Classifying Loan Default

- This project involves predicting loan defaults, where misclassifications carry significant financial implications. A false positive (predicting default when none exists) costs a lot due to lost revenue, and a false negative (failing to predict an actual default) costs even more from unrecovered loan principal and recovery expenses. With false positives and negatives costing over millions annually, optimizing this model is critical to minimize financial losses.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, f1_score, make_scorer, PrecisionRecallDisplay
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold, cross_val_score

import optuna
import logging
optuna.logging.set_verbosity(optuna.logging.WARNING)
```

Data

In [2]:
```
df = pd.read_csv('Loan_default.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	LoanID	Age	Income	LoanAmount	CreditScore	MonthsEmployed	NumCreditLines	InterestRate	LoanTerm	DTIRatio	Education	Employ
0	I38PQUQS96	56	85994	50587	520	80	4	15.23	36	0.44	Bachelor's	
1	HPSK72WA7R	69	50432	124440	458	15	1	4.81	60	0.68	Master's	
2	C1OZ6DPJ8Y	46	84208	129188	451	26	3	21.17	24	0.31	Master's	Un
3	V2KKSFM3UN	32	31713	44799	743	0	3	7.07	24	0.23	High School	
4	EY08JDHTZP	60	20437	9139	633	8	4	6.51	48	0.73	Bachelor's	Un

Clean

In [4]:
```
print(f'shape:{df.shape}')
print(f'missing:{df.isna().sum().sum()}')
print(f'duplicates:{df.duplicated().sum()}')
```

```
shape:(255347, 18)
missing:0
duplicates:0
```

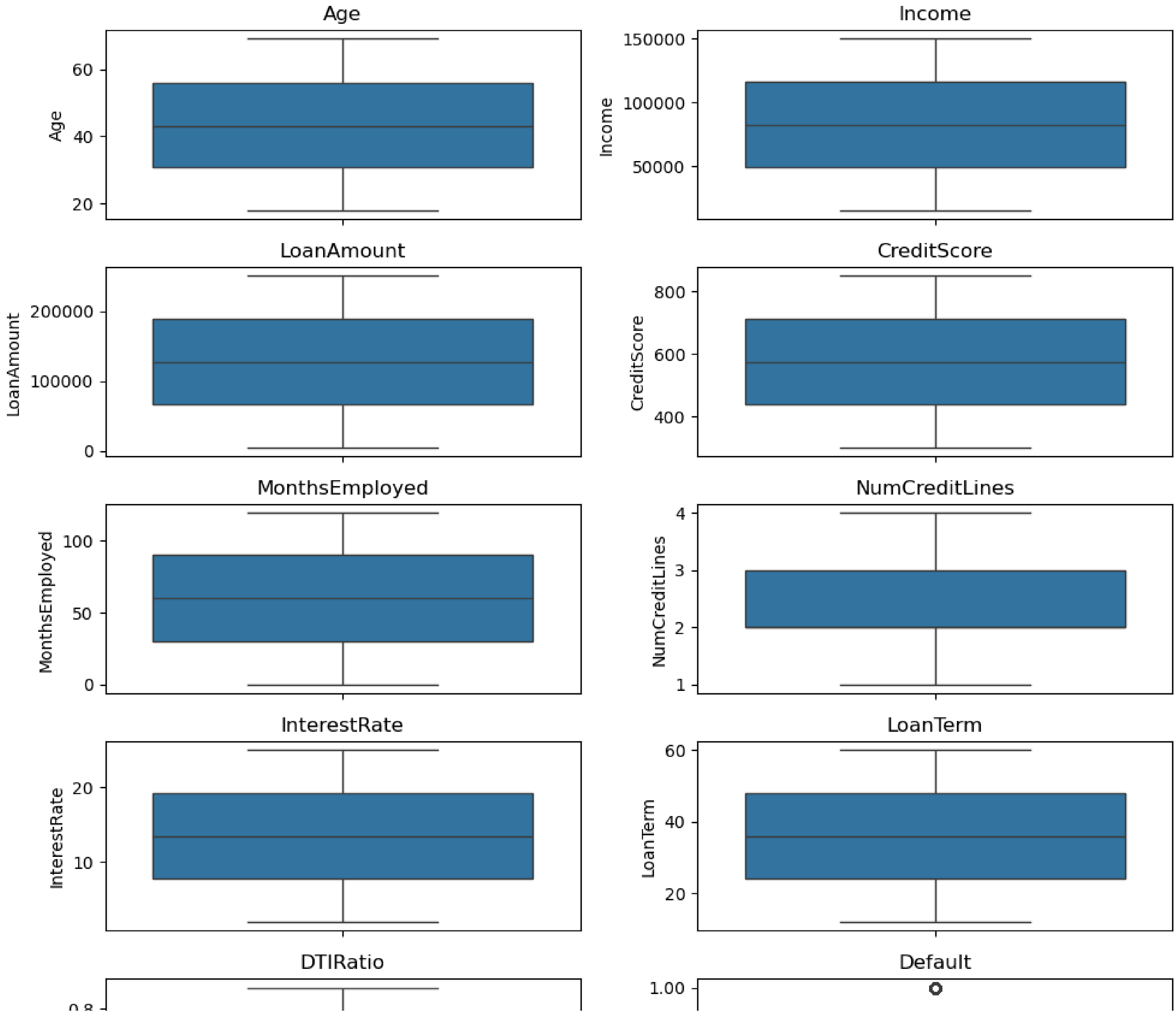
In [5]:
```
df.drop(columns=['LoanID'], inplace=True)
```

