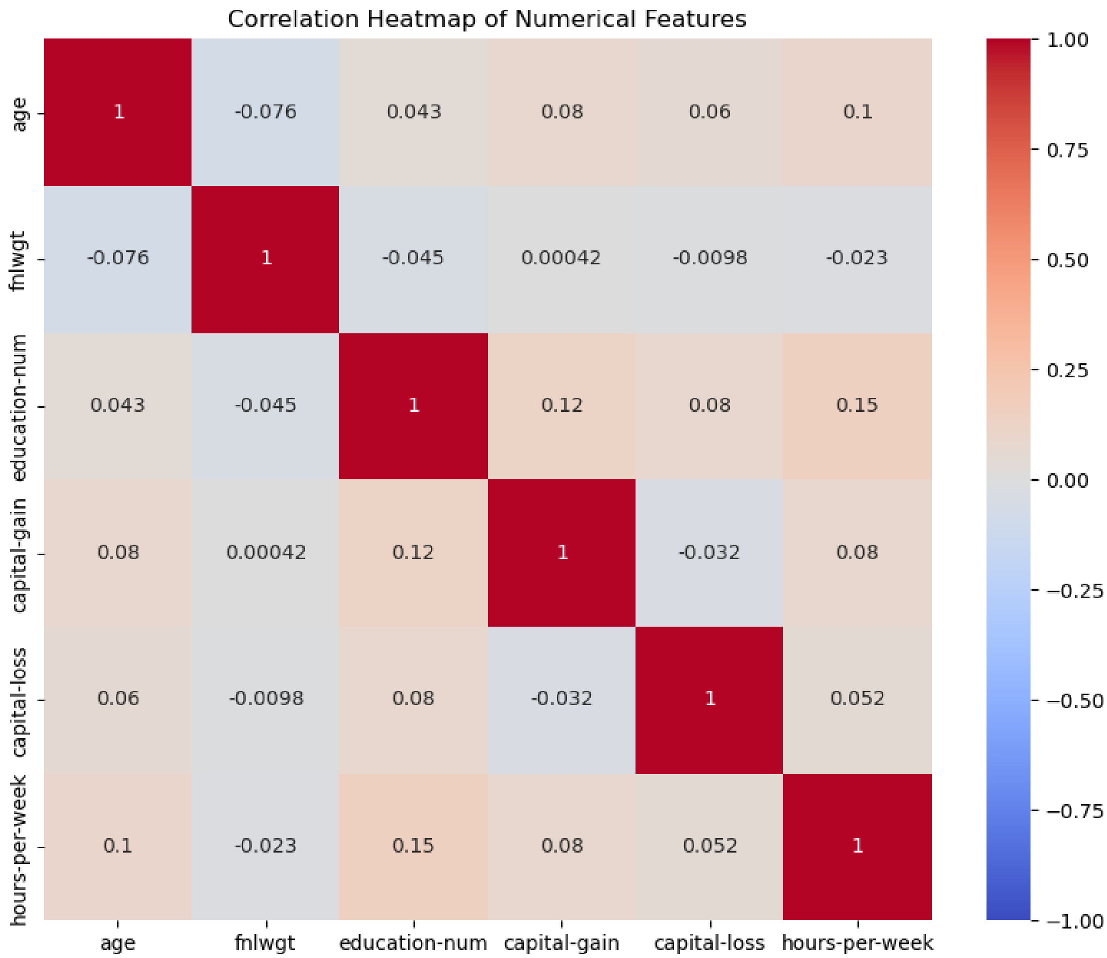
```
32558             40            38
32559             20            38
32560             40            38

[30139 rows x 14 columns]
```

2.1.9 Scaling Numerical Features

[14]:
```
numerical_cols = ['age', 'fnlwgt', 'education-num', 'capital-gain',␣
 ↪'capital-loss', 'hours-per-week']
scaler = StandardScaler()
x[numerical_cols] = scaler.fit_transform(x[numerical_cols])
```

2.1.10 Correlation Heatmap for numerical features

[15]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(data[numerical_cols].corr(), annot=True, cmap='coolwarm', vmin=-1,␣
 ↪vmax=1, center=0)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



- Very high correlation is not present among the variables

2.1.11 Train test split of the data

[16]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,␣
↪random_state=42,stratify=y)
```

2.1.12 Applying SMOTE for class balancing

[17]:
```
smote = SMOTE(random_state=42)
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)

print("\nClass distribution after SMOTE:")
print(y_train_smote.value_counts(normalize=True))
```

```
Class distribution after SMOTE:
income
```

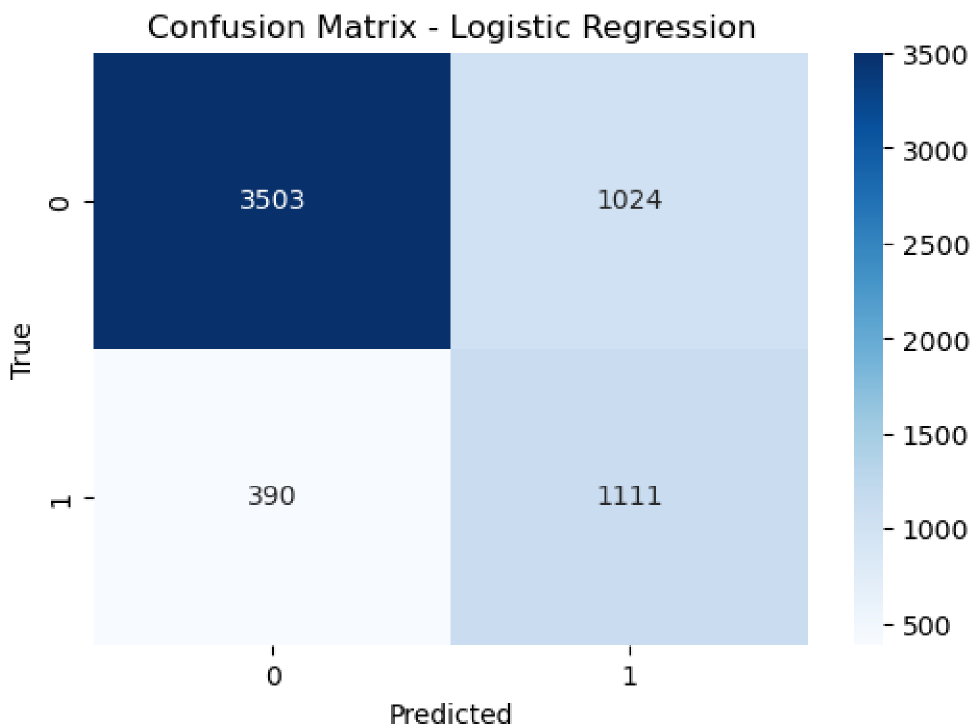
```
0    0.5
1    0.5
Name: proportion, dtype: float64
```

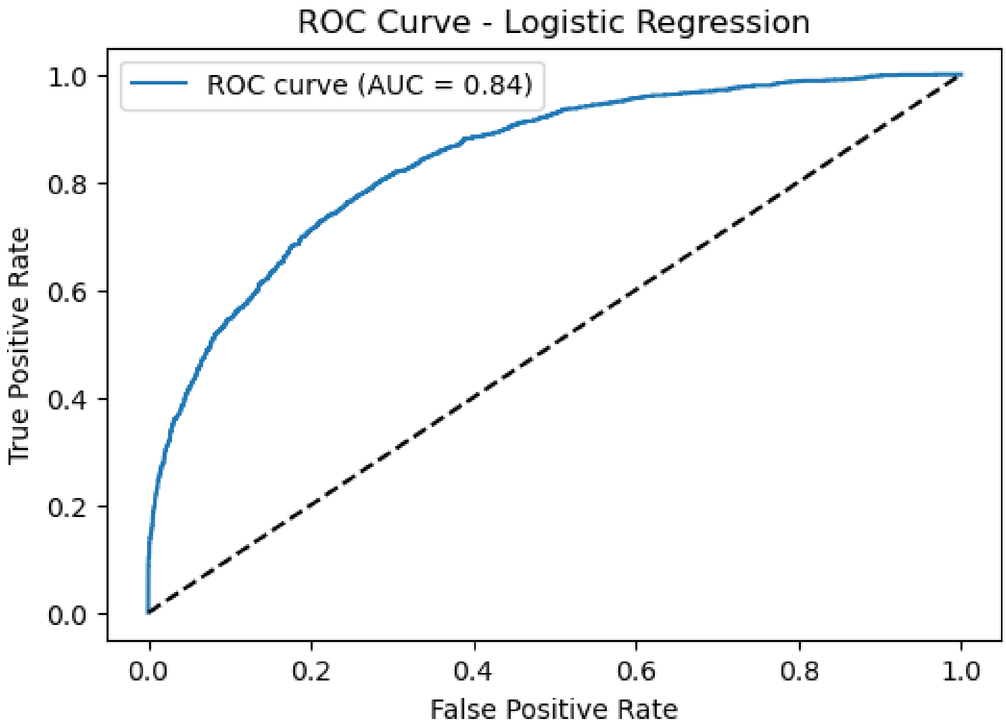
2.1.13 Model building Function

[18]:
```python
def train_and_evaluate_models(x_train, y_train, x_test, y_test):
    # Defining the classification models
    classifiers = {
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(random_state=42),
    'AdaBoost': AdaBoostClassifier(random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'Bagging': BaggingClassifier(random_state=42),
    'SVC': SVC(probability=True, random_state=42, kernel='linear')
}
    # Storing the results results
    results = {}

