

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
p = '/content/loan_data.csv'
df = pd.read_csv(p)
print(df.head())
print(df.info())
print(df.describe())
print(df.isnull().sum())

for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = df[col].fillna(df[col].mode()[0])
    else:
        df[col] = df[col].fillna(df[col].median())

le = LabelEncoder()
for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = le.fit_transform(df[col])

X = df.drop("loan_status", axis=1)
y = df["loan_status"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

log_model = LogisticRegression()
log_model.fit(X_train, y_train)
y_pred_log = log_model.predict(X_test)

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_log))
print(confusion_matrix(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

print(" Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))

importances = rf_model.feature_importances_
features = df.drop("loan_status", axis=1).columns
```

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plt.figure(figsize=(10,5))
sns.barplot(x=importances, y=features)
plt.title("Feature Importance for Loan Approval")
plt.show()
```

```

➡ person_age person_gender person_education person_income person_emp_exp \
0      22.0      female      Master      71948.0      0
1      21.0      female      High School      12282.0      0
2      25.0      female      High School      12438.0      3
3      23.0      female      Bachelor      79753.0      0
4      24.0      male      Master      66135.0      1

```

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person_home_ownership loan_amnt loan_intent loan_int_rate \
0      RENT      35000.0      PERSONAL      16.02
1      OWN      1000.0      EDUCATION      11.14
2      MORTGAGE      5500.0      MEDICAL      12.87
3      RENT      35000.0      MEDICAL      15.23
4      RENT      35000.0      MEDICAL      14.27

```

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loan_percent_income cb_person_cred_hist_length credit_score \
0      0.49      3.0      561
1      0.08      2.0      504
2      0.44      3.0      635
3      0.44      2.0      675
4      0.53      4.0      586

```

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previous_loan_defaults_on_file loan_status
0      No      1
1      Yes      0
2      No      1
3      No      1
4      No      1

```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 45000 entries, 0 to 44999
```

```
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	person_age	45000 non-null	float64
1	person_gender	45000 non-null	object
2	person_education	45000 non-null	object
3	person_income	45000 non-null	float64
4	person_emp_exp	45000 non-null	int64
5	person_home_ownership	45000 non-null	object
6	loan_amnt	45000 non-null	float64
7	loan_intent	45000 non-null	object
8	loan_int_rate	45000 non-null	float64
9	loan_percent_income	45000 non-null	float64
10	cb_person_cred_hist_length	45000 non-null	float64
11	credit_score	45000 non-null	int64
12	previous_loan_defaults_on_file	45000 non-null	object
13	loan_status	45000 non-null	int64

```
dtypes: float64(6), int64(3), object(5)
```

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memory usage: 4.8+ MB
```

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None
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	person_age	person_income	person_emp_exp	loan_amnt
count	45000.000000	4.500000e+04	45000.000000	45000.000000
mean	27.764178	8.031905e+04	5.410333	9583.157556
std	6.045108	8.042250e+04	6.063532	6314.886691
min	20.000000	8.000000e+03	0.000000	500.000000
25%	24.000000	4.720400e+04	1.000000	5000.000000
50%	26.000000	6.704800e+04	4.000000	8000.000000
75%	30.000000	9.578925e+04	8.000000	12237.250000
max	144.000000	7.200766e+06	125.000000	35000.000000

	loan_int_rate	loan_percent_income	cb_person_cred_hist_length
count	45000.000000	45000.000000	45000.000000
mean	11.006606	0.120725	5.067100

mean	11.000000	0.137723	3.807403
std	2.978808	0.087212	3.879702
min	5.420000	0.000000	2.000000
25%	8.590000	0.070000	3.000000
50%	11.010000	0.120000	4.000000
75%	12.990000	0.190000	8.000000
max	20.000000	0.660000	30.000000

	credit_score	loan_status
count	45000.000000	45000.000000
mean	632.608756	0.222222
std	50.435865	0.415744
min	390.000000	0.000000
25%	601.000000	0.000000
50%	640.000000	0.000000
75%	670.000000	0.000000
max	850.000000	1.000000

person_age	0
person_gender	0
person_education	0
person_income	0
person_emp_exp	0
person_home_ownership	0
loan_amnt	0
loan_intent	0
loan_int_rate	0
loan_percent_income	0
cb_person_cred_hist_length	0
credit_score	0
previous_loan_defaults_on_file	0
loan_status	0

dtype: int64

Logistic Regression Accuracy: 0.8901111111111111

[[6542 448]

[541 1469]]

	precision	recall	f1-score	support
0	0.92	0.94	0.93	6990
1	0.77	0.73	0.75	2010
accuracy			0.89	9000
macro avg	0.84	0.83	0.84	9000
weighted avg	0.89	0.89	0.89	9000

Random Forest Accuracy: 0.9273333333333333

[[6792 198]

[456 1554]]

	precision	recall	f1-score	support
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