In [1]:
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in /Users/pravinanandpawar/miniforge3/envs/tensorflow_silicon/lib/p
ython3.9/site-packages (1.7.6)
Requirement already satisfied: scipy in /Users/pravinanandpawar/miniforge3/envs/tensorflow_silicon/lib/pyt
hon3.9/site-packages (from xgboost) (1.10.0)
Requirement already satisfied: numpy in /Users/pravinanandpawar/miniforge3/envs/tensorflow_silicon/lib/pyt
hon3.9/site-packages (from xgboost) (1.23.2)
```

In [2]:
```
# Import necessary libraries
import joblib
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.decomposition import PCA
```

In [3]:
```
data = pd.read_csv('data.csv')
```

In [4]:
```
data
```

Out[4]:

	Unnamed: 0	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X15	X16	
0	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_A
1	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	
2	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3
3	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	15
4	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	29
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
29996	29996	220000	1	3	1	39	0	0	0	0	...	88004	31237	15
29997	29997	150000	1	3	2	43	-1	-1	-1	-1	...	8979	5190	
29998	29998	30000	1	2	2	37	4	3	2	-1	...	20878	20582	19
29999	29999	80000	1	3	1	41	1	-1	0	0	...	52774	11855	48
30000	30000	50000	1	2	1	46	0	0	0	0	...	36535	32428	15

30001 rows × 25 columns

In [5]:
```
# Exploratory Data Analysis (EDA)
```

In [6]:
```
# Display basic information about the dataset
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30001 entries, 0 to 30000
Data columns (total 25 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Unnamed: 0  30001 non-null  object
 1   X1          30001 non-null  object
 2   X2          30001 non-null  object
 3   X3          30001 non-null  object
 4   X4          30001 non-null  object
 5   X5          30001 non-null  object
 6   X6          30001 non-null  object
 7   X7          30001 non-null  object
 8   X8          30001 non-null  object
 9   X9          30001 non-null  object
 10  X10         30001 non-null  object
 11  X11         30001 non-null  object
 12  X12         30001 non-null  object
 13  X13         30001 non-null  object
 14  X14         30001 non-null  object
 15  X15         30001 non-null  object
 16  X16         30001 non-null  object
 17  X17         30001 non-null  object
 18  X18         30001 non-null  object
 19  X19         30001 non-null  object
 20  X20         30001 non-null  object
 21  X21         30001 non-null  object
 22  X22         30001 non-null  object
 23  X23         30001 non-null  object
 24  Y           30001 non-null  object
dtypes: object(25)
memory usage: 5.7+ MB
None
```

In [7]:
```
print(data.describe())
```

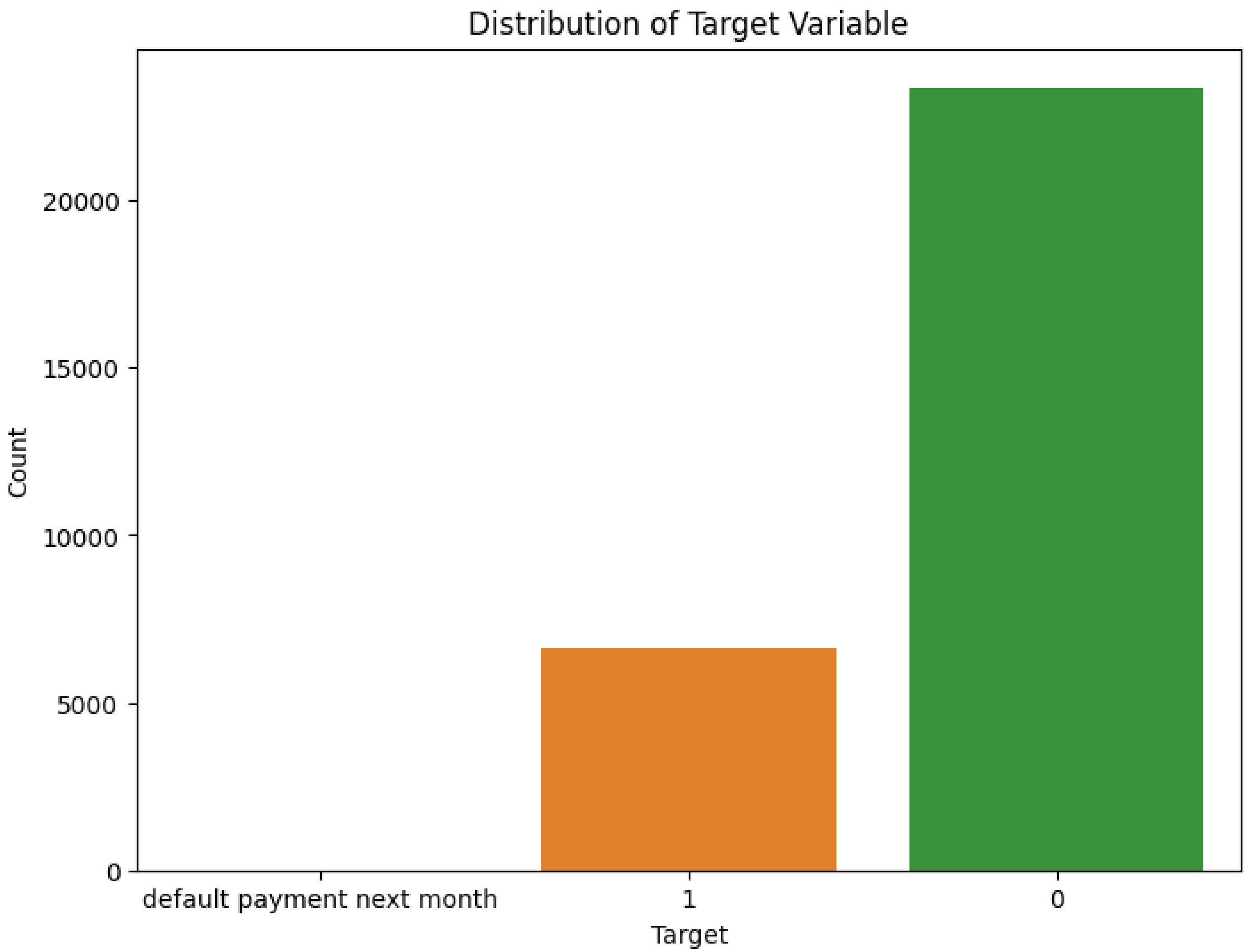
```
       Unnamed: 0     X1     X2     X3     X4     X5     X6     X7     X8  \
count       30001  30001  30001  30001  30001  30001  30001  30001  30001   
unique      30001     82      3      8      5     57     12     12     12   
top            ID  50000      2      2      2     29      0      0      0   
freq            1   3365  18112  14030  15964   1605  14737  15730  15764   