    for name, clf in classifiers.items():
        clf.fit(x_train, y_train)
        y_pred = clf.predict(x_test)
        results[name] = classification_report(y_test, y_pred, output_dict=True)
        print(f"\n{name}:\n", classification_report(y_test, y_pred))

        # Confusion Matrix
        cm = confusion_matrix(y_test, y_pred)
        plt.figure(figsize=(6, 4))
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
        plt.title(f'Confusion Matrix - {name}')
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.show()

        # ROC Curve
        y_prob = clf.predict_proba(x_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        roc_auc = auc(fpr, tpr)
        plt.figure(figsize=(6, 4))
        plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
        plt.plot([0, 1], [0, 1], 'k--')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title(f'ROC Curve - {name}')
        plt.legend(loc='best')
        plt.show()
```

```
    return results

# Calling the function
results = train_and_evaluate_models(x_train_smote, y_train_smote, x_test,
 ↪y_test)
```

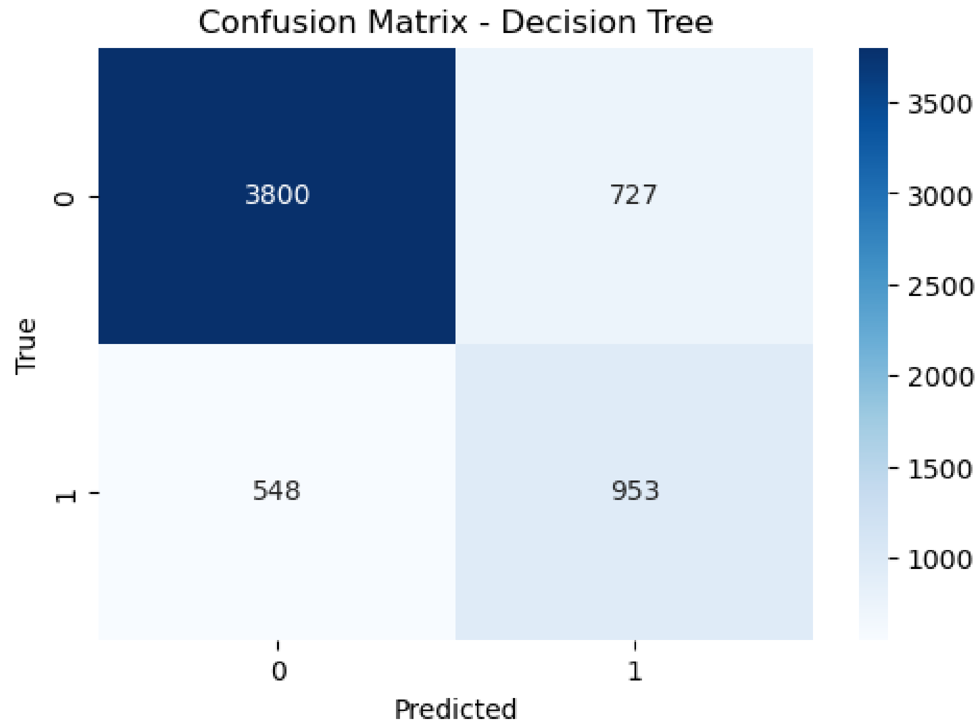
```
Logistic Regression:
              precision    recall  f1-score   support

           0       0.90      0.77      0.83      4527
           1       0.52      0.74      0.61      1501