Outliers

In [6]:
```
numerical = df.select_dtypes(include=[np.number])
```

In [7]:

```
fig, ax = plt.subplots(5,2, figsize=(10,10))
ax = ax.flatten()
for i,col in enumerate(numerical.columns):
    sns.boxplot(df[col], ax=ax[i])
    ax[i].set_title(f'{col}', fontsize=12)
plt.tight_layout()
```


Age
Age
60
40
20
Income
Income
150000
100000
50000
LoanAmount
LoanAmount
200000
100000
0
CreditScore
CreditScore
800
600
400
MonthsEmployed
MonthsEmployed
100
50
0
NumCreditLines
NumCreditLines
4
3
2
1
InterestRate
InterestRate
20
10
LoanTerm
LoanTerm
60
40
20
DTIRatio
Default
1.00

- There doesn't appear to be any outliers.

Categorical Variables

In [8]:
```
education_mappings = {"High School":1,"Bachelor's":2, "Master's":3, "PhD":4}
df['Education']    = df['Education'].map(education_mappings)
```

In [9]:
```
dummies = df.select_dtypes(include=['object']).columns
df = pd.get_dummies(df, columns=dummies, drop_first=False)
```

In [10]:
```
df.iloc[:,16:]
```

Out[10]:

	MaritalStatus_Married	MaritalStatus_Single	HasMortgage_No	HasMortgage_Yes	HasDependents_No	HasDependents_Yes	LoanPurpose_Auto
0	False	False	False	True	False	True	False
1	True	False	True	False	True	False	False
2	False	False	False	True	False	True	True
3	True	False	True	False	True	False	False
4	False	False	True	False	False	True	True
...	...	...	...	...	...	...	...
255342	True	False	True	False	True	False	False
255343	False	False	True	False	True	False	False
255344	True	False	False	True	False	True	True
255345	False	True	False	True	False	True	False
255346	False	False	False	True	True	False	False