           X9  ...    X15    X16    X17    X18    X19    X20    X21    X22  \
count   30001  ...  30001  30001  30001  30001  30001  30001  30001  30001   
unique     12  ...  21549  21011  20605   7944   7900   7519   6938   6898   
top         0  ...      0      0      0      0      0      0      0      0   
freq    16455  ...   3195   3506   4020   5249   5396   5968   6408   6703   

          X23      Y  
count   30001  30001  
unique   6940      3  
top         0      0  
freq     7173  23364  

[4 rows x 25 columns]
```

In [8]:
```
# Check for missing values
missing_values = data.isnull().sum()
print("Missing Values:")
print(missing_values)
```

```
Missing Values:
Unnamed: 0    0
X1            0
X2            0
X3            0
X4            0
X5            0
X6            0
X7            0
X8            0
X9            0
X10           0
X11           0
X12           0
X13           0
X14           0
X15           0
X16           0
X17           0
X18           0
X19           0
X20           0
X21           0
X22           0
X23           0
Y             0
dtype: int64
```

In [9]:

```
# Visualize the distribution of the target variable
plt.figure(figsize=(8, 6))
sns.countplot(x='Y', data=data)
plt.title('Distribution of Target Variable')
plt.xlabel('Target')
plt.ylabel('Count')
plt.show()
```



In [10]:
```
data = data.drop(0)
data
```

Out[10]:

	Unnamed: 0	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X15	X16	X17	X18	X19	X20	X21	X22
1	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	0	0	689	0	0	0
2	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3261	0	1000	1000	1000	0
3	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	15549	1518	1500	1000	1000	1000
4	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	29547	2000	2019	1200	1100	1069
5	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	19131	2000	36681	10000	9000	689
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29996	29996	220000	1	3	1	39	0	0	0	0	...	88004	31237	15980	8500	20000	5003	3047	5000
29997	29997	150000	1	3	2	43	-1	-1	-1	-1	...	8979	5190	0	1837	3526	8998	129	0
29998	29998	30000	1	2	2	37	4	3	2	-1	...	20878	20582	19357	0	0	22000	4200	2000
29999	29999	80000	1	3	1	41	1	-1	0	0	...	52774	11855	48944	85900	3409	1178	1926	52964
30000	30000	50000	1	2	1	46	0	0	0	0	...	36535	32428	15313	2078	1800	1430	1000	1000

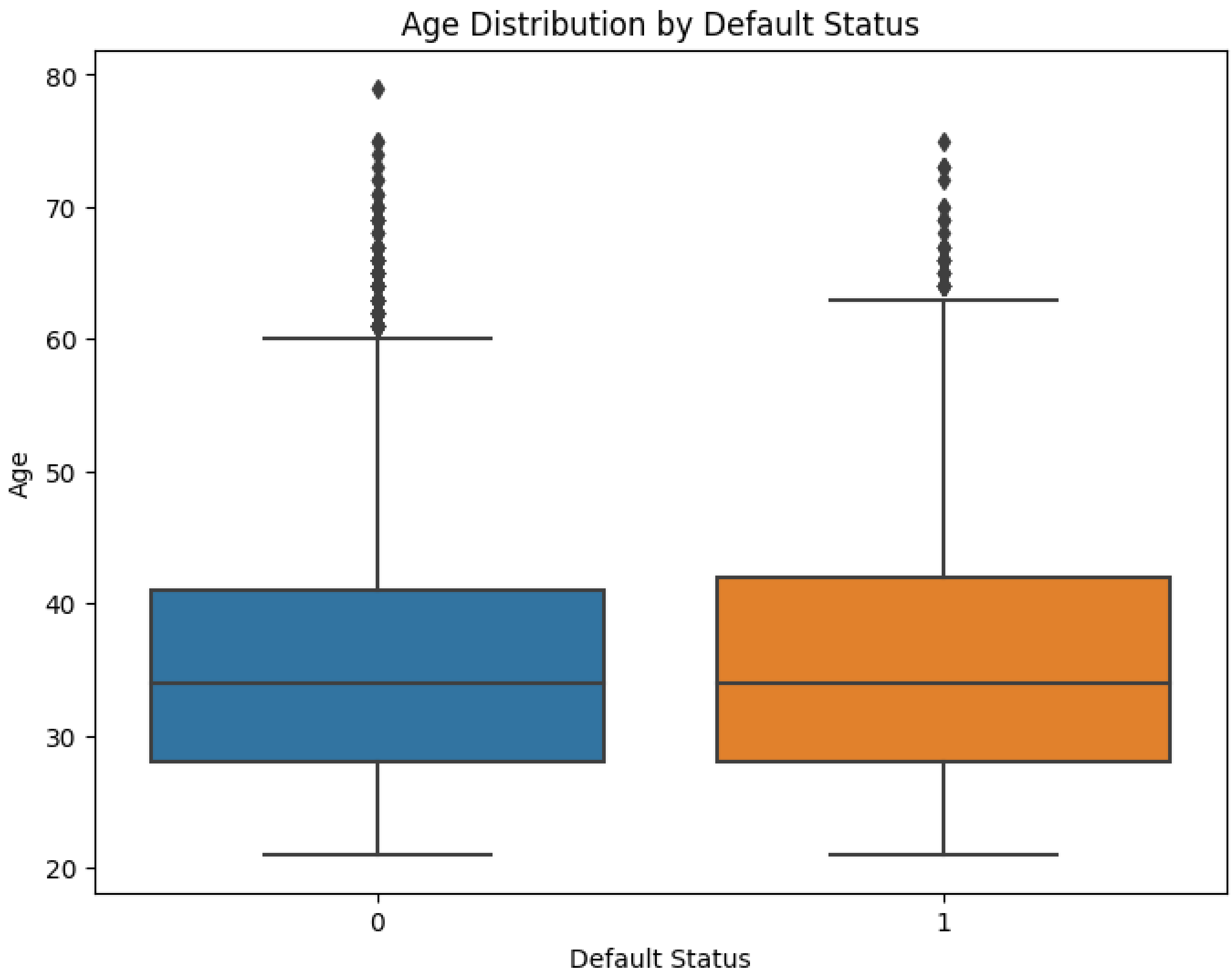
30000 rows × 25 columns

In [11]:

```
# Convert all columns to numeric
data = data.apply(pd.to_numeric, errors='coerce')
```

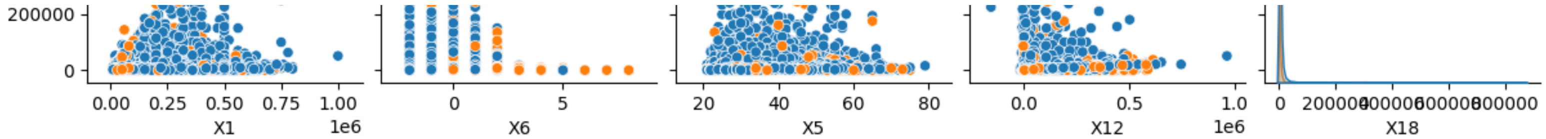
In [12]:

```
# Box plot for age distribution by default status
plt.figure(figsize=(8, 6))
sns.boxplot(x='Y', y='X5', data=data)
plt.title('Age Distribution by Default Status')
plt.xlabel('Default Status')
plt.ylabel('Age')
plt.show()
```



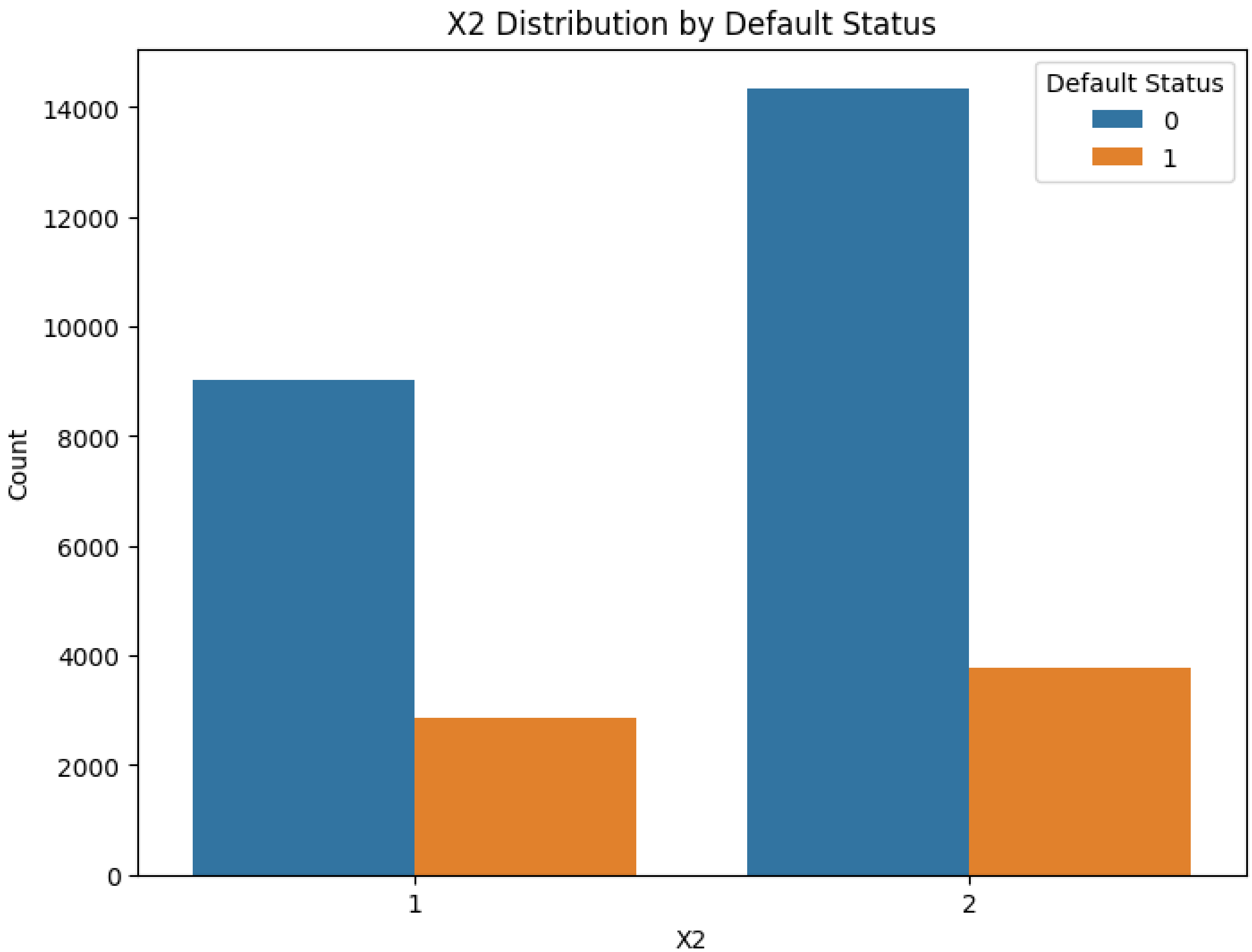
In [13]:
```
# Pair plot for selected numerical features
# Pair plot for selected numerical features
#['LIMIT_BAL', 'AGE', 'PAY_0', 'BILL_AMT1', 'PAY_AMT1', 'default payment next month']], hue='default paymen