    accuracy                           0.77      6028
   macro avg       0.71      0.76      0.72      6028
weighted avg       0.81      0.77      0.78      6028
```



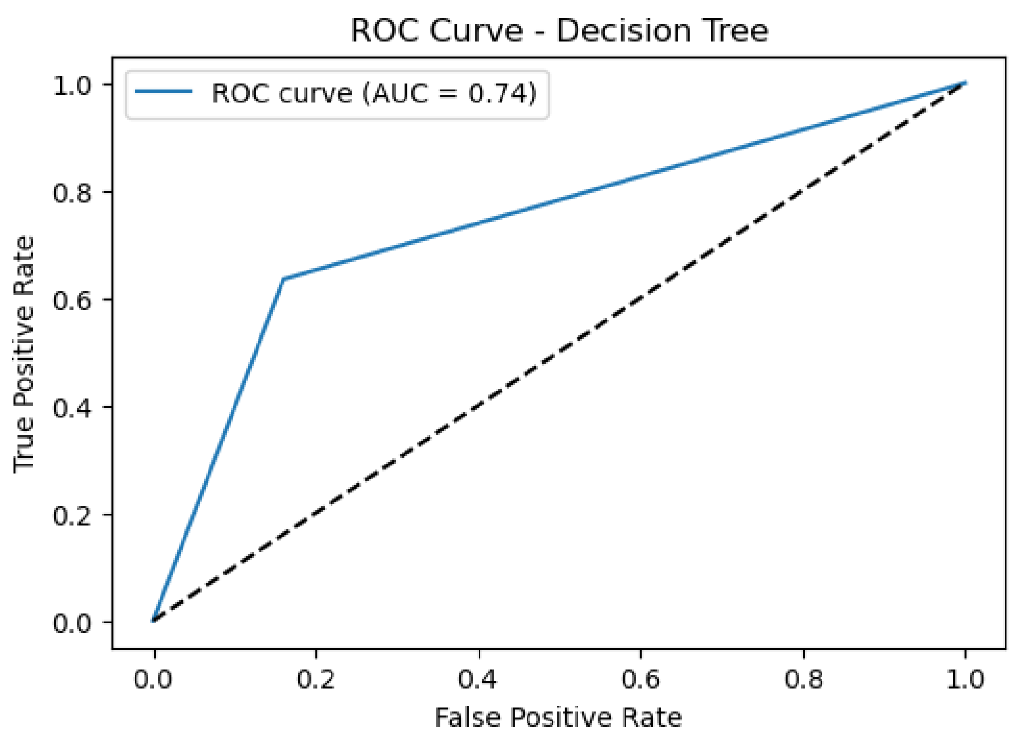


Decision Tree:

	precision	recall	f1-score	support
0	0.87	0.84	0.86	4527
1	0.57	0.63	0.60	1501
accuracy			0.79	6028
macro avg	0.72	0.74	0.73	6028
weighted avg	0.80	0.79	0.79	6028

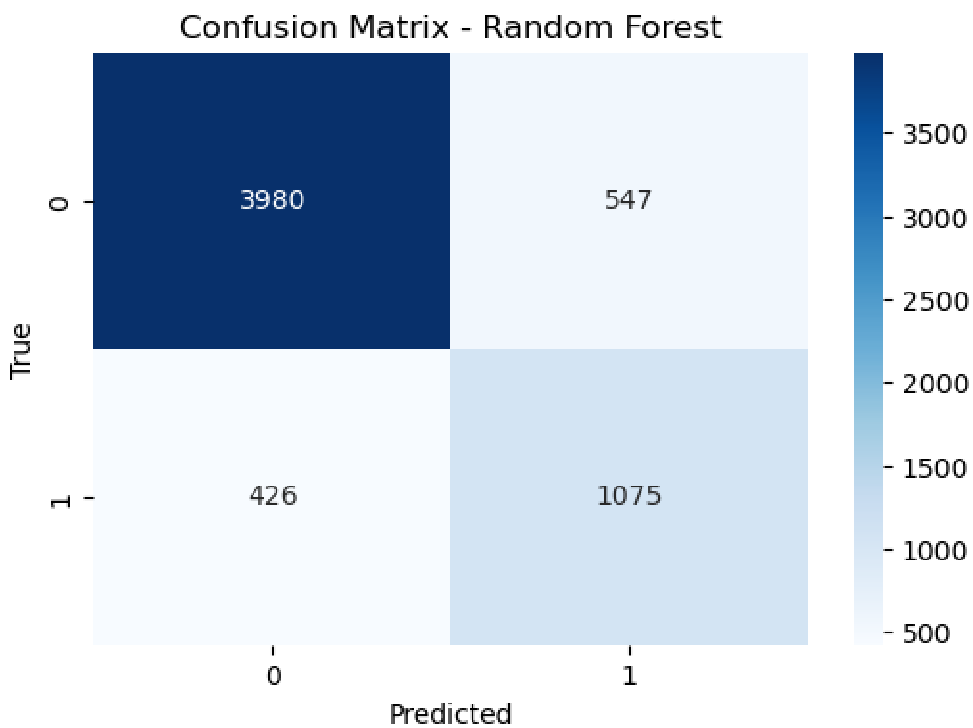


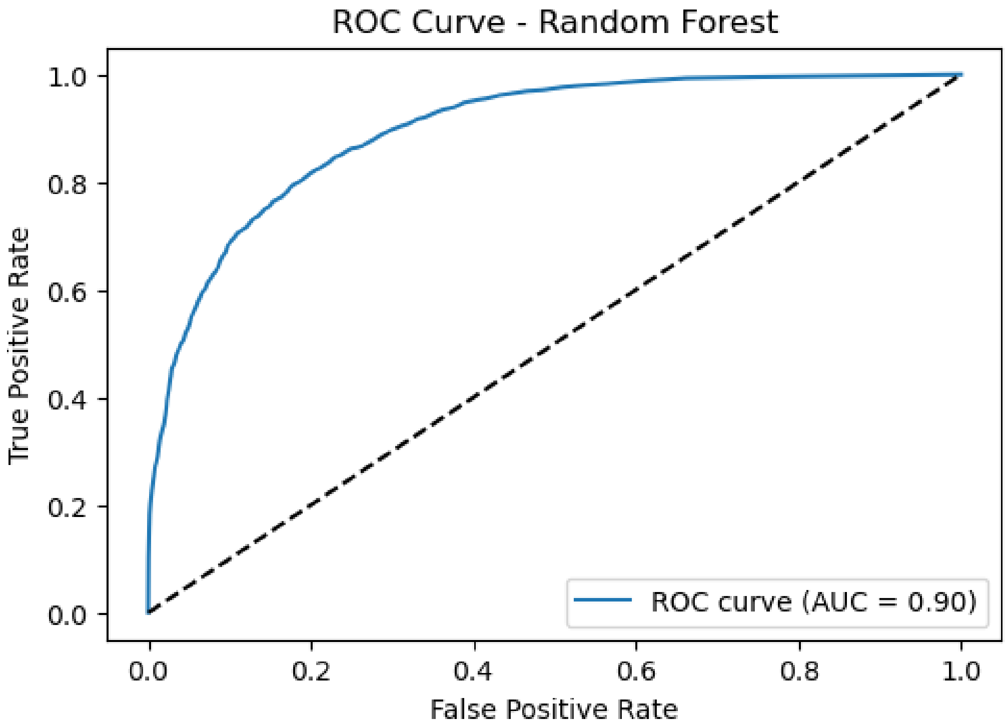
Confusion Matrix - Decision Tree
3800
727
548
953
True
0
1
Predicted
3500
3000
2500
2000
1500
1000



ROC Curve - Decision Tree
ROC curve (AUC = 0.74)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

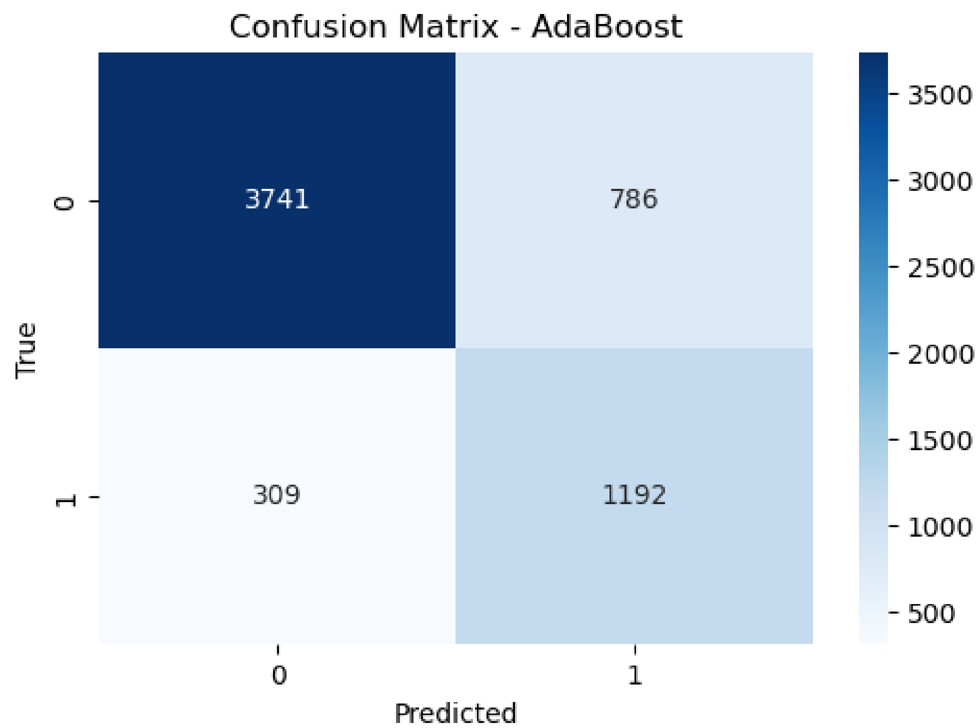
```
Random Forest:
              precision    recall  f1-score   support