255347 rows × 13 columns

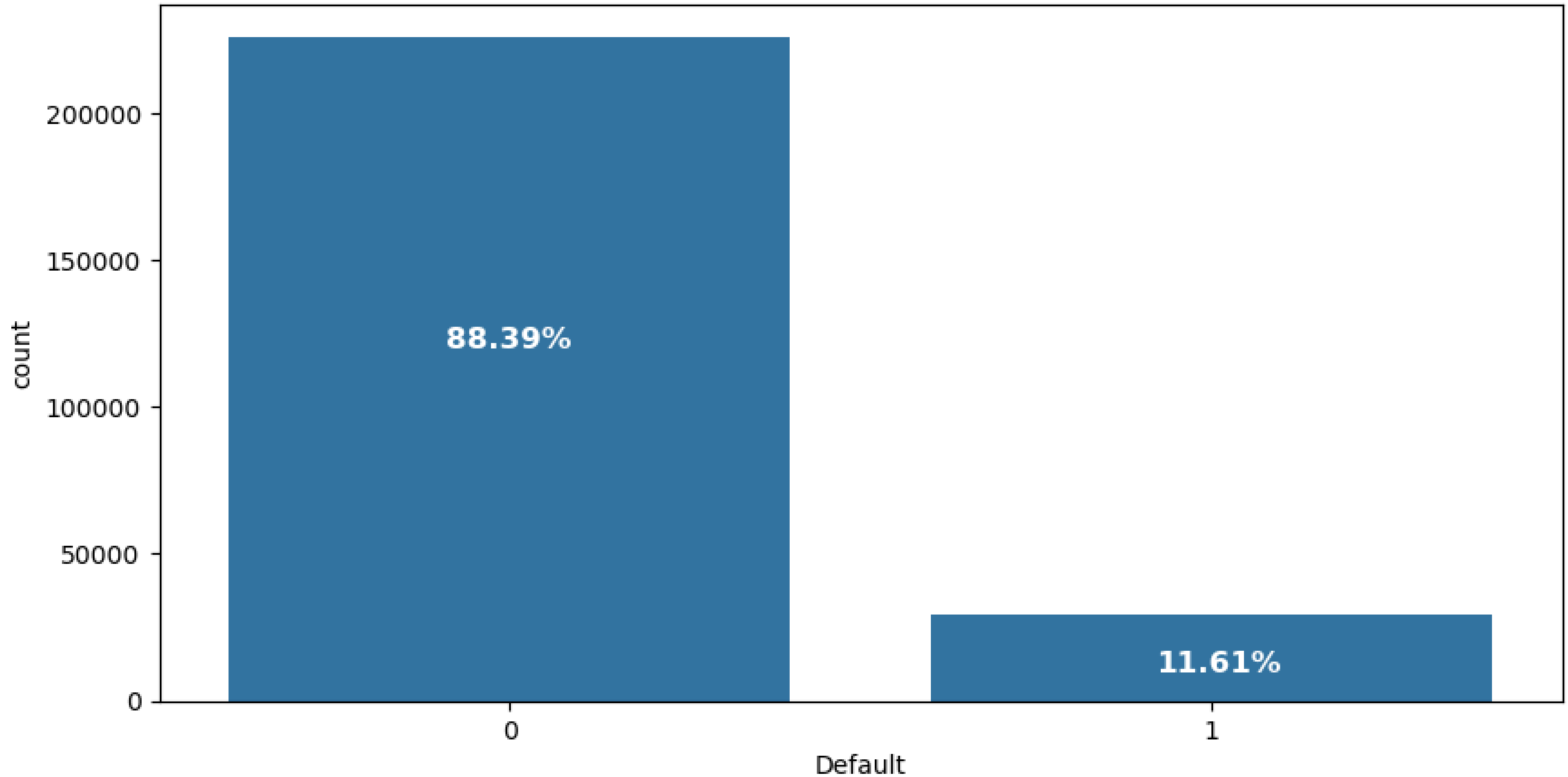
Class Balance

In [11]:
```
plt.figure(figsize=(10,5))

sns.barplot(df.Default.value_counts())

negative = len(df[df.Default==0])/len(df)*100
positive = len(df[df.Default==1])/len(df)*100

plt.text(-0.09, 120000, f'{round(negative,2)}%', fontsize = 12, color='white', weight='bold')
plt.text(0.92, 10000, f'{round(positive,2)}%', fontsize = 12, color='white', weight='bold');
```



- If someone guessed no every time they would be right about 88% of the time.

Train/Validation/Test Split

In [12]:
```
X = df.drop(columns='Default')
y = df.Default

# Train (60%), Temp (40%)
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, random_state=1, stratify=y)

# Validation (20%) and Test (20%) from Temp
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=1, stratify=y_temp)
```

- The target variable is stratified to ensure it is equally represented in the splits.