sns.pairplot(data[['X1', 'X6', 'X5', 'X12', 'X18', 'Y']], hue='Y')
plt.show()
```

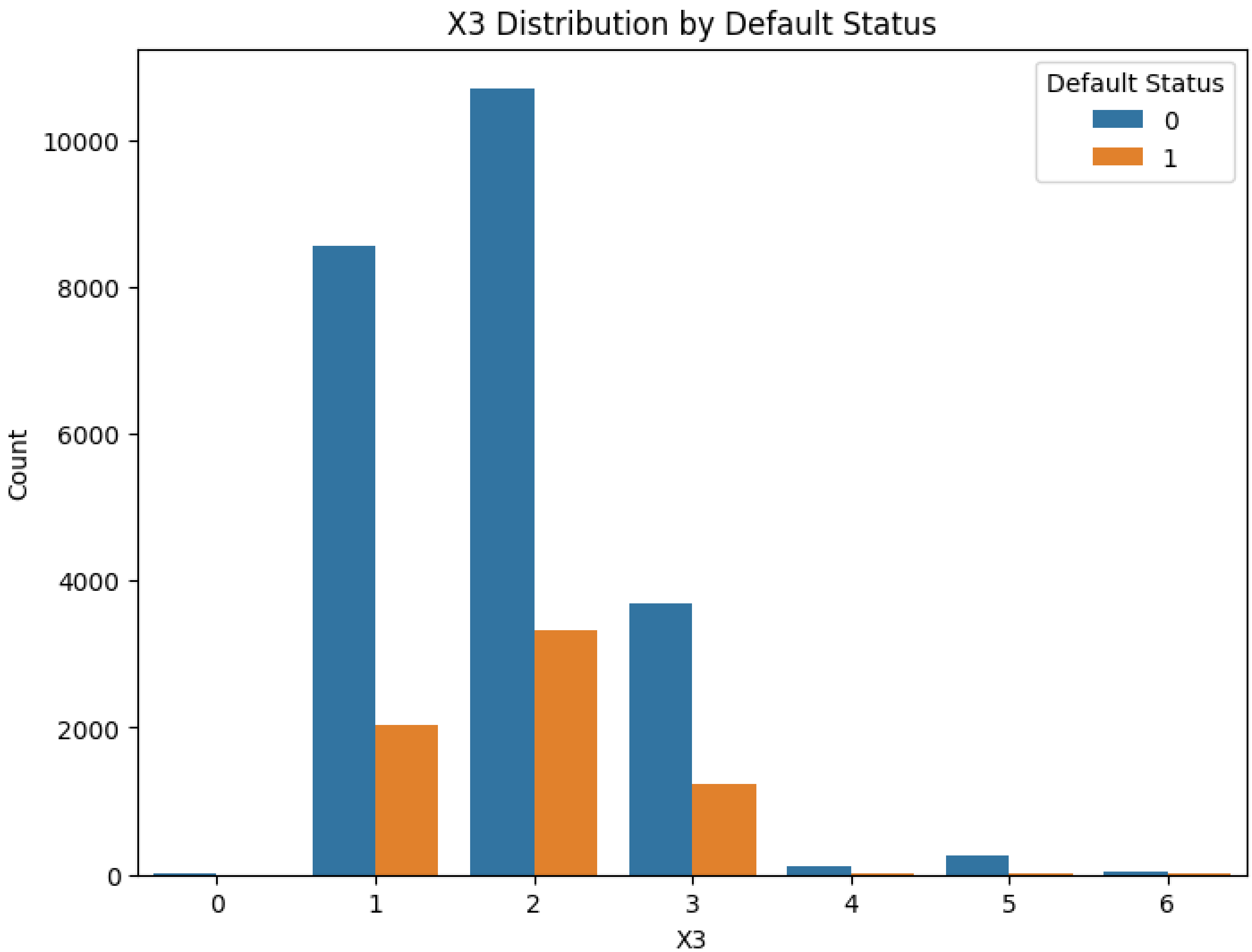

1e6
X1
X6
X5
1e6
X12
X18
Y
0
1

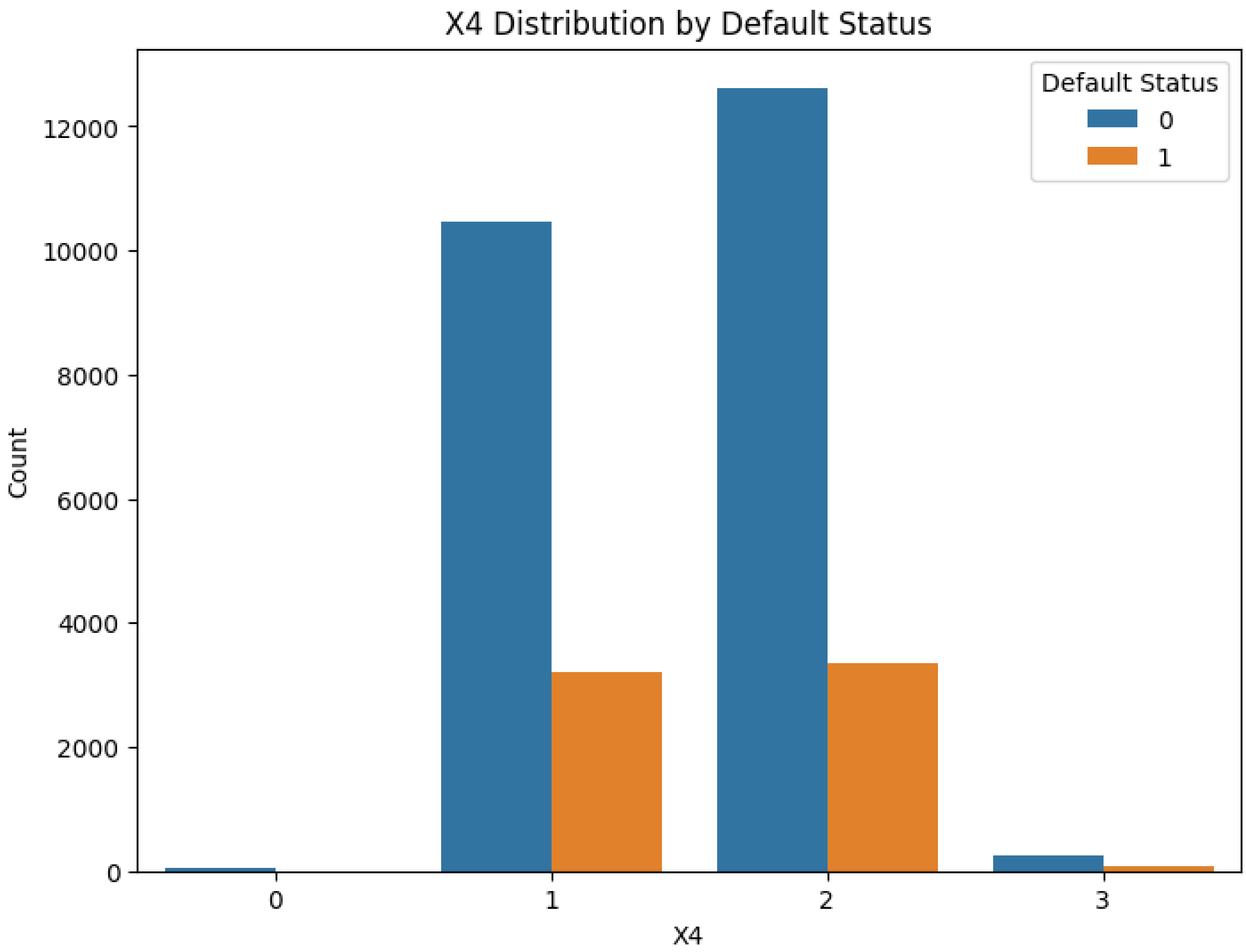


In [14]:

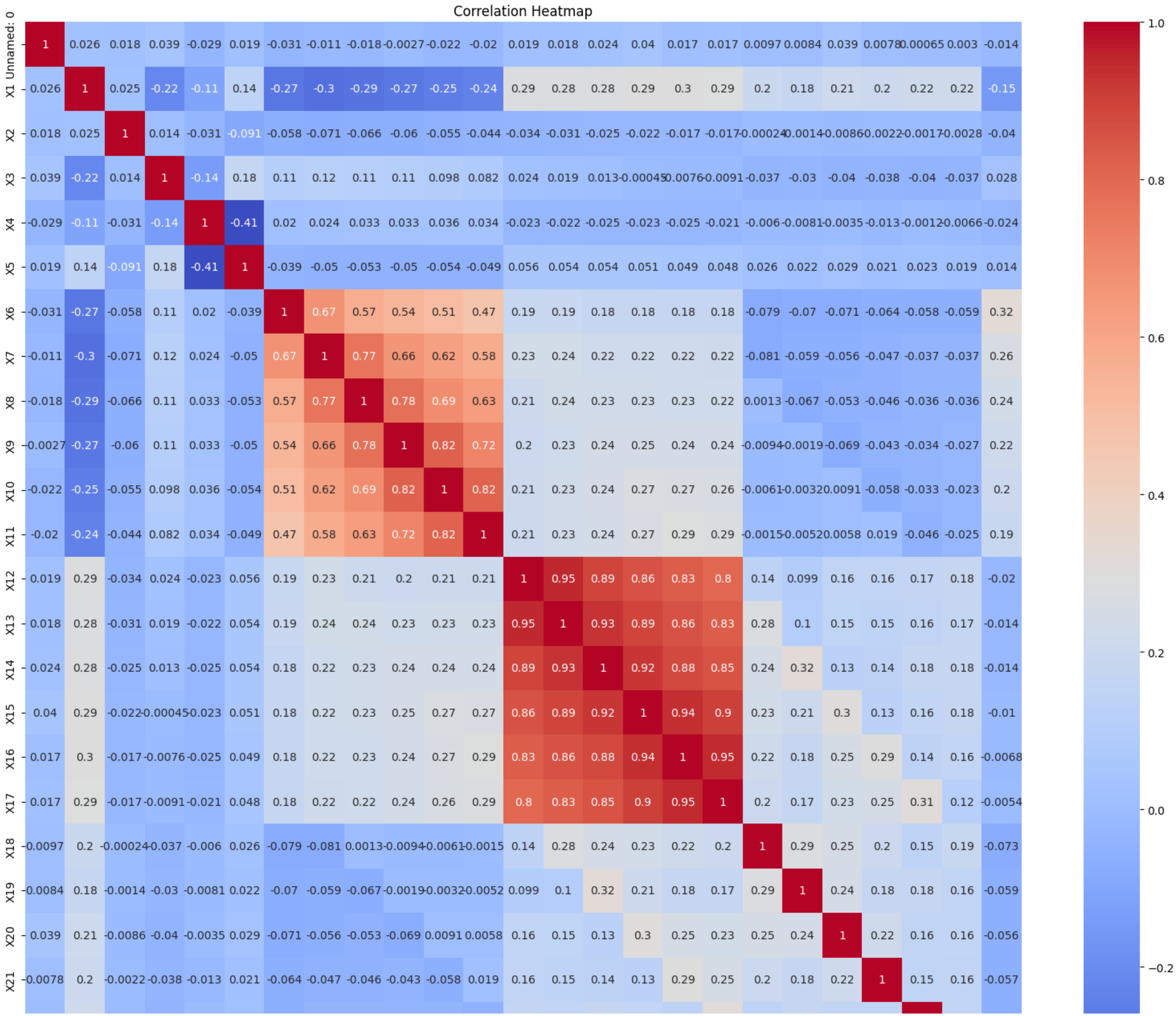
```python
# Explore categorical features  ['SEX', 'EDUCATION', 'MARRIAGE']
categorical_cols = ['X2', 'X3', 'X4']
for col in categorical_cols:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=col, hue='Y', data=data)