           0       0.90      0.88      0.89      4527
           1       0.66      0.72      0.69      1501

    accuracy                           0.84      6028
   macro avg       0.78      0.80      0.79      6028
weighted avg       0.84      0.84      0.84      6028
```

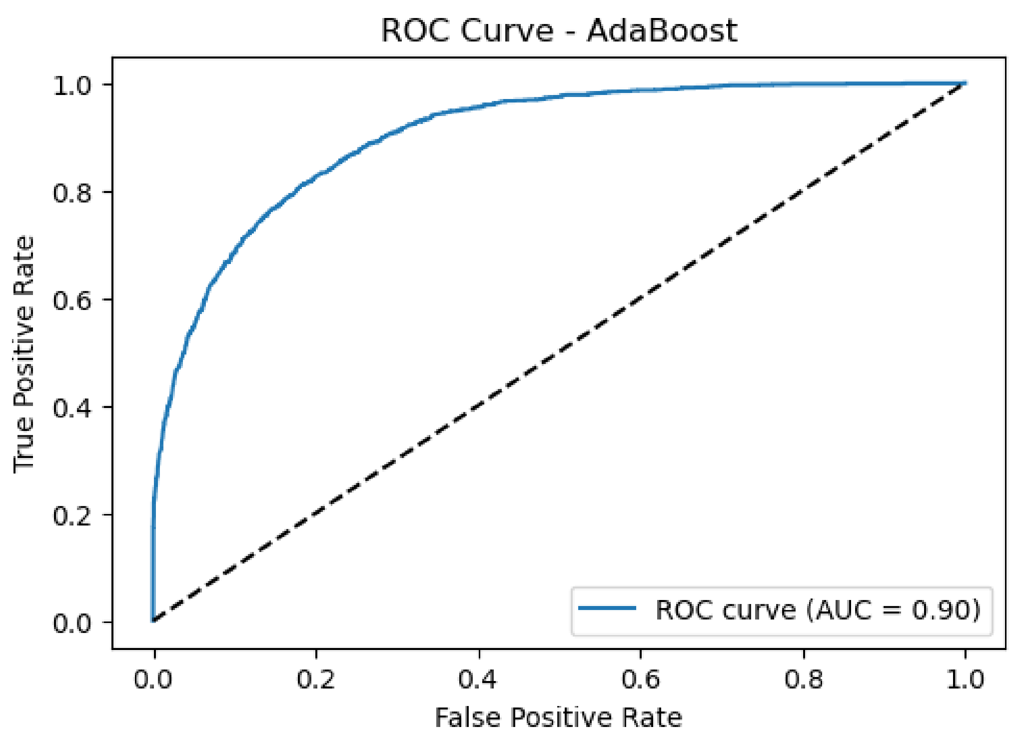




AdaBoost:

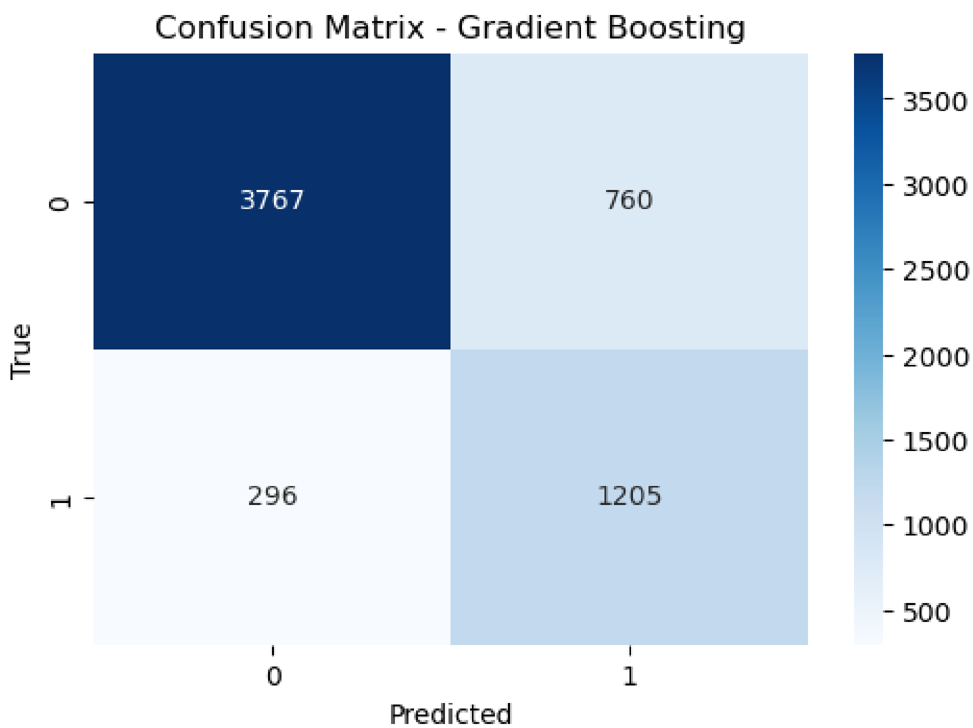
	precision	recall	f1-score	support
0	0.92	0.83	0.87	4527
1	0.60	0.79	0.69	1501
accuracy			0.82	6028
macro avg	0.76	0.81	0.78	6028
weighted avg	0.84	0.82	0.83	6028

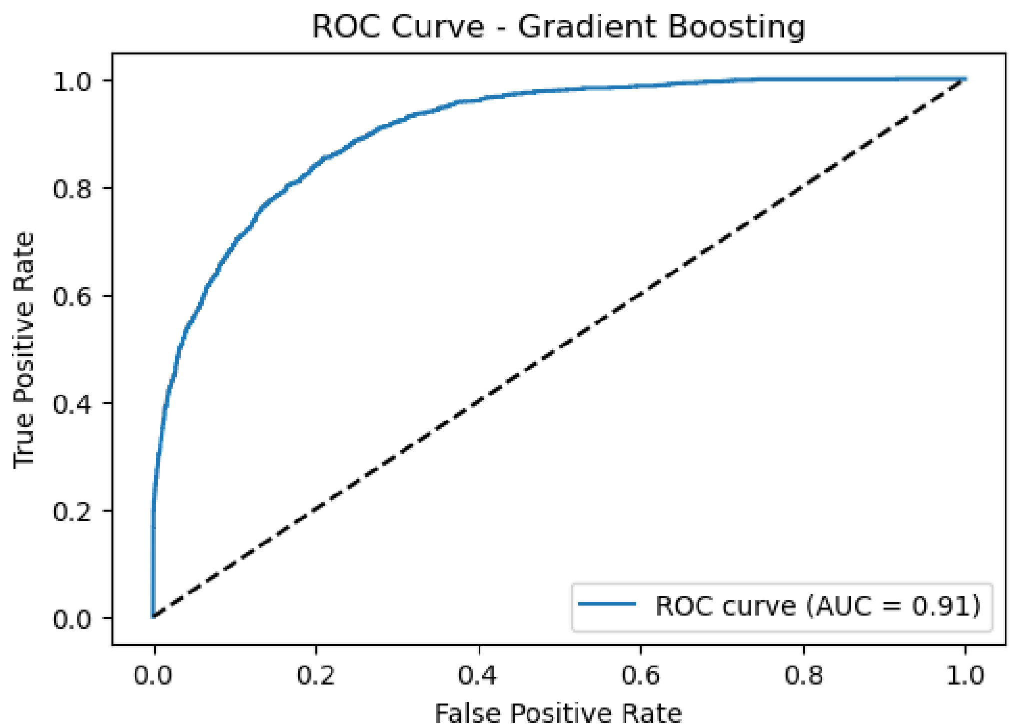

Confusion Matrix - AdaBoost
3741
786
309
1192
0
1
True