Baseline Model

In [13]:
```
model = RandomForestClassifier(random_state=1, n_jobs=-1)
model.fit(X_train,y_train)
y_pred = model.predict(X_val)
print(classification_report(y_val,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      1.00      0.94     45139
           1       0.63      0.03      0.06      5930

    accuracy                           0.89     51069
   macro avg       0.76      0.51      0.50     51069
weighted avg       0.86      0.89      0.84     51069
```

- This first model is getting 3% of the people who defaulted. The f1 score for the positive class is 0.06.

Feature Engineering

In [14]:
```
def credit_cats(score):
    if score >= 750:
        return 3
    elif score >= 650:
        return 2
    elif score >= 550:
        return 1
    else:
        return 0
```

In [15]:

```python
# features for training data
X_train['LoanToIncomeRatio'] = X_train['LoanAmount'] / X_train['Income']
X_train['InterestToIncomeRatio'] = X_train['InterestRate'] / X_train['Income']
X_train['MonthlyDebtToIncomeRatio'] = (X_train['LoanAmount'] / X_train['LoanTerm']) / (X_train['Income'] / 12)
X_train['CreditUtilization'] = X_train['LoanAmount'] / X_train['NumCreditLines']
X_train['LoanBurdenMonths'] = X_train['LoanAmount'] / (X_train['Income'] / 12)
X_train['CreditCategory'] = X_train['CreditScore'].apply(credit_cats)
X_train['LoanTermCategory'] = X_train['LoanTerm'].apply(lambda x: 0 if x < 36 else 1 if x < 60 else 2)

X_train['LoanSizeCategory'] = pd.cut(X_train['LoanAmount'], bins=[0, 5000, 20000, 50000, 100000, np.inf],
                                     labels=[0, 1, 2, 3, 4])

# applying same features to validation and test set
for df_subset in [X_val, X_test]:
    df_subset['LoanToIncomeRatio'] = df_subset['LoanAmount'] / df_subset['Income']
    df_subset['InterestToIncomeRatio'] = df_subset['InterestRate'] / df_subset['Income']
    df_subset['MonthlyDebtToIncomeRatio'] = (df_subset['LoanAmount'] / df_subset['LoanTerm']) / (df_subset['Income'] /
    df_subset['CreditUtilization'] = df_subset['LoanAmount'] / df_subset['NumCreditLines']
    df_subset['LoanBurdenMonths'] = df_subset['LoanAmount'] / (df_subset['Income'] / 12)
    df_subset['CreditCategory'] = df_subset['CreditScore'].apply(credit_cats)
    df_subset['LoanTermCategory'] = df_subset['LoanTerm'].apply(lambda x: 0 if x < 36 else 1 if x < 60 else 2)

    df_subset['LoanSizeCategory'] = pd.cut(df_subset['LoanAmount'], bins=[0, 5000, 20000, 50000, 100000, np.inf],
                                           labels=[0, 1, 2, 3, 4])
```

In [16]:
```
X_train.iloc[:, 29:]
```

Out[16]:

	InterestToIncomeRatio	MonthlyDebtToIncomeRatio	CreditUtilization	LoanBurdenMonths	CreditCategory	LoanTermCategory	LoanSizeCategor
81133	0.000052	0.585708	76387.500000	14.057001	0	0	
165234	0.000142	0.493794	149104.000000	23.702102	2	1	
242324	0.000115	0.187743	53238.000000	9.011680	2	1	
224777	0.000280	0.560673	96087.000000	26.912299	3	1	
115292	0.000023	0.164290	21442.500000	3.942965	0	0	
...	...	...	...	...	...	...	.
52242	0.000051	0.345334	25627.666667	8.288006	2	0	
96610	0.000116	0.166025	85485.000000	7.969205	0	1	
41562	0.000079	0.559495	59509.250000	33.569679	0	2	
235280	0.000141	1.713994	55318.000000	20.567923	1	0	
61614	0.000138	1.785579	62034.000000	21.426951	0	0	

153208 rows × 7 columns

Model 2

In [17]:
```
model2 = RandomForestClassifier(random_state=1, n_jobs=-1)
model2.fit(X_train,y_train)
y_pred = model2.predict(X_val)
print(classification_report(y_val,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      1.00      0.94     45139
           1       0.60      0.04      0.08      5930

    accuracy                           0.89     51069
   macro avg       0.75      0.52      0.51     51069
weighted avg       0.86      0.89      0.84     51069
```

- The recall increased to 4% and the f1 score increased to 0.08.