    plt.title(f'{col} Distribution by Default Status')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.legend(title='Default Status', loc='upper right')
    plt.show()
```

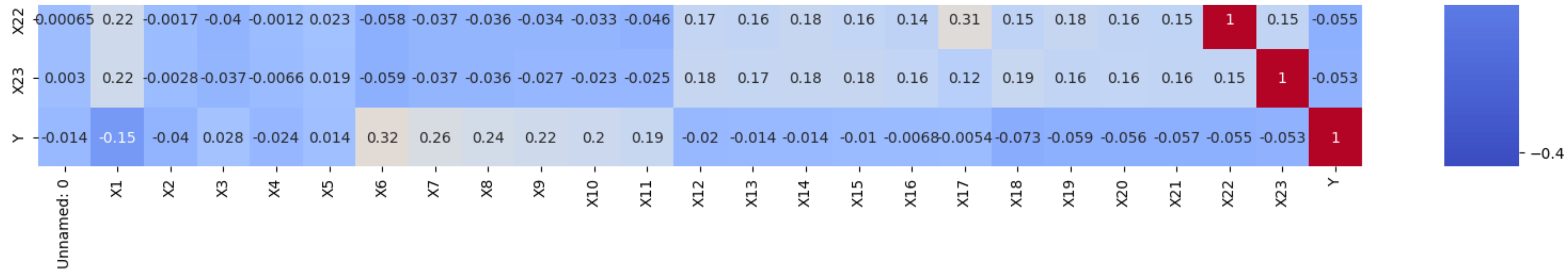

X2 Distribution by Default Status
Default Status
0
1
Count
14000
12000
10000
8000
6000
4000
2000
0
1
2
X2


X3 Distribution by Default Status
Default Status
0
1
Count
10000
8000
6000
4000
2000
0
0
1
2
3
4
5
6
X3



In [15]:
```
# Visualize correlations between features
correlation_matrix = data.corr()
plt.figure(figsize=(20, 18))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```