0
1
Predicted
3500
3000
2500
2000
1500
1000
500


ROC Curve - AdaBoost
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (AUC = 0.90)

Gradient Boosting:

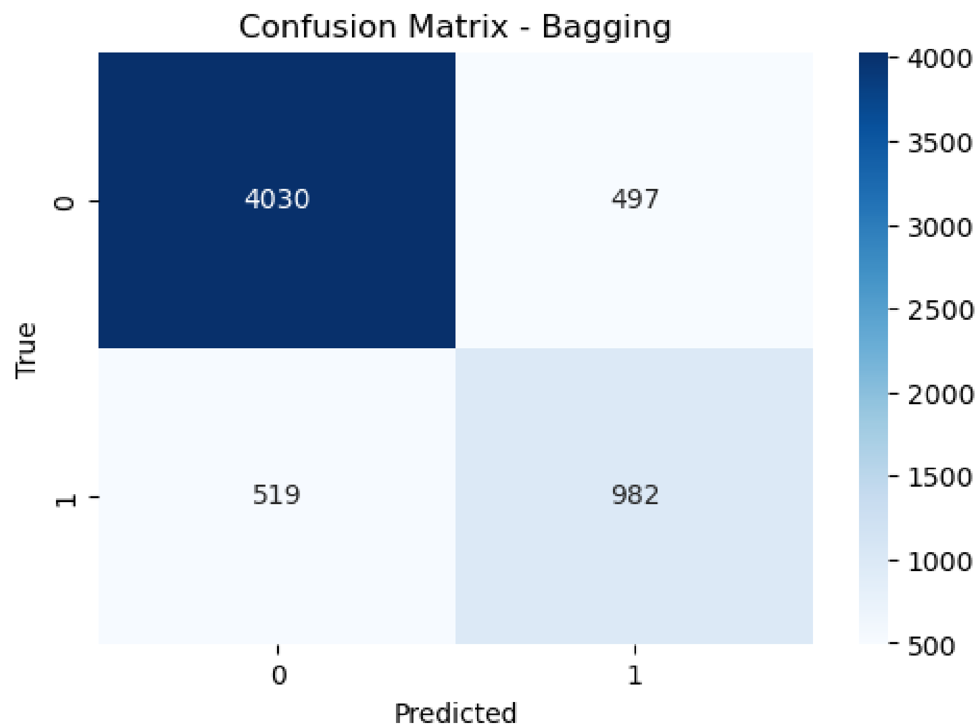
	precision	recall	f1-score	support
0	0.93	0.83	0.88	4527
1	0.61	0.80	0.70	1501
accuracy			0.82	6028
macro avg	0.77	0.82	0.79	6028
weighted avg	0.85	0.82	0.83	6028



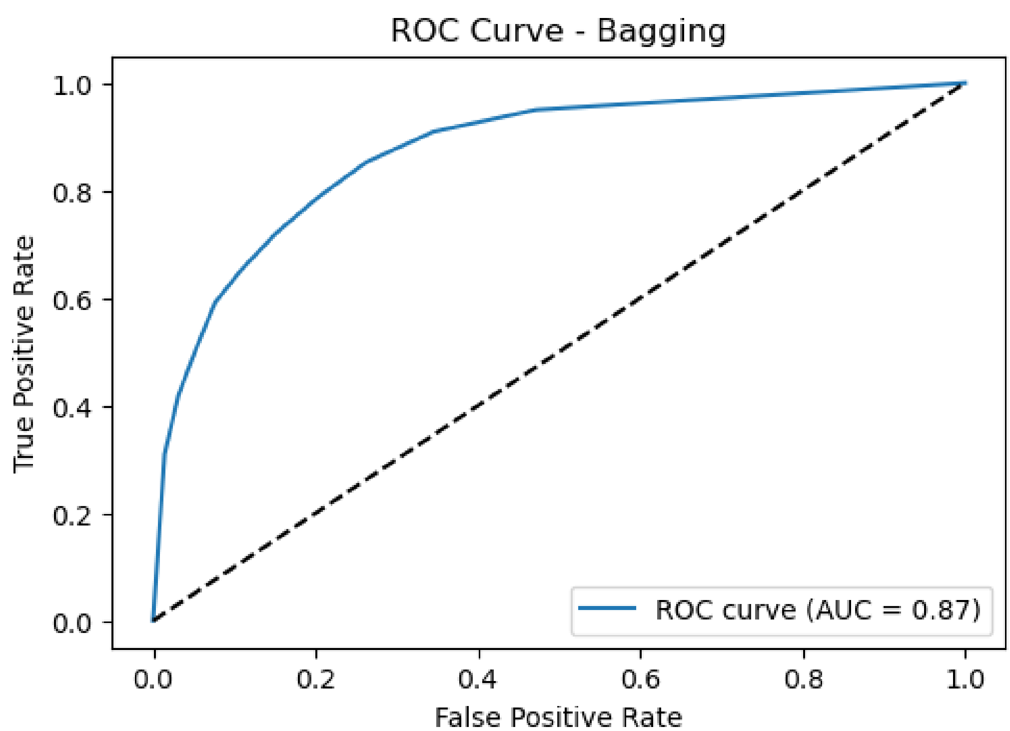


Bagging:

	precision	recall	f1-score	support
0	0.89	0.89	0.89	4527
1	0.66	0.65	0.66	1501
accuracy			0.83	6028
macro avg	0.77	0.77	0.77	6028
weighted avg	0.83	0.83	0.83	6028



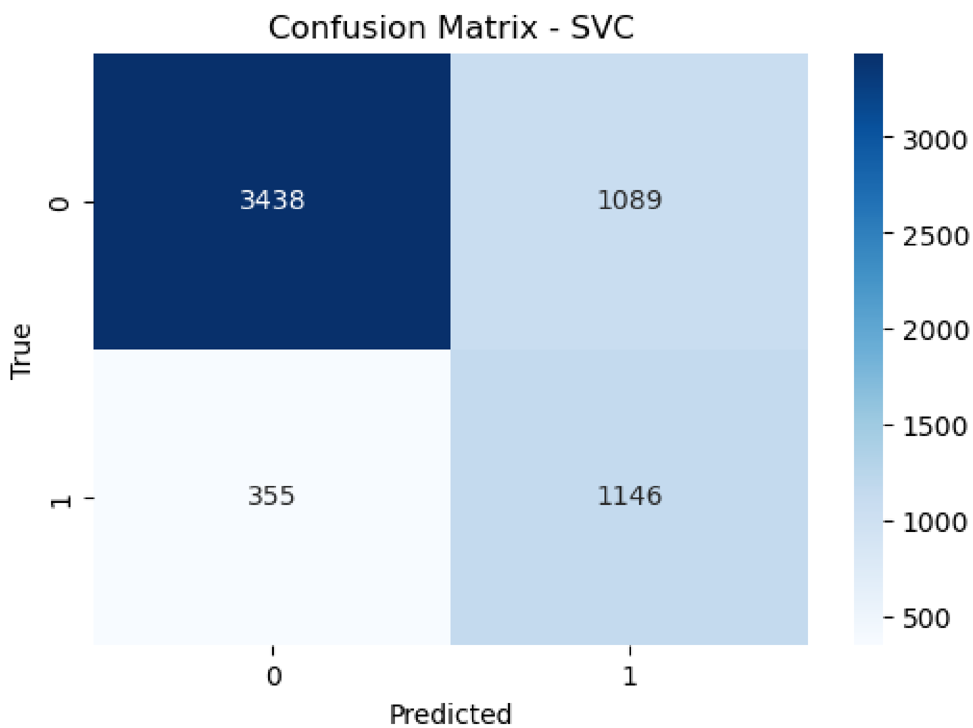