Feature Elimination (maximize f1 for positive class)

In [18]:

```python
remaining_features = list(X_train.columns[:])
best_f1 = 0
best_features = None

while len(remaining_features) > 1:
    model.fit(X_train[remaining_features], y_train)

    # predict on validation set and compute f1
    y_pred = model.predict(X_val[remaining_features])
    f1 = f1_score(y_val, y_pred, pos_label=1)
    print(f"Features: {remaining_features},\nValidation F1 Score: {f1:.4f}")

    # track best feature set
    if f1 > best_f1:
        best_f1 = f1
        best_features = remaining_features[:]

    # find least important feature
    feature_importances = model.feature_importances_
    least_important_idx = np.argmin(feature_importances)
    least_important_feature = remaining_features[least_important_idx]

    # remove least important feature
    print(f"Removing least important feature: {least_important_feature}\n")
    remaining_features.pop(least_important_idx)

print('-' * 100)
print("\nBest Features Selected:", best_features)
print(f"Best Validation F1 Score: {best_f1:.4f}")
```

```
Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Full-time', 'EmploymentType_Part-time', 'EmploymentType_Self-employed',
'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_N
o', 'HasMortgage_Yes', 'HasDependents_No', 'HasDependents_Yes', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpo
se_Education', 'LoanPurpose_Home', 'LoanPurpose_Other', 'HasCoSigner_No', 'HasCoSigner_Yes', 'LoanToIncomeRatio', 'Int
erestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermC
ategory', 'LoanSizeCategory'],
Validation F1 Score: 0.0818
Removing least important feature: HasCoSigner_Yes

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Full-time', 'EmploymentType_Part-time', 'EmploymentType_Self-employed',
'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_N
o', 'HasMortgage_Yes', 'HasDependents_No', 'HasDependents_Yes', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpo
se_Education', 'LoanPurpose_Home', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRati
o', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory', 'LoanSi
zeCategory'],
Validation F1 Score: 0.0823
Removing least important feature: LoanSizeCategory

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Full-time', 'EmploymentType_Part-time', 'EmploymentType_Self-employed',
'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_N
o', 'HasMortgage_Yes', 'HasDependents_No', 'HasDependents_Yes', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpo
se_Education', 'LoanPurpose_Home', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRati
o', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0830
Removing least important feature: EmploymentType_Full-time

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_No', 'HasMortgage_Yes', 'HasDe
pendents_No', 'HasDependents_Yes', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpose_Education', 'LoanPurpose_H
ome', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio',
'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0839
Removing least important feature: HasDependents_Yes

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_No', 'HasMortgage_Yes', 'HasDe
pendents_No', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpose_Education', 'LoanPurpose_Home', 'LoanPurpose_Ot
her', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization',
'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0818
```

```
Removing least important feature: LoanPurpose_Home

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single', 'HasMortgage_No', 'HasMortgage_Yes', 'HasDe
pendents_No', 'LoanPurpose_Auto', 'LoanPurpose_Business', 'LoanPurpose_Education', 'LoanPurpose_Other', 'HasCoSigner_N
o', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths',
'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0868
Removing least important feature: MaritalStatus_Married

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortgage_No', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpos
e_Auto', 'LoanPurpose_Business', 'LoanPurpose_Education', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio',
'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanT
ermCategory'],
Validation F1 Score: 0.0853
Removing least important feature: LoanPurpose_Education

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortgage_No', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpos
e_Auto', 'LoanPurpose_Business', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio',
'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0827
Removing least important feature: HasMortgage_No

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpose_Auto', 'LoanPurp
ose_Business', 'LoanPurpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToInco
meRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0873
Removing least important feature: LoanPurpose_Auto

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Self-employed', 'EmploymentType_Unemployed',
'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpose_Business', 'Loan
Purpose_Other', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUti
lization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0846
Removing least important feature: EmploymentType_Self-employed

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
```

```
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'Marit
alStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpose_Business', 'LoanPurpose_Other', 'HasCoSigner_N
o', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths',
'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0879
Removing least important feature: LoanPurpose_Other

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'Marit
alStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'LoanPurpose_Business', 'HasCoSigner_No', 'LoanToIncomeRati
o', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'L
oanTermCategory'],
Validation F1 Score: 0.0912
Removing least important feature: LoanPurpose_Business
```

```
Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'Marit
alStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'HasCoSigner_No', 'LoanToIncomeRatio', 'InterestToIncomeRati
o', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0880
Removing least important feature: HasCoSigner_No

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Part-time', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'Marit
alStatus_Single', 'HasMortgage_Yes', 'HasDependents_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToI
ncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0890
Removing least important feature: EmploymentType_Part-time

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortga
ge_Yes', 'HasDependents_No', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilizat
ion', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0815
Removing least important feature: HasDependents_No

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'MaritalStatus_Single', 'HasMortga
ge_Yes', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMon
ths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0885
Removing least important feature: MaritalStatus_Single

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'EmploymentType_Unemployed', 'MaritalStatus_Divorced', 'HasMortgage_Yes', 'LoanToIncomeRa
tio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory',
'LoanTermCategory'],
Validation F1 Score: 0.0890
Removing least important feature: EmploymentType_Unemployed

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'MaritalStatus_Divorced', 'HasMortgage_Yes', 'LoanToIncomeRatio', 'InterestToIncomeRati
o', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0929
Removing least important feature: MaritalStatus_Divorced

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'HasMortgage_Yes', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRati
o', 'CreditUtilization', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0907
```

```
Removing least important feature: HasMortgage_Yes

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilizat
ion', 'LoanBurdenMonths', 'CreditCategory', 'LoanTermCategory'],
Validation F1 Score: 0.0948
Removing least important feature: LoanTermCategory

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilizat
ion', 'LoanBurdenMonths', 'CreditCategory'],
Validation F1 Score: 0.0948
Removing least important feature: CreditCategory

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'NumCreditLines', 'InterestRate', 'LoanTer
m', 'DTIRatio', 'Education', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilizat
ion', 'LoanBurdenMonths'],
Validation F1 Score: 0.0898
Removing least important feature: NumCreditLines

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'InterestRate', 'LoanTerm', 'DTIRatio', 'Ed
ucation', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMo
nths'],
Validation F1 Score: 0.0910
Removing least important feature: LoanTerm

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'InterestRate', 'DTIRatio', 'Education', 'L
oanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0940
Removing least important feature: Education

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'InterestRate', 'DTIRatio', 'LoanToIncomeRa
tio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0995
Removing least important feature: DTIRatio

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'InterestRate', 'LoanToIncomeRatio', 'Inter
estToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0987
Removing least important feature: MonthsEmployed

Features: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio',
'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0850
Removing least important feature: Age
```

```
Features: ['Income', 'LoanAmount', 'CreditScore', 'InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'Month
lyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0548
Removing least important feature: LoanAmount

Features: ['Income', 'CreditScore', 'InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncome
Ratio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0502
Removing least important feature: CreditScore

Features: ['Income', 'InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'Credit
Utilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0535
Removing least important feature: Income

Features: ['InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilizatio
n', 'LoanBurdenMonths'],
Validation F1 Score: 0.0529
Removing least important feature: MonthlyDebtToIncomeRatio

Features: ['InterestRate', 'LoanToIncomeRatio', 'InterestToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0648
Removing least important feature: InterestRate

Features: ['LoanToIncomeRatio', 'InterestToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths'],
Validation F1 Score: 0.0732
Removing least important feature: LoanBurdenMonths

Features: ['LoanToIncomeRatio', 'InterestToIncomeRatio', 'CreditUtilization'],
Validation F1 Score: 0.0626
Removing least important feature: CreditUtilization

Features: ['LoanToIncomeRatio', 'InterestToIncomeRatio'],
Validation F1 Score: 0.0779
Removing least important feature: LoanToIncomeRatio

----------------------------------------------------------------------------------------------------

Best Features Selected: ['Age', 'Income', 'LoanAmount', 'CreditScore', 'MonthsEmployed', 'InterestRate', 'DTIRatio',
'LoanToIncomeRatio', 'InterestToIncomeRatio', 'MonthlyDebtToIncomeRatio', 'CreditUtilization', 'LoanBurdenMonths']
Best Validation F1 Score: 0.0995
```