Correlation Heatmap
Unnamed: 0
X1
X2
X3
X4
X5
X6
X7
X8
X9
X10
X11
X12
X13
X14
X15
X16
X17
X18
X19
X20
X21
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



In [16]:
```
data
```

Out[16]:

	Unnamed: 0	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X15	X16	X17	X18	X19	X20	X21	X22
1	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	0	0	689	0	0	0
2	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3261	0	1000	1000	1000	0
3	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	15549	1518	1500	1000	1000	1000
4	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	29547	2000	2019	1200	1100	1069
5	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	19131	2000	36681	10000	9000	689
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29996	29996	220000	1	3	1	39	0	0	0	0	...	88004	31237	15980	8500	20000	5003	3047	5000
29997	29997	150000	1	3	2	43	-1	-1	-1	-1	...	8979	5190	0	1837	3526	8998	129	0
29998	29998	30000	1	2	2	37	4	3	2	-1	...	20878	20582	19357	0	0	22000	4200	2000
29999	29999	80000	1	3	1	41	1	-1	0	0	...	52774	11855	48944	85900	3409	1178	1926	52964
30000	30000	50000	1	2	1	46	0	0	0	0	...	36535	32428	15313	2078	1800	1430	1000	1000

30000 rows × 25 columns

In [17]:
```
#Preprocessing
def preprocessing(data):
    # Assuming you have a DataFrame named 'data'
    data.dropna(inplace=True)  # Drop rows with null or NaN values

    # Reset the index if needed
```

```
    data.reset_index(drop=True, inplace=True)

    data = data.drop(0)

    #Drop target
    X = data.drop('Y', axis=1)

    #Drop ID
    X = X.drop('Unnamed: 0', axis=1)

    #Target
    y = data['Y']

    return X, y
```

In [18]:
```
# Transform data
def transformData(X_train, X_test, y_train, y_test):
    # Label Encoding
    label_encoder = LabelEncoder()
    y_train = label_encoder.fit_transform(y_train)
    y_test = label_encoder.fit_transform(y_test)

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

    return X_train_scaled, X_test_scaled, y_train, y_test
```