Confusion Matrix - Bagging
4030
497
519
982
True
Predicted
0
1
0
1
4000
3500
3000
2500
2000
1500
1000
500

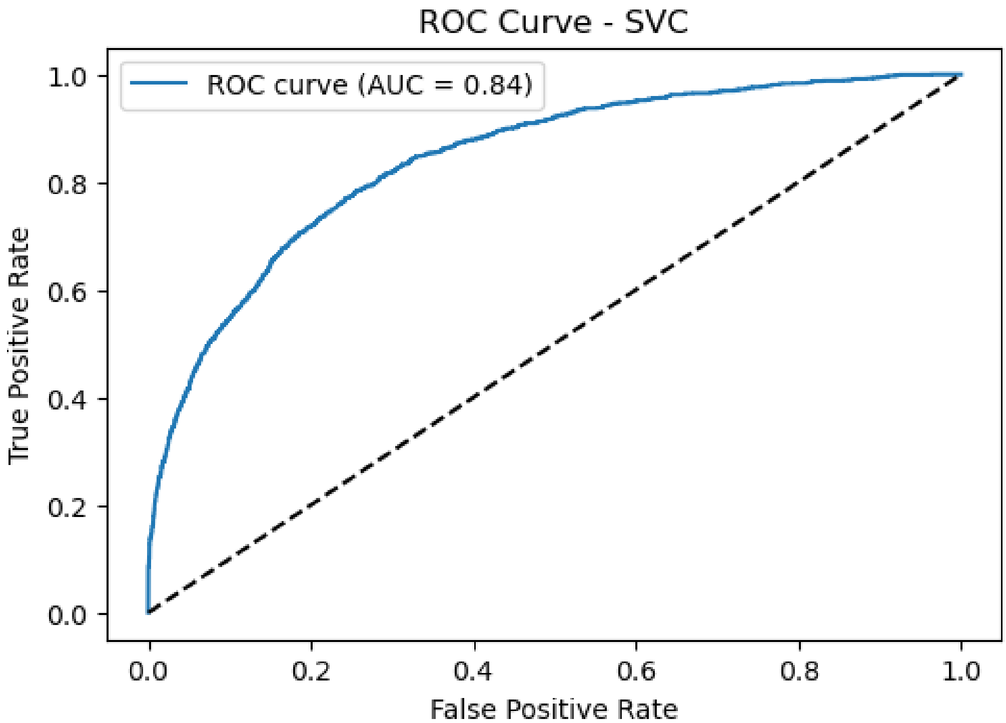


ROC Curve - Bagging
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.87)
0.0
0.2
0.4
0.6
0.8
1.0

SVC:

	precision	recall	f1-score	support
0	0.91	0.76	0.83	4527
1	0.51	0.76	0.61	1501
accuracy			0.76	6028
macro avg	0.71	0.76	0.72	6028
weighted avg	0.81	0.76	0.77	6028





2.1.14 Model Comparison

[19]:
```
top_models = sorted(results.items(), key=lambda x: x[1]['1']['f1-score'],␣
↪reverse=True)[:3]  # Top 3 models
print("\nTop Models for Tuning:", [name for name, _ in top_models])
```