- The f1 score for the positive class increased from 0.0818 to 0.0995. It appears the created features were useful as 5 out of 8 of them made it through this selection process.

Model 3

In [19]:
```
X_train = X_train[best_features]
X_val = X_val[best_features]
X_test = X_test[best_features]
```

In [20]:
```
model3 = RandomForestClassifier(random_state=1, n_jobs=-1)
model3.fit(X_train,y_train)
y_pred = model3.predict(X_val)
print(classification_report(y_val,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94     45139
           1       0.54      0.05      0.10      5930

    accuracy                           0.88     51069
   macro avg       0.71      0.52      0.52     51069
weighted avg       0.85      0.88      0.84     51069
```

Hyperparameter Tuning

In [21]:
```
def objective(trial):
    #hyperparameters
    params = {
    'n_estimators': trial.suggest_int('n_estimators', 250, 500, step=50),
    'max_depth': trial.suggest_categorical('max_depth', [10, 20, 30, None]),
    'min_samples_split': trial.suggest_int('min_samples_split', 2, 10, step=2),
    'min_samples_leaf': trial.suggest_int('min_samples_leaf', 1, 11, step=2),
    'class_weight': trial.suggest_categorical('class_weight', [None, 'balanced', 'balanced_subsample'])
}

    #classifier
    rf = RandomForestClassifier(**params,random_state=1,n_jobs=-1)

    #cross val
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)
    scorer = make_scorer(f1_score, average='binary', pos_label=1)
    scores = cross_val_score(rf, X_train, y_train, cv=skf, scoring=scorer, n_jobs=-1)
    return scores.mean()

#run optimization
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=50, n_jobs=-1)

print("Best Parameters:", study.best_params)
print("Best F1 Score for Class 1:", study.best_value)
```

```
Best Parameters: {'n_estimators': 350, 'max_depth': 10, 'min_samples_split': 2, 'min_samples_leaf': 11, 'class_weigh
t': 'balanced'}
Best F1 Score for Class 1: 0.34326191851810794
```

Best Random Forest Model

In [22]:
```
best_params = study.best_params

best_rf = RandomForestClassifier(
    **best_params,
    random_state=1,
    n_jobs=-1)

best_rf.fit(X_train, y_train)
y_pred = best_rf.predict(X_val)
```

In [23]:
```
print(classification_report(y_val,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.75      0.83     45139
           1       0.24      0.60      0.34      5930

    accuracy                           0.73     51069
   macro avg       0.59      0.68      0.59     51069
weighted avg       0.85      0.73      0.78     51069
```

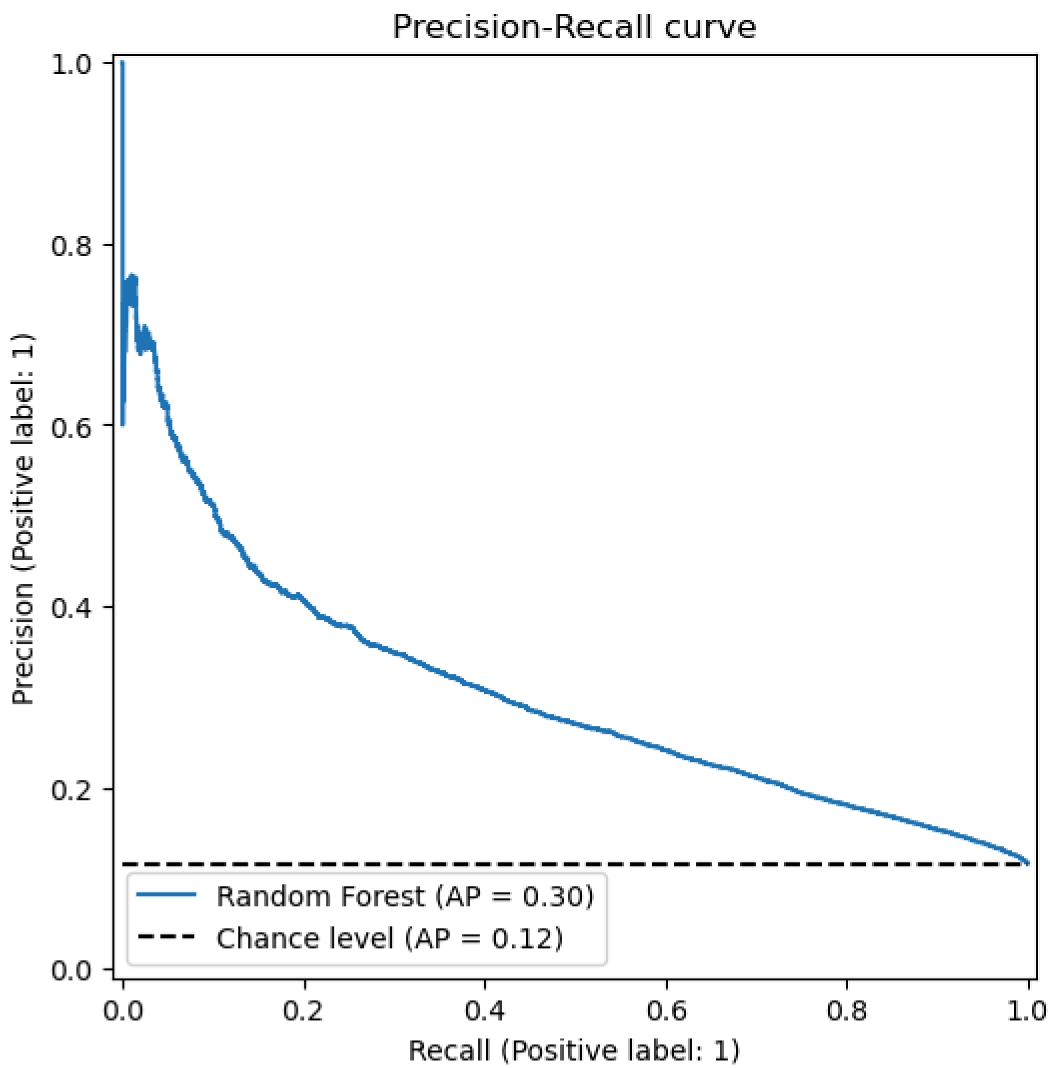
- The recall is up to 60% after tuning, but the precision went down to 24%. This model might offer a better tradeoff at a different threshold.

Precision-Recall Curve

In [24]:
```
fig, ax = plt.subplots(figsize=(10, 6))

display = PrecisionRecallDisplay.from_estimator(
    best_rf, X_val, y_val, name="Random Forest", plot_chance_level=True, ax=ax
)

_ = display.ax_.set_title("Precision-Recall curve");
```



- The average precision (AP) for the Random Forest model is 0.30 which indicates the model has some predictive power but it is still low.

- The chance level (baseline) AP is 0.12 so the model is performing better than random guessing but there is room for significant improvement.
- To show a significant improvement over a naive approach a recall ≥ 60–70% and precision ≥ 40% is the goal.
- This is a work in progress. My next approach will be to use an ensemble of models (random forest + lightgbm + catboost) to take a majority vote. These models will be tuned on the training and validation set, and if they can achieve those metrics, the last step will be verifying performance with the test set.