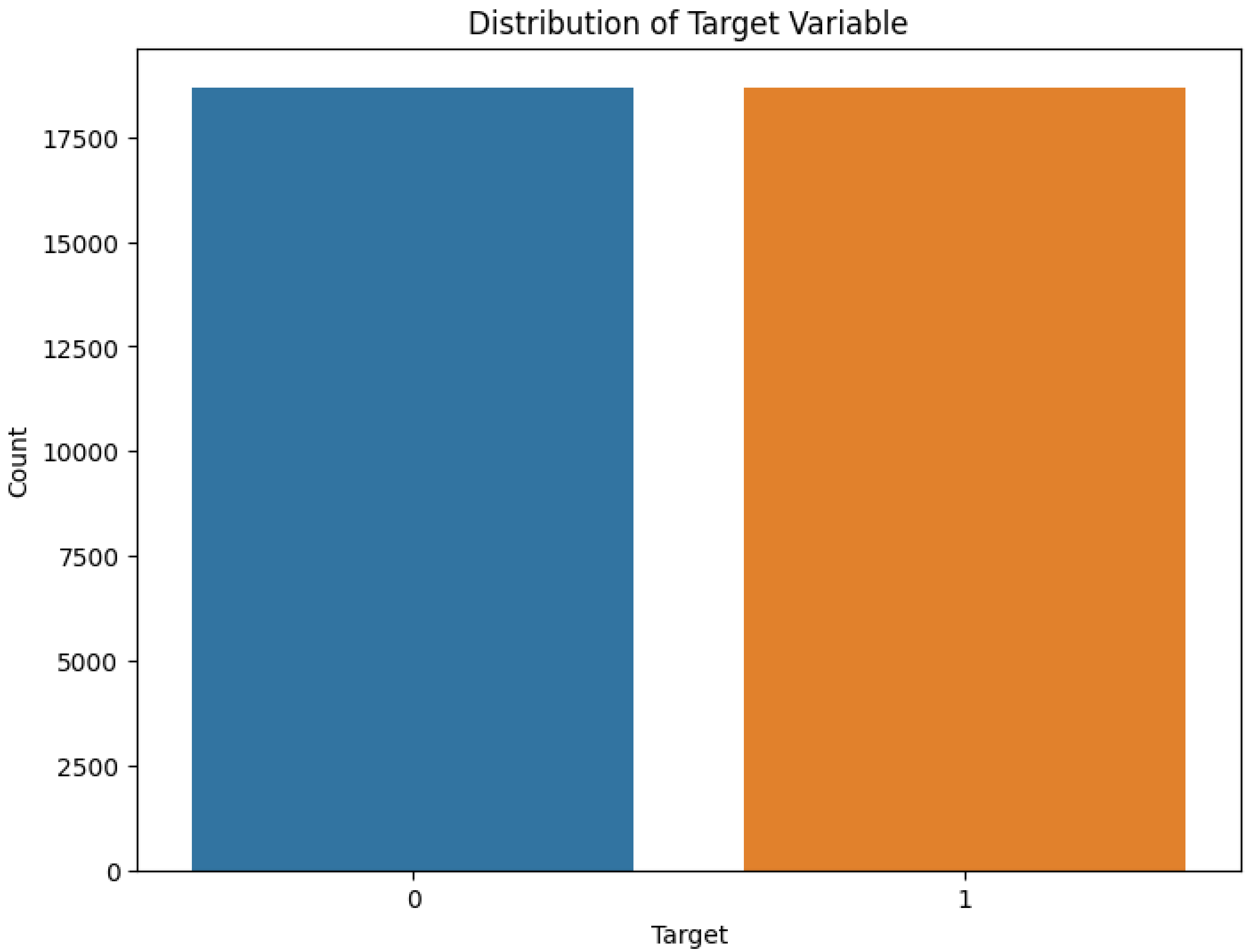
In [19]:
```
X, y = preprocessing(data)
```

In [20]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train_scaled, X_test_scaled, y_train, y_test = transformData(X_train, X_test, y_train, y_test)
```

In [21]:
```
smote = SMOTE(random_state=42)
X_train_scaled, y_train = smote.fit_resample(X_train_scaled, y_train)
```

In [22]:
```
# Visualize the distribution of the target variable
plt.figure(figsize=(8, 6))
sns.countplot(x=y_train)
```

```
plt.title('Distribution of Target Variable')
plt.xlabel('Target')
plt.ylabel('Count')
plt.show()
```



In [23]:
```
X_train_scaled
```

Out[23]:
```
array([[-0.12932766,  0.80797506, -1.08017445, ..., -0.27320499,
        -0.30860887,  0.05512315],
       [-0.20627352,  0.80797506,  0.18270403, ..., -0.06002346,
        -0.07028379, -0.10942503],
       [-0.66794869,  0.80797506,  0.18270403, ..., -0.30664523,
        -0.2115158 , -0.11556093],
       ...,
       [-0.59862837,  0.80797506,  0.18270403, ..., -0.30664523,
        -0.05002744, -0.22959035],
       [ 1.82798748,  0.80797506,  0.41946765, ...,  0.54477458,
         0.50664753,  0.48744941],
       [ 1.61190291,  0.80797506, -0.86379513, ...,  0.26408898,
         0.2580822 ,  0.51612305]])
```

In [24]:
```
# Train multiple models
models = [
    ('Logistic Regression', LogisticRegression(random_state=42)),
    ('Random Forest', RandomForestClassifier(n_estimators=100, random_state=42)),
    ('SVC', SVC(probability=True, random_state=42)),
    ('XGBoost', XGBClassifier(n_estimators=100, random_state=42))
]

# Perform grid search on individual models
best_models = []

for name, model in models:
    if name == 'Logistic Regression':
        param_grid = {'C': [0.1, 1.0, 10.0]}
    elif name == 'Random Forest':
        param_grid = {'n_estimators': [100, 200]}
    elif name == 'SVC':
        param_grid = {'C': [0.1, 1.0, 10.0]}
    elif name == 'XGBoost':
        param_grid = {'n_estimators': [100, 200]}

    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=3)
    grid_search.fit(X_train_scaled, y_train)
    best_model = grid_search.best_estimator_
    best_models.append((name, best_model))

# Evaluate best models
for name, best_model in best_models:
```

```
    y_pred = best_model.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    classification_rep = classification_report(y_test, y_pred)

    print(f"Best {name} Accuracy: {accuracy:.2f}")
    print(f"Best {name} Classification Report:\n", classification_rep)
    print(f"Best {name} Hyperparameters:", grid_search.best_params_)
```

```
Best Logistic Regression Accuracy: 0.68
Best Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.69      0.77      4671
           1       0.38      0.68      0.49      1329

    accuracy                           0.68      6000
   macro avg       0.63      0.68      0.63      6000
weighted avg       0.77      0.68      0.71      6000

Best Logistic Regression Hyperparameters: {'n_estimators': 100}
Best Random Forest Accuracy: 0.80
Best Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.89      0.87      4671
           1       0.56      0.51      0.53      1329

    accuracy                           0.80      6000
   macro avg       0.71      0.70      0.70      6000
weighted avg       0.80      0.80      0.80      6000

Best Random Forest Hyperparameters: {'n_estimators': 100}
Best SVC Accuracy: 0.76
Best SVC Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.81      0.84      4671
           1       0.47      0.59      0.52      1329

    accuracy                           0.76      6000
   macro avg       0.67      0.70      0.68      6000
weighted avg       0.78      0.76      0.77      6000