```
Top Models for Tuning: ['Gradient Boosting', 'Random Forest', 'AdaBoost']
```

2.1.15 Hyper parameter Tuning for the Top performing Models

[20]:
```
classifiers = {
    'Random Forest': RandomForestClassifier(random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'AdaBoost': AdaBoostClassifier(random_state=42)
}

param_grids = {
    'Random Forest':
        {
        'n_estimators': [100, 200,400,500],
        'max_depth': [10, 20, None],
        'min_samples_split': [2, 5],
```

```
        'min_samples_leaf': [1, 2]
        },
    'Gradient Boosting':
        {
        'n_estimators': [100, 200,300,500,700],
        'learning_rate': [0.01, 0.05, 0.1, 0.5],
        'max_depth': [3, 5]
        },
    'AdaBoost':
        {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.05, 0.1, 0.5, 1.0]
        }
}

tuned_models = {}
for name in ['Random Forest', 'Gradient Boosting', 'AdaBoost']:
    print(f"\nTuning {name}...")
    grid = GridSearchCV(
        classifiers[name],
        param_grids[name],
        cv=5,
        scoring='f1',
        n_jobs=-1
    )
    grid.fit(x_train_smote, y_train_smote)
    tuned_models[name] = grid.best_estimator_

    # Report best parameters and performance
    print(f"Tuned {name} Best Params: {grid.best_params_}")
    y_pred_tuned = grid.predict(x_test)
    print(f"Tuned {name} Performance:\n", classification_report(y_test,␣
 ↪y_pred_tuned))
# Select and save the best model
best_model_name = max(tuned_models, key=lambda x: classification_report(y_test,␣
 ↪tuned_models[x].predict(x_test), output_dict=True)['1']['f1-score'])
best_model = tuned_models[best_model_name]
y_pred_final = best_model.predict(x_test)
print(f"\nBest Model ({best_model_name}) Final Performance:\n",␣
 ↪classification_report(y_test, y_pred_final))
```

```
Tuning Random Forest…
Tuned Random Forest Best Params: {'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 500}
Tuned Random Forest Performance:
               precision    recall  f1-score   support
```

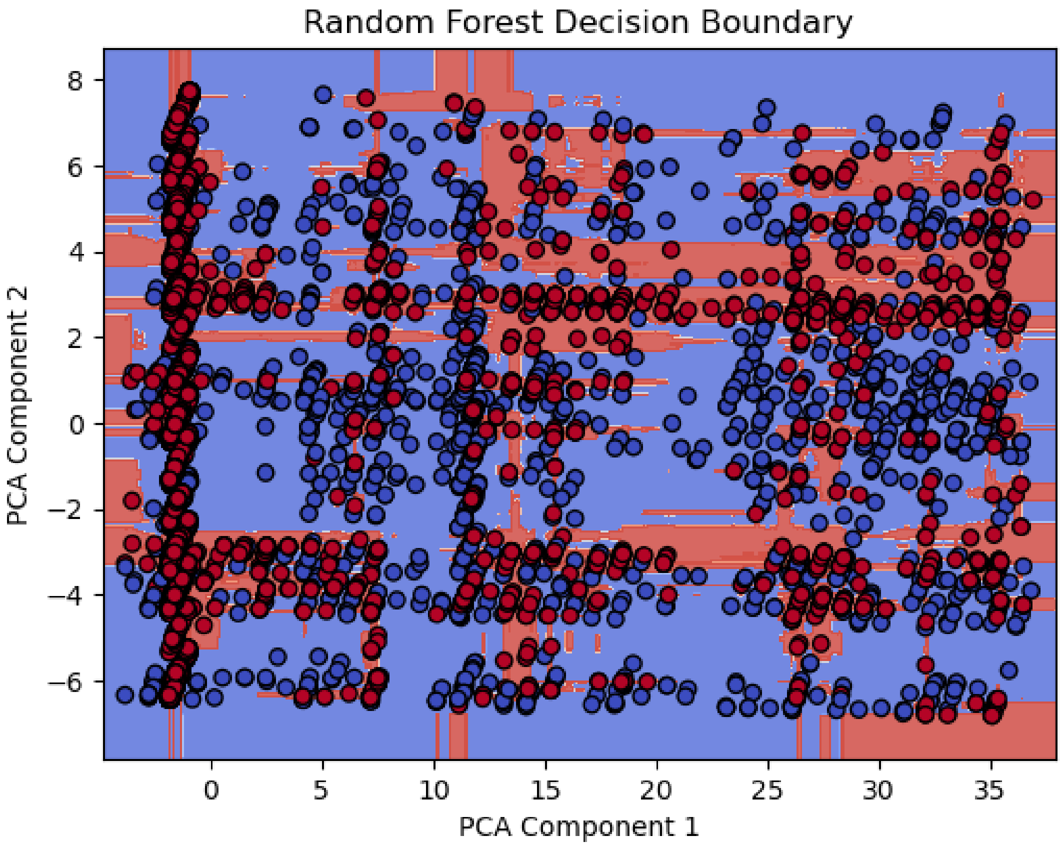
	precision	recall	f1-score	support
0	0.90	0.88	0.89	4527
1	0.67	0.72	0.69	1501
accuracy			0.84	6028
macro avg	0.79	0.80	0.79	6028
weighted avg	0.84	0.84	0.84	6028

```
Tuning Gradient Boosting…
Tuned Gradient Boosting Best Params: {'learning_rate': 0.1, 'max_depth': 5,
'n_estimators': 300}
Tuned Gradient Boosting Performance:
              precision    recall  f1-score   support

           0       0.91      0.90      0.90      4527
           1       0.71      0.73      0.72      1501

    accuracy                           0.86      6028
   macro avg       0.81      0.81      0.81      6028
weighted avg       0.86      0.86      0.86      6028


Tuning AdaBoost…
Tuned AdaBoost Best Params: {'learning_rate': 1.0, 'n_estimators': 200}
Tuned AdaBoost Performance:
              precision    recall  f1-score   support

           0       0.92      0.84      0.88      4527
           1       0.62      0.79      0.70      1501

    accuracy                           0.83      6028
   macro avg       0.77      0.82      0.79      6028
weighted avg       0.85      0.83      0.83      6028


Best Model (Gradient Boosting) Final Performance:
              precision    recall  f1-score   support

           0       0.91      0.90      0.90      4527
           1       0.71      0.73      0.72      1501

    accuracy                           0.86      6028
   macro avg       0.81      0.81      0.81      6028
weighted avg       0.86      0.86      0.86      6028
```

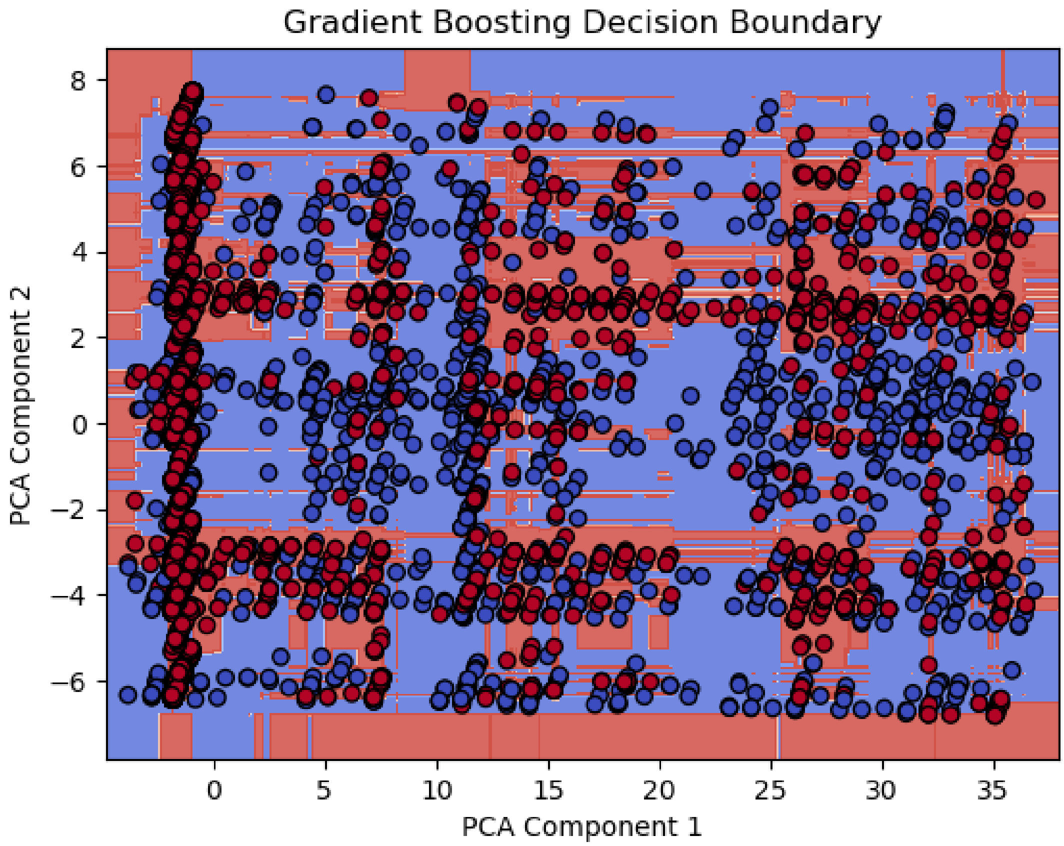
2.1.16 Plotting decision boundaries

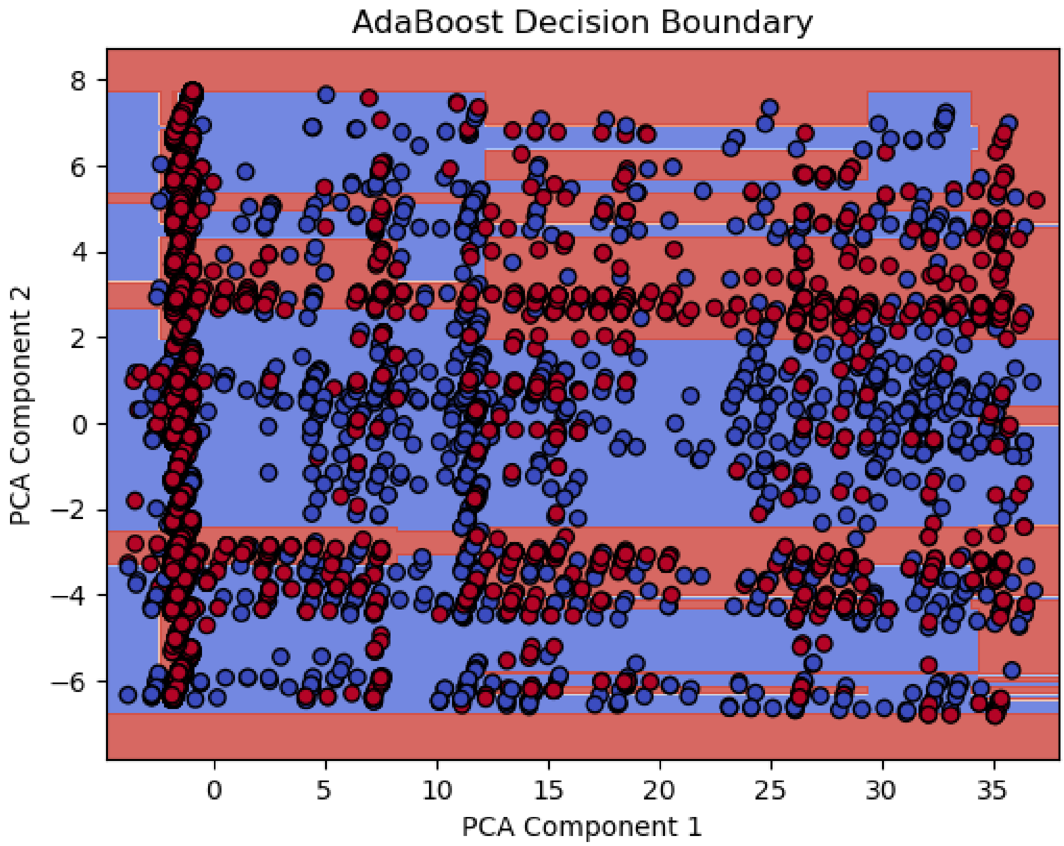
Using PCA to reduce data to 2D

[21]:
```
pca = PCA(n_components=2)
x_train_2d = pca.fit_transform(x_train_smote)
x_test_2d = pca.transform(x_test)

def plot_decision_boundary(clf, X, y, title):
    clf.fit(X, y)
    h = 0.02
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap='coolwarm', alpha=0.8)
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap='coolwarm', edgecolors='k')
    plt.title(title)
    plt.xlabel('PCA Component 1')
    plt.ylabel('PCA Component 2')
    plt.show()

# Plot decision boundaries for tuned models
for name, model in tuned_models.items():
    plot_decision_boundary(model, x_train_2d, y_train_smote, f'{name} Decision␣
 ↪Boundary')
```



Random Forest Decision Boundary
PCA Component 2
PCA Component 1
8
6
4
2
0
−2
−4
−6
0
5
10
15
20
25
30
35


Gradient Boosting Decision Boundary
PCA Component 2
PCA Component 1
8
6
4
2
0
−2
−4
−6
0
5
10
15
20
25
30
35



2.2 Conclusion:

- Model Exploration: Seven classifiers were initially evaluated— **Logistic Regression** (accuracy: 0.77), **Decision Tree** (0.79), **Random Forest** (0.84), **AdaBoost** (0.82), **Gradient Boosting** (0.82), **Bagging** (0.83), and **SVC** (0.76) with Random Forest and Gradient Boosting showing the highest F1-scores for the minority class (>50K).
- Hyperparameter Tuning: The top three models (Gradient Boosting, Random Forest, AdaBoost) were tuned using GridSearchCV with F1-score as the metric:
- Tuned Random Forest: Achieved an accuracy of 0.84 and F1-score of 0.69 for >50K (params: n_estimators=500, max_depth=None, min_samples_split=2, min_samples_leaf=1).
- Tuned Gradient Boosting: Outperformed others with an accuracy of 0.86 and F1-score of 0.72 for >50K (params: n_estimators=300, learning_rate=0.1, max_depth=5).
- Tuned AdaBoost: Recorded an accuracy of 0.83 and F1-score of 0.70 for >50K (params: n_estimators=200, learning_rate=1.0).
- Best Model: Gradient Boosting was selected as the best model, offering the highest F1-score (0.72) and accuracy (0.86), with strong precision (0.71) and recall (0.73) for identifying high-income individuals (>50K).

The tuned Gradient Boosting model effectively predicts whether an individual's income exceeds $50K/year, making it suitable for applications like socioeconomic analysis or targeted resource allocation.