Best SVC Hyperparameters: {'n_estimators': 100}
Best XGBoost Accuracy: 0.81
Best XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.92      0.88      4671
           1       0.60      0.40      0.48      1329
```

```
    accuracy                           0.81      6000
   macro avg       0.72      0.66      0.68      6000
weighted avg       0.79      0.81      0.79      6000

Best XGBoost Hyperparameters: {'n_estimators': 100}
```

In [25]:

```
# Create a soft voting ensemble
voting_models = [(name, best_model) for name, best_model in best_models]
voting_classifier = VotingClassifier(estimators=voting_models, voting='soft')  # 'soft' for probability-ba

# Fit the ensemble model
voting_classifier.fit(X_train_scaled, y_train)

# Make predictions using the ensemble
y_pred_probs = voting_classifier.predict_proba(X_test_scaled)
y_pred = y_pred_probs.argmax(axis=1)
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f"Ensemble Accuracy: {accuracy:.2f}")
print("Ensemble Classification Report:\n", classification_rep)
```

```
Ensemble Accuracy: 0.80
Ensemble Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.88      0.87      4671
           1       0.55      0.53      0.54      1329

    accuracy                           0.80      6000
   macro avg       0.71      0.70      0.71      6000
weighted avg       0.80      0.80      0.80      6000
```

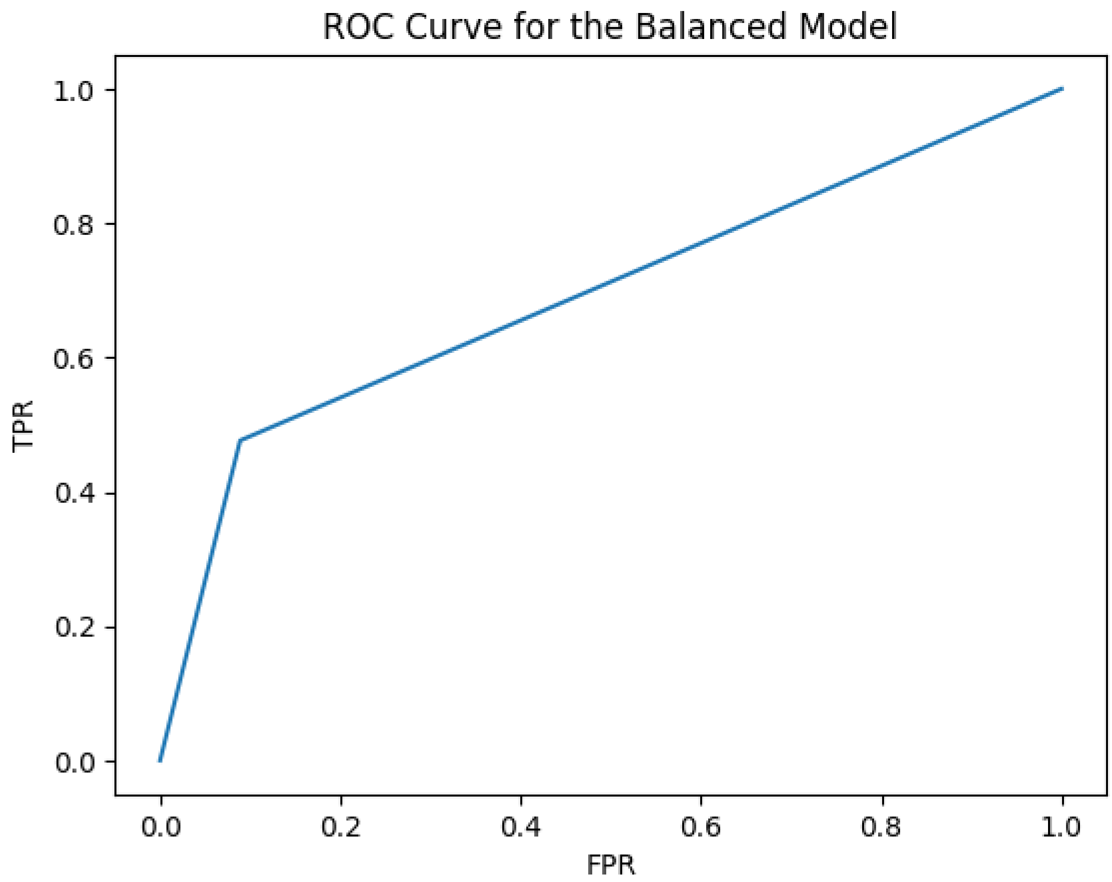
In [26]:

```
# Create a hard voting ensemble
voting_models = [(name, best_model) for name, best_model in best_models]
voting_classifier = VotingClassifier(estimators=voting_models, voting='hard')

# Fit the ensemble model
voting_classifier.fit(X_train_scaled, y_train)
```

```
# Make predictions using the ensemble
y_pred = voting_classifier.predict(X_test_scaled)
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f"Ensemble Accuracy: {accuracy:.2f}")
print("Ensemble Classification Report:\n", classification_rep)
```

```
Ensemble Accuracy: 0.81
Ensemble Classification Report:
               precision    recall  f1-score   support

           0       0.86      0.91      0.88      4671
           1       0.60      0.48      0.53      1329

    accuracy                           0.81      6000
   macro avg       0.73      0.69      0.71      6000
weighted avg       0.80      0.81      0.81      6000
```

In [27]:
```
from sklearn.metrics import roc_curve, roc_auc_score
fpr, tpr, _ = roc_curve(y_test,  y_pred)
plt.plot(fpr,tpr)
plt.ylabel('TPR')
plt.xlabel('FPR')
plt.title("ROC Curve for the Balanced Model")
plt.show()
```



In [28]:
```
#AUC value
auc_value = roc_auc_score(y_test, y_pred)
print("AUC:", auc_value)
```

```
AUC: 0.6937259484461301
```

In [29]:
```
# Save the ensemble model
joblib.dump(voting_classifier, 'CreditDefaultPrediction.pkl')
```

Out[29]: ['CreditDefaultPrediction.pkl']

In [ ]: