Loan Approval Model

```
#importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# reading the data
data = 
pd.read_json('/Users/yogeshdhaliya/Desktop/Task/loan_approval_dataset.
json')

df=pd.DataFrame(data)

df.head()
```

```
   Id   Income  Age  Experience Married/Single House_Ownership 
Car_Ownership  \
0   1  1303834   23           3         single          rented 
no
1   2  7574516   40          10         single          rented 
no
2   3  3991815   66           4        married          rented 
no
3   4  6256451   41           2         single          rented 
yes
4   5  5768871   47          11         single          rented 
no

            Profession                 CITY           STATE 
CURRENT_JOB_YRS  \
0  Mechanical_engineer                 Rewa  Madhya_Pradesh 
3
1   Software_Developer             Parbhani     Maharashtra 
9
2     Technical_writer            Alappuzha          Kerala 
4
3   Software_Developer          Bhubaneswar          Odisha 
2
4        Civil_servant  Tiruchirappalli[10]      Tamil_Nadu 
3

   CURRENT_HOUSE_YRS  Risk_Flag
0                 13          0
1                 13          0
2                 10          0
3                 12          1
4                 14          1
```

Data Exploration

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 252000 entries, 0 to 251999
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype 
---  ------             --------------   ----- 
 0   Id                 252000 non-null  int64 
 1   Income             252000 non-null  int64 
 2   Age                252000 non-null  int64 
 3   Experience         252000 non-null  int64 
 4   Married/Single     252000 non-null  object
 5   House_Ownership    252000 non-null  object
 6   Car_Ownership      252000 non-null  object
 7   Profession         252000 non-null  object
 8   CITY               252000 non-null  object
 9   STATE              252000 non-null  object
 10  CURRENT_JOB_YRS    252000 non-null  int64 
 11  CURRENT_HOUSE_YRS  252000 non-null  int64 
 12  Risk_Flag          252000 non-null  int64 
dtypes: int64(7), object(6)
memory usage: 26.9+ MB
```

```
df.shape
```

```
(252000, 13)
```

```
df.dtypes
```

```
Id                    int64
Income                int64
Age                   int64
Experience            int64
Married/Single       object
House_Ownership      object
Car_Ownership        object
Profession           object
CITY                 object
STATE                object
CURRENT_JOB_YRS       int64
CURRENT_HOUSE_YRS     int64
Risk_Flag             int64
dtype: object
```

```
df.isnull().sum()
```

```
Id                   0
Income               0
Age                  0
```

```
Experience              0
Married/Single          0
House_Ownership         0
Car_Ownership           0
Profession              0
CITY                    0
STATE                   0
CURRENT_JOB_YRS         0
CURRENT_HOUSE_YRS       0
Risk_Flag               0
dtype: int64
```

No missing values detected in the data

```
#Checking the unique values in the data
df.nunique()
```

```
Id                   252000
Income                41920
Age                      59
Experience               21
Married/Single            2
House_Ownership           3
Car_Ownership             2
Profession               51
CITY                    317
STATE                    29
CURRENT_JOB_YRS          15
CURRENT_HOUSE_YRS         5
Risk_Flag                 2
dtype: int64
```

```
df.describe()  #Checking the summary statistics of the data
```

```
                  Id        Income            Age     Experience  \
count  252000.000000  2.520000e+05  252000.000000  252000.000000
mean   126000.500000  4.997117e+06      49.954071      10.084437
std     72746.278255  2.878311e+06      17.063855       6.002590
min         1.000000  1.031000e+04      21.000000       0.000000
25%     63000.750000  2.503015e+06      35.000000       5.000000
50%    126000.500000  5.000694e+06      50.000000      10.000000
75%    189000.250000  7.477502e+06      65.000000      15.000000
max    252000.000000  9.999938e+06      79.000000      20.000000

       CURRENT_JOB_YRS  CURRENT_HOUSE_YRS      Risk_Flag
count    252000.000000      252000.000000  252000.000000
mean          6.333877          11.997794       0.123000
std           3.647053           1.399037       0.328438
min           0.000000          10.000000       0.000000
25%           3.000000          11.000000       0.000000
```

```
50%              6.000000          12.000000        0.000000
75%              9.000000          13.000000        0.000000
max             14.000000          14.000000        1.000000
```

Categorical Variables

```python
# check how many columns are categorical
for i in df.columns:
    if df[i].dtype == 'object':
        print(i)
```

```
Married/Single
House_Ownership
Car_Ownership
Profession
CITY
STATE
```

```python
df["Married/Single"].value_counts()
```

```
single     226272
married     25728
Name: Married/Single, dtype: int64
```

```python
df["House_Ownership"].value_counts()
```

```
rented          231898
owned            12918
norent_noown      7184
Name: House_Ownership, dtype: int64
```

```python
df["Car_Ownership"].value_counts()
```

```
no     176000
yes     76000
Name: Car_Ownership, dtype: int64
```

```python
df["Profession"].value_counts()
```

```
Physician                     5957
Statistician                  5806
Web_designer                  5397
Psychologist                  5390
Computer_hardware_engineer    5372
Drafter                       5359
Magistrate                    5357
Fashion_Designer              5304
Air_traffic_controller        5281
Comedian                      5259
Industrial_Engineer           5250
Mechanical_engineer           5217
```

```
Chemical_engineer             5205
Technical_writer              5195
Hotel_Manager                 5178
Financial_Analyst             5167
Graphic_Designer              5166
Flight_attendant              5128
Biomedical_Engineer           5127
Secretary                     5061
Software_Developer            5053
Petroleum_Engineer            5041
Police_officer                5035
Computer_operator             4990
Politician                    4944
Microbiologist                4881
Technician                    4864
Artist                        4861
Lawyer                        4818
Consultant                    4808
Dentist                       4782
Scientist                     4781
Surgeon                       4772
Aviator                       4758
Technology_specialist         4737
Design_Engineer               4729
Surveyor                      4714
Geologist                     4672
Analyst                       4668
Army_officer                  4661
Architect                     4657
Chef                          4635
Librarian                     4628
Civil_engineer                4616
Designer                      4598
Economist                     4573
Firefighter                   4507
Chartered_Accountant          4493
Civil_servant                 4413
Official                      4087
Engineer                      4048
Name: Profession, dtype: int64
```

```
df["CITY"].value_counts()
```

```
Vijayanagaram       1259
Bhopal              1208
Bulandshahr         1185
Saharsa[29]         1180
Vijayawada          1172
                    ...
Ujjain               486
```

```
Warangal[11][12]     459
Bettiah[33]          457
Katni                448
Karaikudi            431
Name: CITY, Length: 317, dtype: int64
```

```
df["STATE"].value_counts()
```

```
Uttar_Pradesh        28400
Maharashtra          25562
Andhra_Pradesh       25297
West_Bengal          23483
Bihar                19780
Tamil_Nadu           16537
Madhya_Pradesh       14122
Karnataka            11855
Gujarat              11408
Rajasthan             9174
Jharkhand             8965
Haryana               7890
Telangana             7524
Assam                 7062
Kerala                5805
Delhi                 5490
Punjab                4720
Odisha                4658
Chhattisgarh          3834
Uttarakhand           1874
Jammu_and_Kashmir     1780
Puducherry            1433
Mizoram                849
Manipur                849
Himachal_Pradesh       833
Tripura                809
Uttar_Pradesh[5]       743
Chandigarh             656
Sikkim                 608
Name: STATE, dtype: int64
```

Feature Selection - chi square test - to check association between categorical features and target feature

```
from scipy.stats import chi2_contingency
for i in
['Married/Single','House_Ownership','Car_Ownership','Profession','CITY
','STATE']:
    chi2, pval, _, _ = chi2_contingency(pd.crosstab(df[i],
df['Risk_Flag']))
    print(i, '---', pval)
```

```
Married/Single --- 3.773053705715196e-26
House_Ownership --- 1.8381930028370595e-40
Car_Ownership --- 1.7350853850183746e-33
Profession --- 5.108641602000937e-98
CITY --- 0.0
STATE --- 2.0057472384130266e-136
```

Since all the categorical feature have p-value <=0.05, we will accept all

Numerical Variables

```
# check how many columns are numerical
for i in df.columns:
    if df[i].dtype == 'int':
        print(i)
```

```
Id
Income
Age
Experience
CURRENT_JOB_YRS
CURRENT_HOUSE_YRS
Risk_Flag
```

```
from scipy.stats import pointbiserialr

# Calculate point biserial correlation for each integer variable
corr1, p_value1 = pointbiserialr(df['Income'], df['Risk_Flag'])
corr2, p_value2 = pointbiserialr(df['Age'], df['Risk_Flag'])
corr3, p_value3 = pointbiserialr(df['Experience'], df['Risk_Flag'])
corr4, p_value4 = pointbiserialr(df['CURRENT_JOB_YRS'],
df['Risk_Flag'])
corr5, p_value5 = pointbiserialr(df['CURRENT_HOUSE_YRS'],
df['Risk_Flag'])

print(f'Correlation between integer_variable1 and Target: {corr1}, p-
value: {p_value1}')
print(f'Correlation between integer_variable2 and Target: {corr2}, p-
value: {p_value2}')
print(f'Correlation between integer_variable2 and Target: {corr3}, p-
value: {p_value3}')
print(f'Correlation between integer_variable2 and Target: {corr4}, p-
value: {p_value4}')
print(f'Correlation between integer_variable2 and Target: {corr5}, p-
value: {p_value5}')
```

```
Correlation between integer_variable1 and Target: -
0.003091168122271239, p-value: 0.12072203190827889
Correlation between integer_variable2 and Target: -
0.02180927605070088, p-value: 6.687623645092961e-28
```

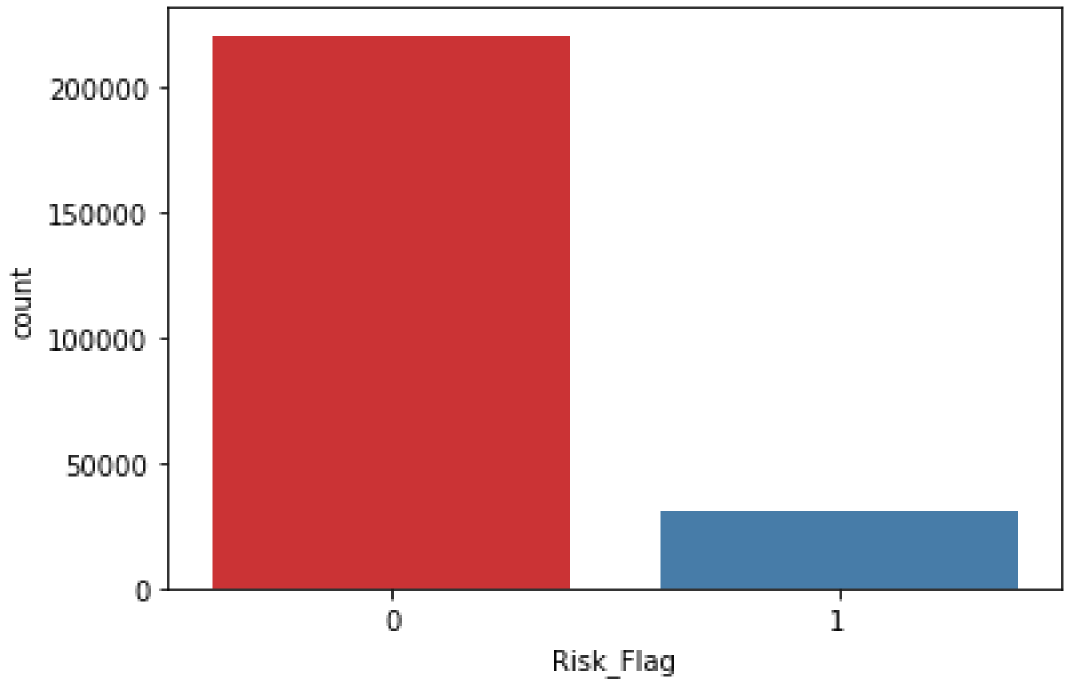
```
Correlation between integer_variable2 and Target: -
0.03452261289070651, p-value: 2.5475634857843415e-67
Correlation between integer_variable2 and Target: -
0.01694158205212183, p-value: 1.8132212225854788e-17
Correlation between integer_variable2 and Target: -
0.0043751630776717836, p-value: 0.028069472763846918
```

Interpretation of Results:

1. Income:
- Correlation: -0.0031
- p-value: 0.1207
- Interpretation: Weak correlation and not statistically significant ($p > 0.05$).
1. Age:
- Correlation: -0.0218
- p-value: 6.6876e-28
- Interpretation: Weak correlation but statistically significant ($p < 0.05$).
1. Experience:
- Correlation: -0.0345
- p-value: 2.5476e-67
- Interpretation: Weak correlation but statistically significant ($p < 0.05$).
1. CURRENT_JOB_YRS:
- Correlation: -0.0169
- p-value: 1.8132e-17
- Interpretation: Weak correlation but statistically significant ($p < 0.05$).
1. CURRENT_HOUSE_YRS:
- Correlation: -0.0044
- p-value: 0.0281
- Interpretation: Very weak correlation but statistically significant ($p < 0.05$).

Data Visualization

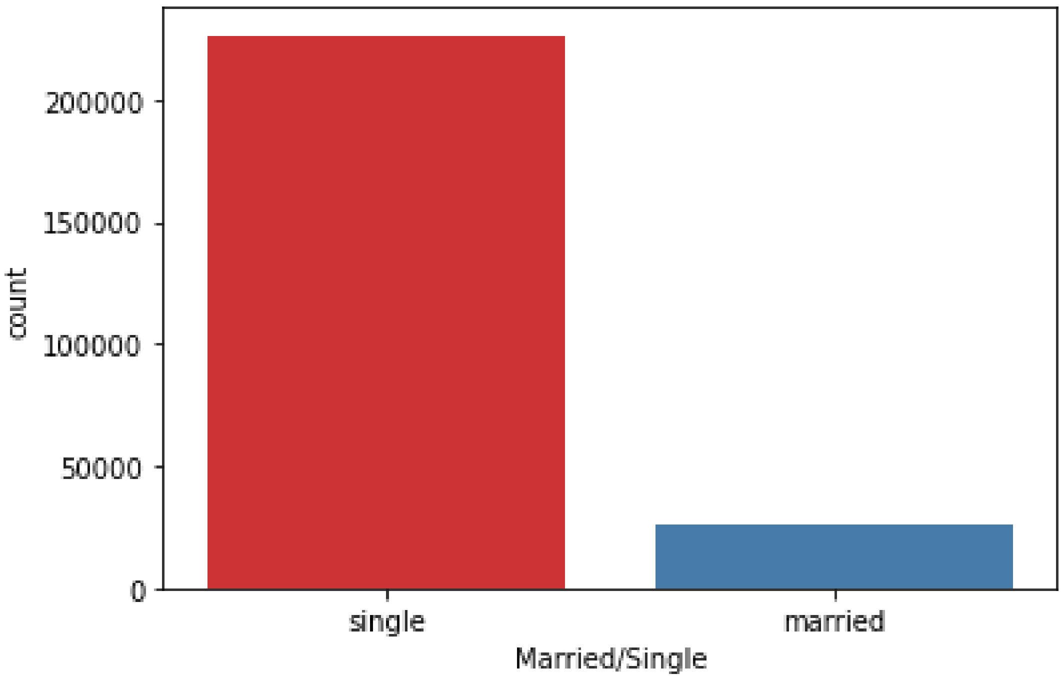
```
# checking distribution between target variables
sns.countplot(df['Risk_Flag'],palette='Set1')

/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  warnings.warn(

<AxesSubplot:xlabel='Risk_Flag', ylabel='count'>
```




```
sns.countplot(df['Married/Single'],palette='Set1')
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  warnings.warn(
```

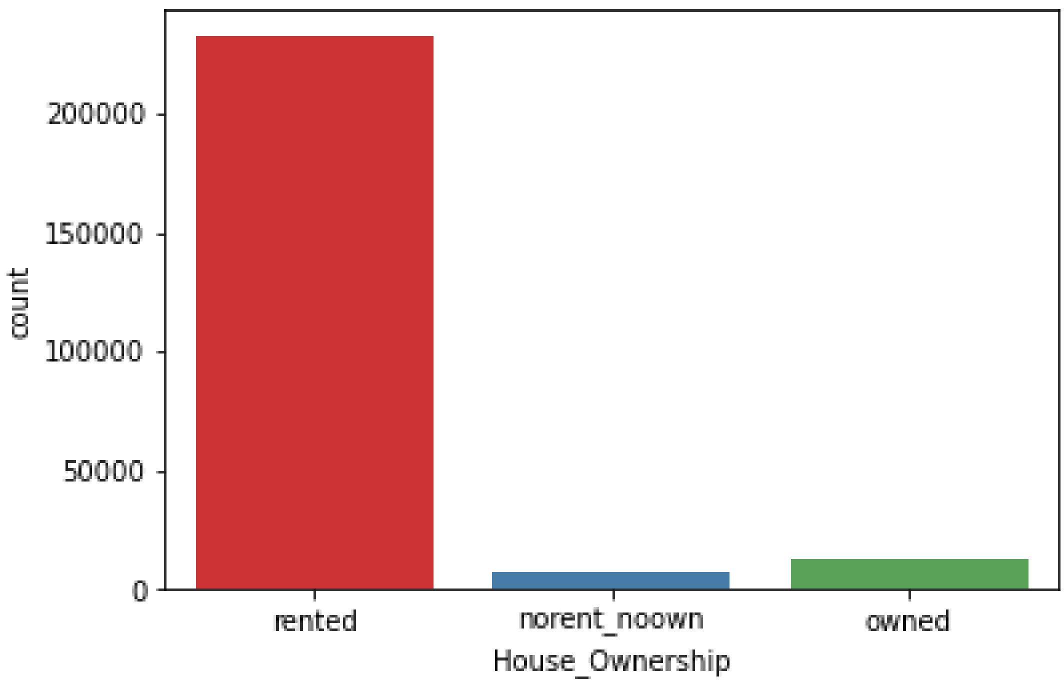
```
<AxesSubplot:xlabel='Married/Single', ylabel='count'>
```




```
sns.countplot(df['House_Ownership'],palette='Set1')
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  warnings.warn(
```

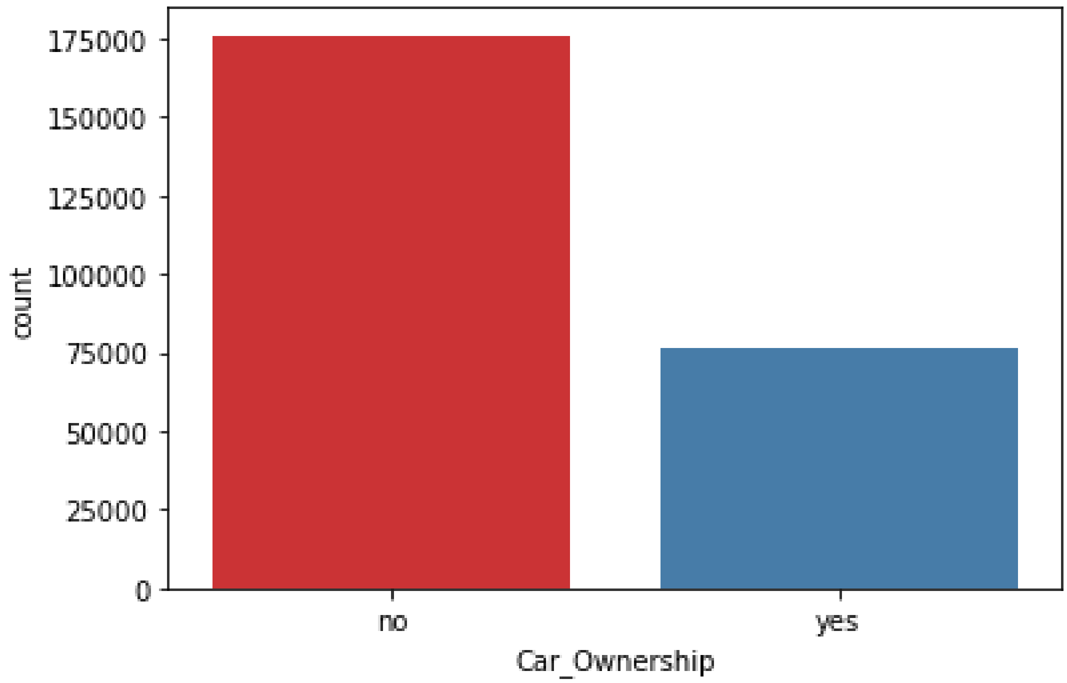
```
<AxesSubplot:xlabel='House_Ownership', ylabel='count'>
```



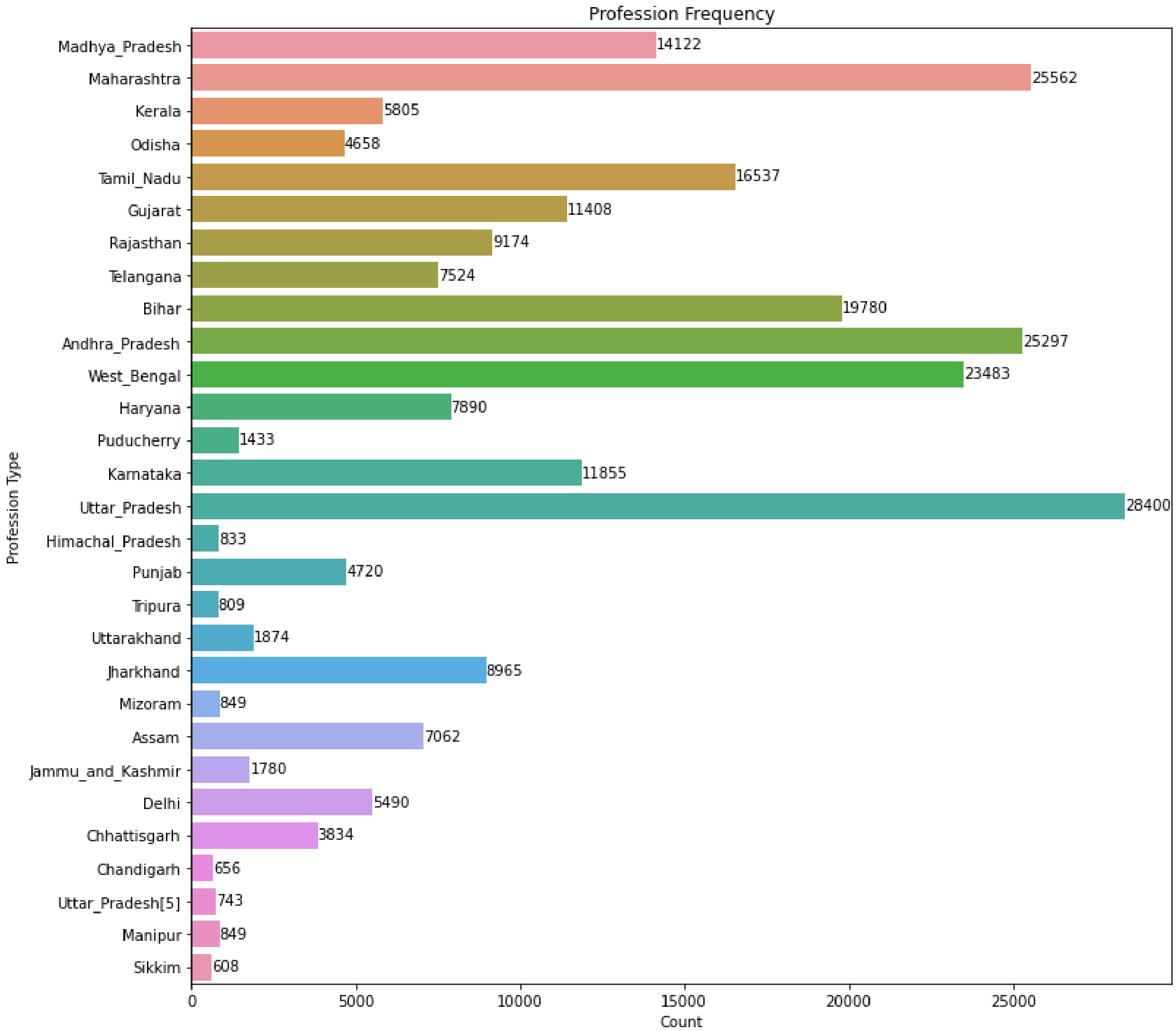

```
sns.countplot(df['Car_Ownership'],palette='Set1')
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  warnings.warn(
```

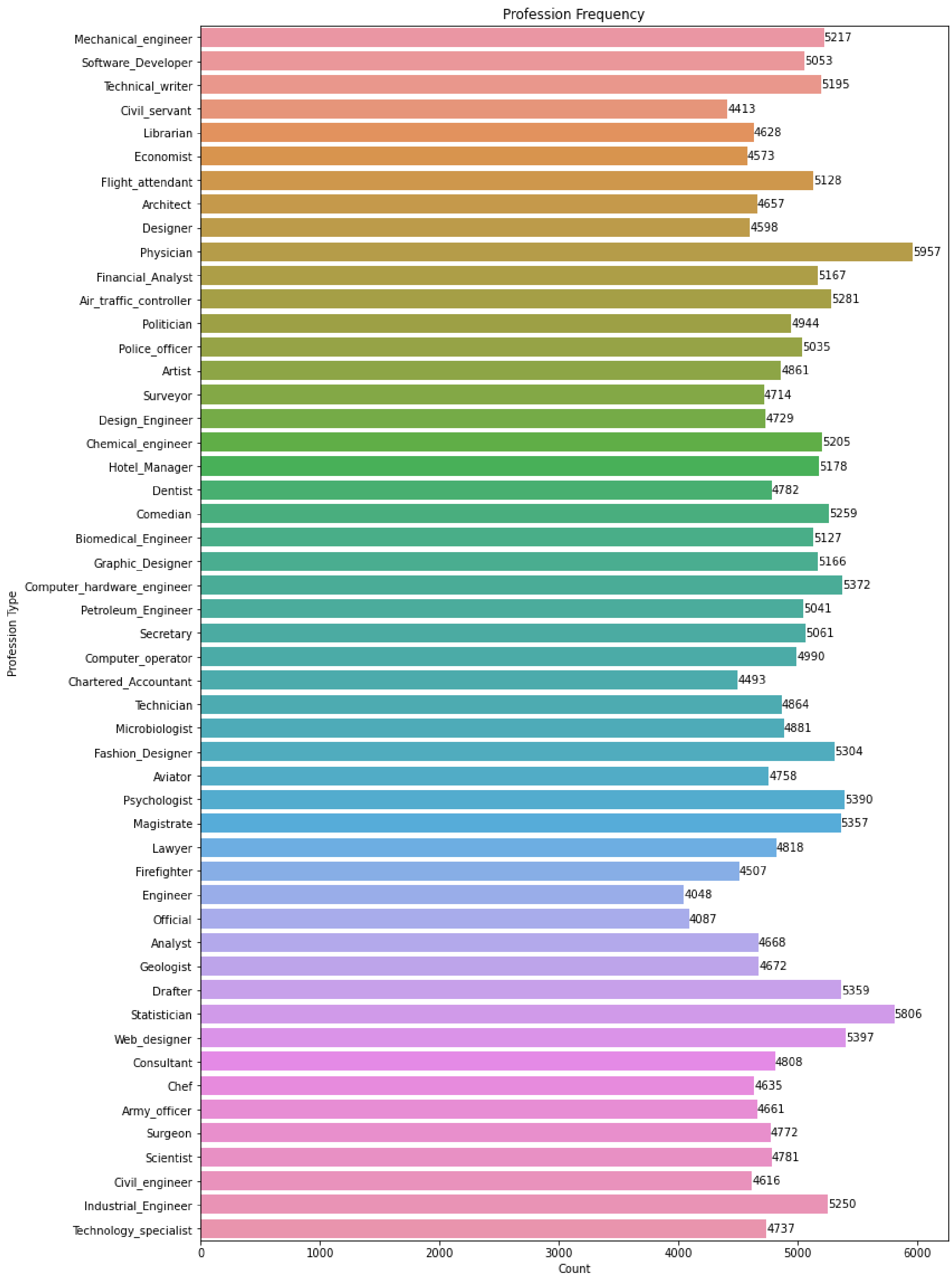
```
<AxesSubplot:xlabel='Car_Ownership', ylabel='count'>
```



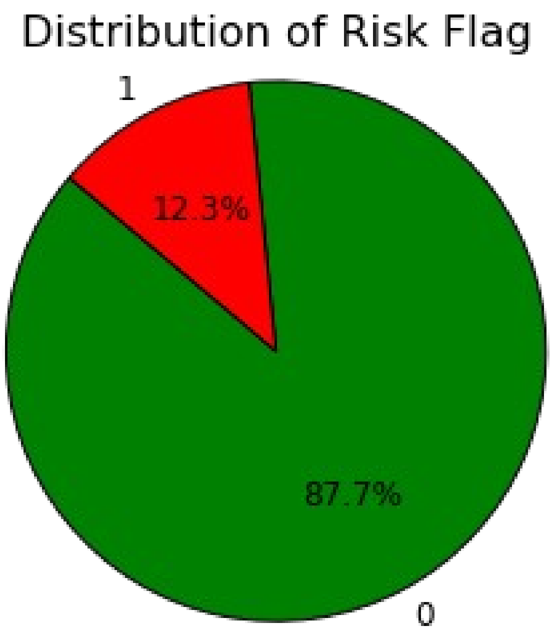

```
plt.figure(figsize=(12, 12))
ax = sns.countplot(y=df['STATE'])

plt.title("Profession Frequency")
plt.ylabel("Profession Type")
plt.xlabel("Count")

for container in ax.containers:
    ax.bar_label(container)
plt.show()
```




```
plt.figure(figsize=(12, 20))
ax = sns.countplot(y=df['Profession'])

plt.title("Profession Frequency")
plt.ylabel("Profession Type")
plt.xlabel("Count")

for container in ax.containers:
    ax.bar_label(container)
plt.show()
```

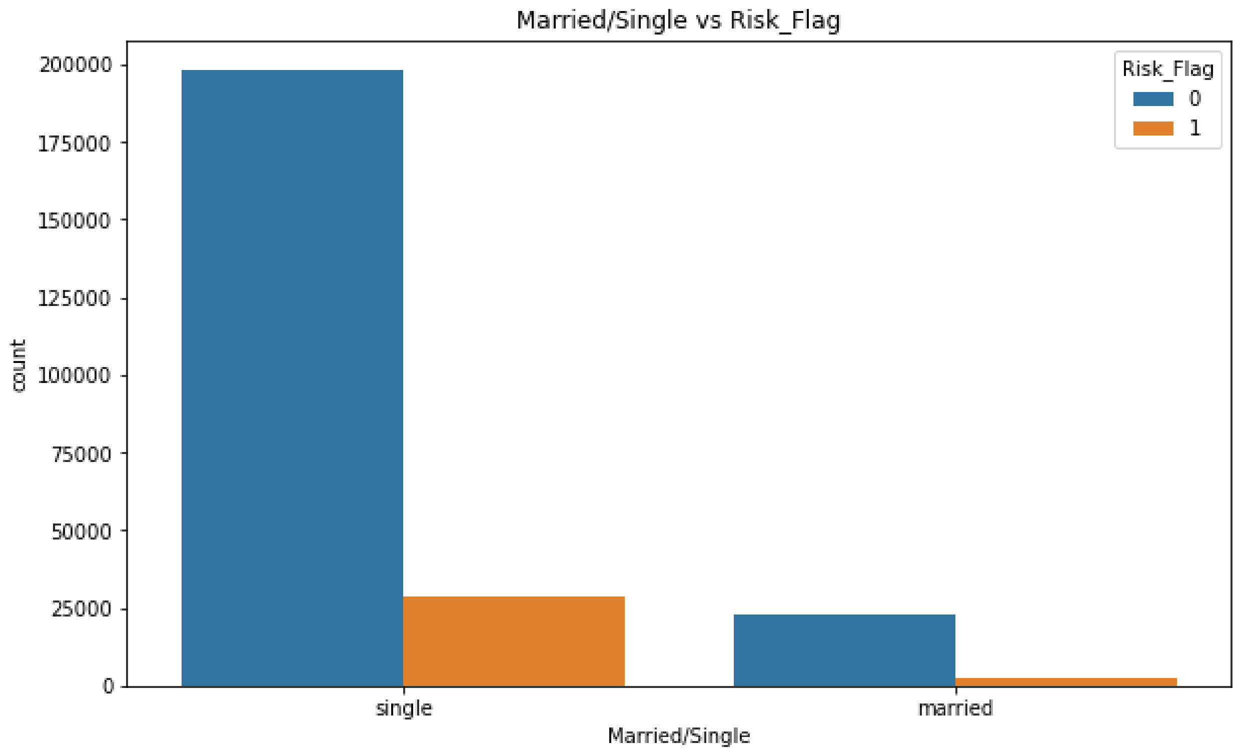

Profession Frequency
Mechanical_engineer 5217
Software_Developer 5053
Technical_writer 5195
Civil_servant 4413
Librarian 4628
Economist 4573
Flight_attendant 5128
Architect 4657
Designer 4598
Physician 5957
Financial_Analyst 5167
Air_traffic_controller 5281
Politician 4944
Police_officer 5035
Artist 4861
Surveyor 4714
Design_Engineer 4729
Chemical_engineer 5205
Hotel_Manager 5178
Dentist 4782
Comedian 5259
Biomedical_Engineer 5127
Graphic_Designer 5166
Computer_hardware_engineer 5372
Petroleum_Engineer 5041
Secretary 5061
Computer_operator 4990
Chartered_Accountant 4493
Technician 4864
Microbiologist 4881
Fashion_Designer 5304
Aviator 4758
Psychologist 5390
Magistrate 5357
Lawyer 4818
Firefighter 4507
Engineer 4048
Official 4087
Analyst 4668
Geologist 4672
Drafter 5359
Statistician 5806
Web_designer 5397
Consultant 4808
Chef 4635
Army_officer 4661
Surgeon 4772
Scientist 4781
Civil_engineer 4616
Industrial_Engineer 5250
Technology_specialist 4737
Profession Type
0
1000
2000
3000
4000
5000
6000
Count

```
plt.figure(figsize=(4, 4))

counts = df['Risk_Flag'].value_counts().sort_values(ascending=False)
custom_colors = ['green', 'red']

plt.pie(counts, labels=counts.index, autopct='%1.1f%%',
startangle=140, colors=custom_colors,
        wedgeprops={'edgecolor': 'black', 'linewidth': 1},
textprops={'fontsize': 12})

plt.axis('equal')
plt.title('Distribution of Risk Flag', fontsize=16)
plt.show()
```

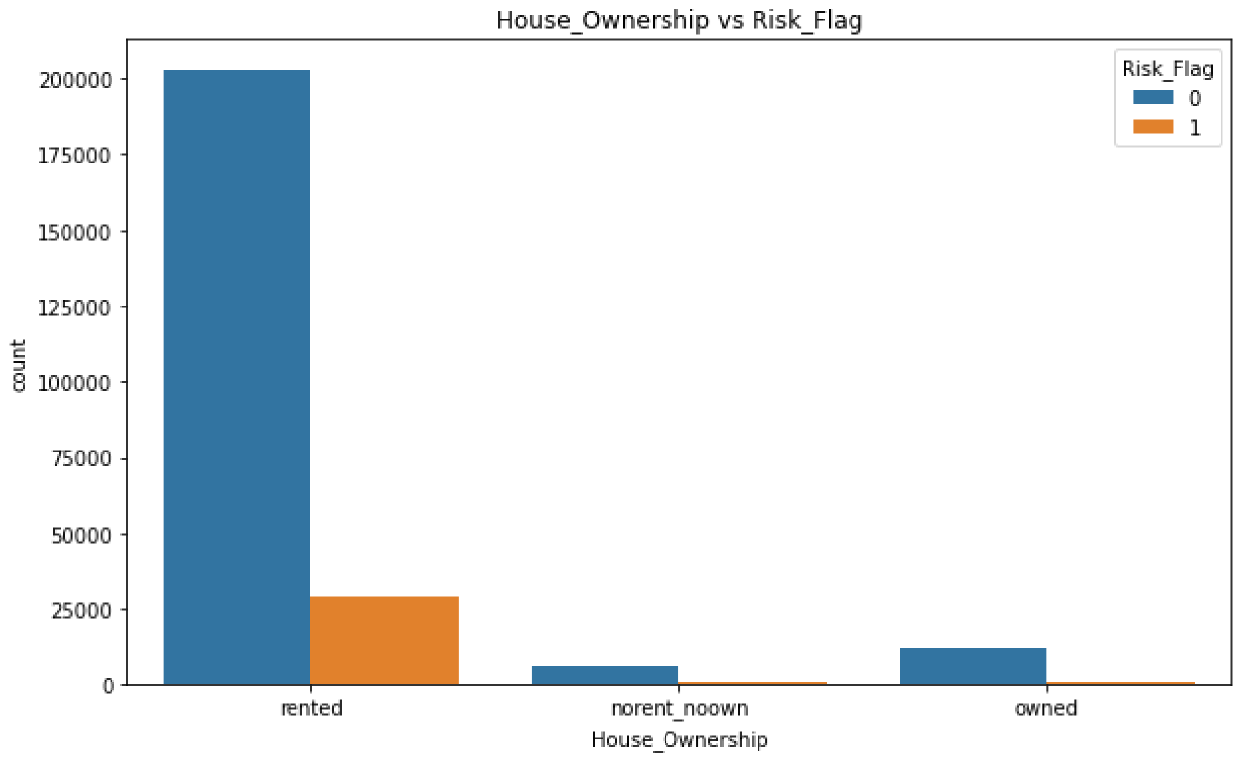


In target variable 12.3% of clients are high risk individuals & 87.7% of clients are low risk individuals.

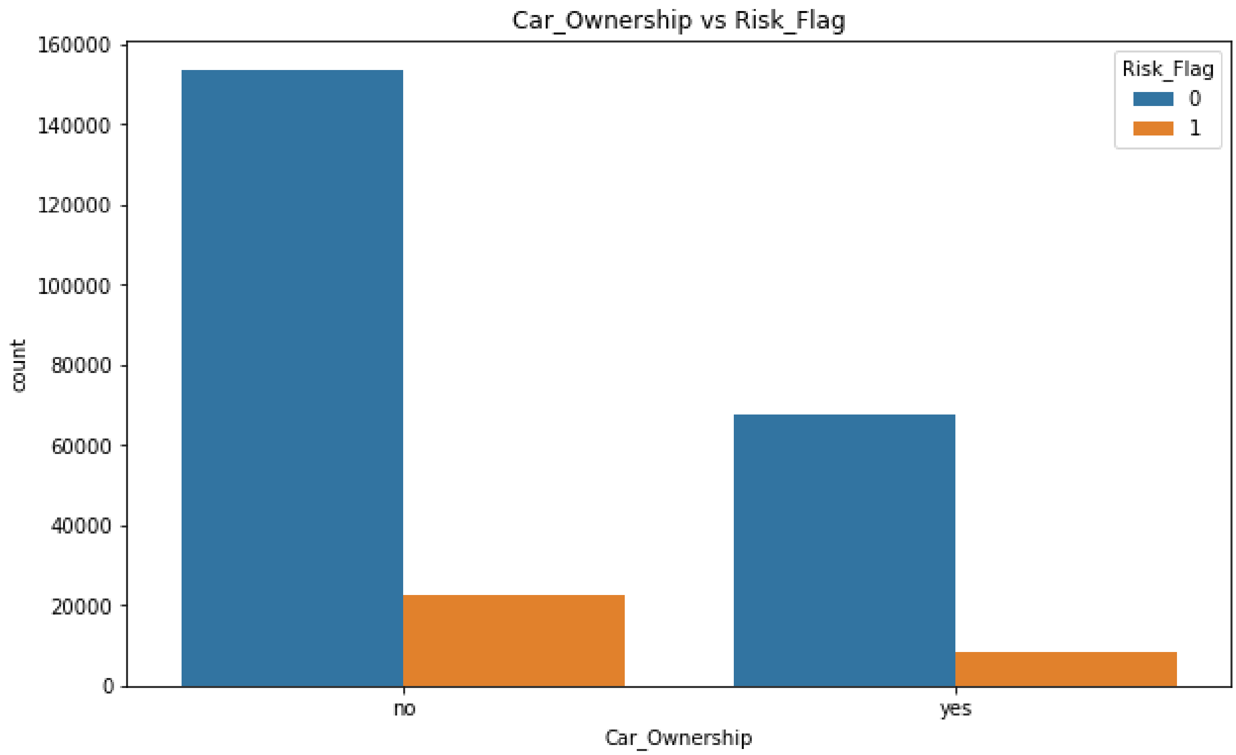
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Married/Single', hue='Risk_Flag', data=df)
plt.title('Married/Single vs Risk_Flag')
plt.show()
```



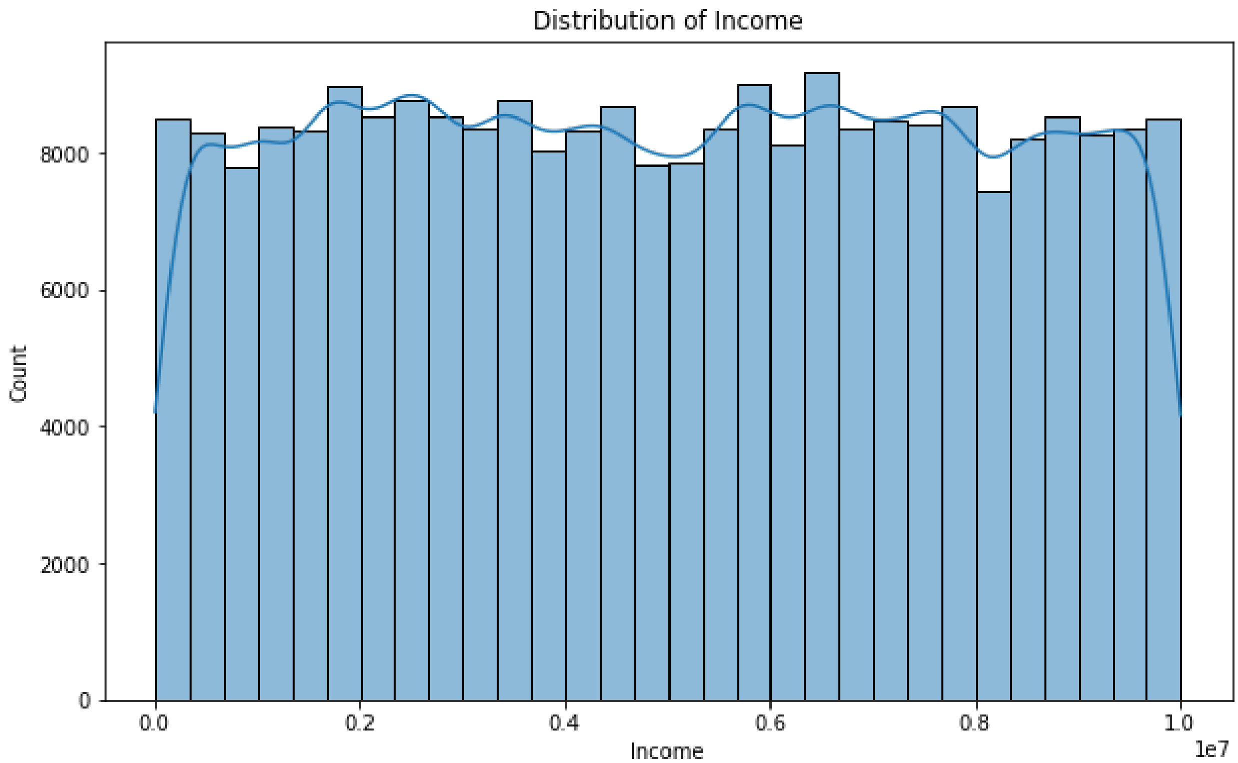

```
plt.figure(figsize=(10, 6))
sns.countplot(x='House_Ownership', hue='Risk_Flag', data=df)
plt.title('House_Ownership vs Risk_Flag')
plt.show()
```



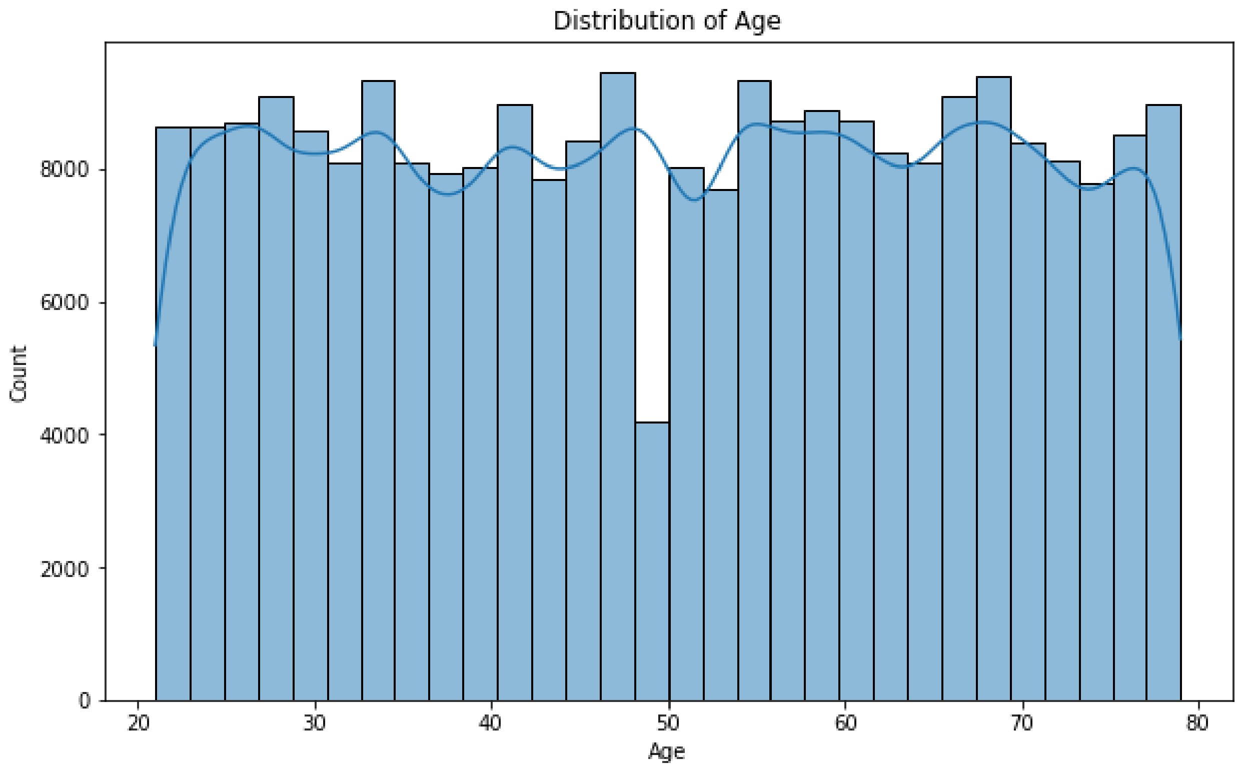

```
plt.figure(figsize=(10, 6))
sns.countplot(x='Car_Ownership', hue='Risk_Flag', data=df)
plt.title('Car_Ownership vs Risk_Flag')
plt.show()
```




```
# Histogram of Income
plt.figure(figsize=(10, 6))
sns.histplot(df['Income'], bins=30, kde=True)
plt.title('Distribution of Income')
plt.show()
```

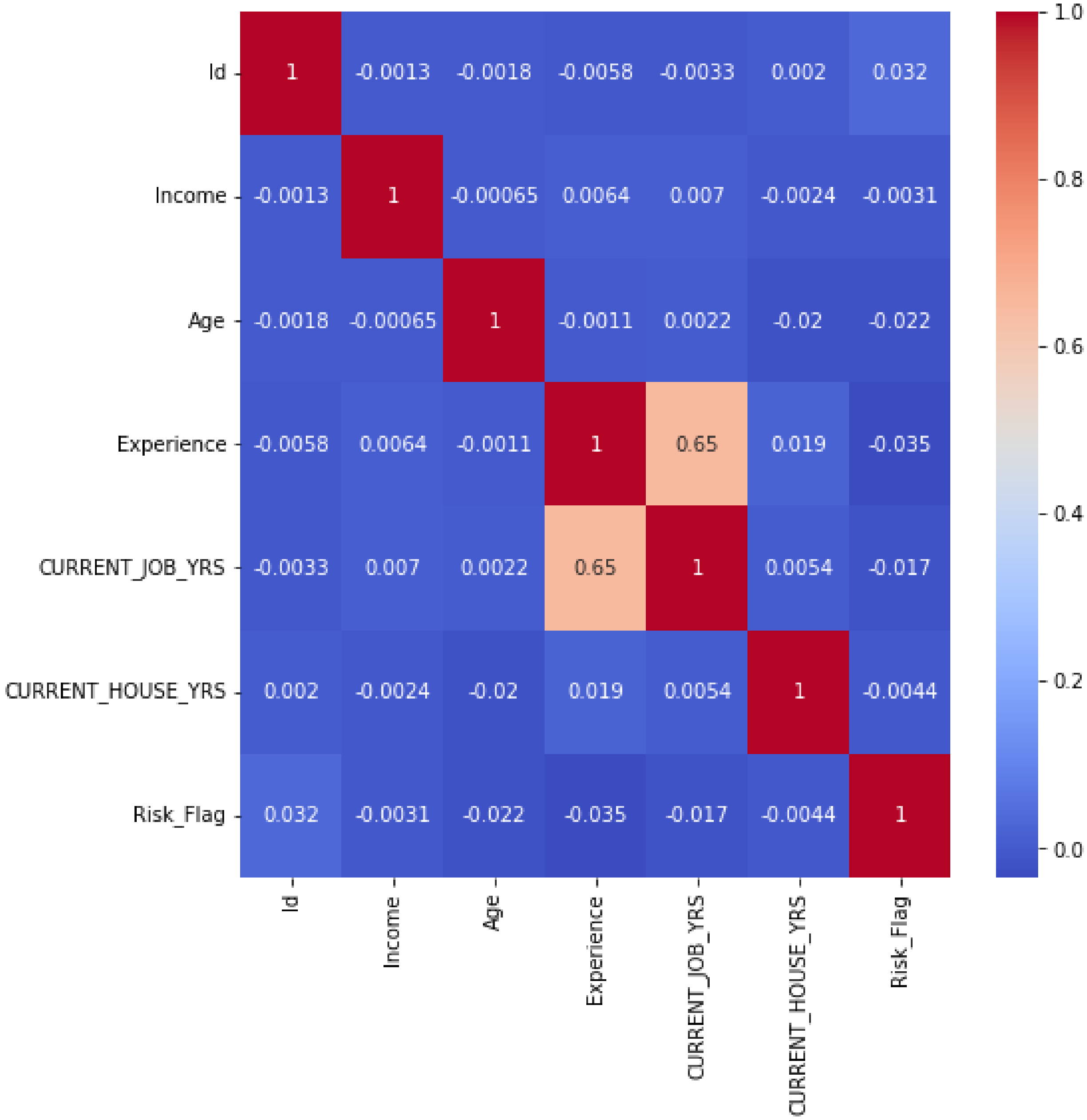



```
# Histogram of Age
plt.figure(figsize=(10, 6))
sns.histplot(df['Age'], bins=30, kde=True)
plt.title('Distribution of Age')
plt.show()
```




```
plt.figure(figsize=(8,8))
sns.heatmap(df.corr(),annot=True,cmap='coolwarm')
```

```
<AxesSubplot:>
```




```
#Splitting the data into X and y
from sklearn.model_selection import train_test_split
X=df.drop('Risk_Flag',axis=1)
y=df['Risk_Flag']
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,rando
m_state=42)
X_val,X_test,y_val,y_test=train_test_split(X_test,y_test,test_size=0.5
,random_state=42)

from sklearn.preprocessing import LabelEncoder
```

```python
# Initialize LabelEncoder
le = LabelEncoder()

categorical_columns = X.select_dtypes(include=['object']).columns

# Fit and transform categorical columns in training set
for col in categorical_columns:
    X_train[col] = le.fit_transform(X_train[col])

# Transform categorical columns in validation set, handle unknown
labels
for col in categorical_columns:
    # Handle unknown labels by assigning them a default value (e.g.,
0)
    X_val[col] = le.transform(X_val[col].map(lambda x: 0 if x not in
le.classes_ else x))

# Transform categorical columns in testing set, handle unknown labels
for col in categorical_columns:
    # Handle unknown labels by assigning them a default value (e.g.,
0)
    X_test[col] = le.transform(X_test[col].map(lambda x: 0 if x not in
le.classes_ else x))

# Print the encoded datasets
print("X_train:")
print(X_train.head())

print("\nX_val:")
print(X_val.head())

print("\nX_test:")
print(X_test.head())
```

```
----------------------------------------------------------------------
-----
TypeError                                 Traceback (most recent call
last)
Input In [35], in <cell line: 13>()
     12 # Transform categorical columns in validation set, handle
unknown labels
     13 for col in categorical_columns:
     14     # Handle unknown labels by assigning them a default value
(e.g., 0)
---> 15     X_val[col] = le.transform(X_val[col].map(lambda x: 0 if x
not in le.classes_ else x))
     17 # Transform categorical columns in testing set, handle unknown
labels
     18 for col in categorical_columns:
     19     # Handle unknown labels by assigning them a default value
```

```
(e.g., 0)

File
/opt/anaconda3/lib/python3.9/site-packages/sklearn/preprocessing/_labe
l.py:138, in LabelEncoder.transform(self, y)
    135 if _num_samples(y) == 0:
    136     return np.array([])
--> 138 return _encode(y, uniques=self.classes_)

File
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/_encode.py:18
7, in _encode(values, uniques, check_unknown)
    185 else:
    186     if check_unknown:
--> 187         diff = _check_unknown(values, uniques)
    188         if diff:
    189             raise ValueError(f"y contains previously unseen
labels: {str(diff)}")

File
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/_encode.py:26
1, in _check_unknown(values, known_values, return_mask)
    258         valid_mask = np.ones(len(values), dtype=bool)
    260 # check for nans in the known_values
--> 261 if np.isnan(known_values).any():
    262     diff_is_nan = np.isnan(diff)
    263     if diff_is_nan.any():
    264         # removes nan from valid_mask

TypeError: ufunc 'isnan' not supported for the input types, and the
inputs could not be safely coerced to any supported types according to
the casting rule ''safe''
```

```python
from sklearn.preprocessing import StandardScaler

numerical_features =
X.select_dtypes(include=['int64','float64']).columns

# Initialize StandardScaler
scaler = StandardScaler()

# Scale numerical features in training set
X_train[numerical_features] =
scaler.fit_transform(X_train[numerical_features])

# Scale numerical features in validation set
X_val[numerical_features] =
scaler.transform(X_val[numerical_features])

# Scale numerical features in testing set
```

```
X_test[numerical_features] =
scaler.transform(X_test[numerical_features])

X_train.head()

              Id    Income       Age  Experience  Married/Single  \
200471  1.024787  1.430422  1.170436    1.318759               1
92611  -0.457717 -0.820701 -0.644922   -1.680840               1
86397  -0.543127 -1.385148 -0.644922   -0.181041               1
110500 -0.211838 -0.383000 -1.699001   -1.347551               1
185133  0.813971  1.551521 -0.527803   -0.847618               1

        House_Ownership  Car_Ownership  Profession  CITY  STATE  \
200471                2              0           4   270     20
92611                 2              0          13   311     22
86397                 2              0          42   123     23
110500                2              0          48   295      1
185133                0              1          50    56     11

        CURRENT_JOB_YRS  CURRENT_HOUSE_YRS
200471        -0.914084          -0.712569
92611         -1.736837          -0.712569
86397         -0.639833           0.717243
110500        -1.188335           0.002337
185133        -0.365582           0.717243

# Remove the 'Id' column from all datasets
X_train = X_train.drop('Id', axis=1)
X_val = X_val.drop('Id', axis=1)
X_test = X_test.drop('Id', axis=1)

#Saving the preprocessed data
X_train.to_csv('/Users/yogeshdhaliya/Desktop/Task/X_train.csv',index=F
alse)
X_val.to_csv('/Users/yogeshdhaliya/Desktop/Task/X_val.csv',index=False
)
X_test.to_csv('/Users/yogeshdhaliya/Desktop/Task/X_test.csv',index=Fal
se)
y_train.to_csv('/Users/yogeshdhaliya/Desktop/Task/y_train.csv',index=F
alse)
y_val.to_csv('/Users/yogeshdhaliya/Desktop/Task/y_val.csv',index=False
)
y_test.to_csv('/Users/yogeshdhaliya/Desktop/Task/y_test.csv',index=Fal
se)

import pandas as pd

# Load the preprocessed data
X_train = pd.read_csv("/Users/yogeshdhaliya/Desktop/Task/X_train.csv")
X_val = pd.read_csv('/Users/yogeshdhaliya/Desktop/Task/X_val.csv')
X_test = pd.read_csv('/Users/yogeshdhaliya/Desktop/Task/X_test.csv')
```

```
y_train = pd.read_csv('/Users/yogeshdhaliya/Desktop/Task/y_train.csv')
y_val = pd.read_csv('/Users/yogeshdhaliya/Desktop/Task/y_val.csv')
y_test = pd.read_csv('/Users/yogeshdhaliya/Desktop/Task/y_test.csv')

# Determine the number of classes in the target variable
n_classes = len(y_train['Risk_Flag'].unique())
print(f'Number of classes: {n_classes}')
```

```
Number of classes: 2
```

```
#maximum number of LDA components(Applying LDA)
max_components = n_classes - 1
print(f'Maximum number of LDA components: {max_components}')
```

```
Maximum number of LDA components: 1
```

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

# Apply LDA
lda = LinearDiscriminantAnalysis(n_components=max_components)
# Fit LDA and transform the training data
X_train_lda = lda.fit_transform(X_train_scaled,
y_train.values.ravel())
X_val_lda = lda.transform(X_val_scaled)
X_test_lda = lda.transform(X_test_scaled)

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
# Convert the transformed arrays back to DataFrames for easier
inspection
X_train_lda_df = pd.DataFrame(X_train_lda, columns=[f'LDA{i+1}' for i
in range(X_train_lda.shape[1])])
X_val_lda_df = pd.DataFrame(X_val_lda, columns=[f'LDA{i+1}' for i in
range(X_val_lda.shape[1])])
X_test_lda_df = pd.DataFrame(X_test_lda, columns=[f'LDA{i+1}' for i in
range(X_test_lda.shape[1])])
# Train and evaluate a classifier using the LDA-transformed data
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train_lda_df, y_train.values.ravel())
y_pred_val = clf.predict(X_val_lda_df)
y_pred_test = clf.predict(X_test_lda_df)
accuracy = accuracy_score(y_val, y_pred_val)
accuracy1=accuracy_score(y_test,y_pred_test)
print(f'Validation Accuracy with LDA: {accuracy}')
print(f'Test Accuracy with LDA: {accuracy1}')
```

```
Validation Accuracy with LDA: 0.720515873015873
Test Accuracy with LDA: 0.7209126984126984
```

```
#using smote to balance the data
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_lda_df,
y_train)
# Convert the transformed arrays back to DataFrames for easier
inspection
X_train_smote = pd.DataFrame(X_train_smote, columns=[f'LDA{i+1}' for i
in range(X_train_smote.shape[1])])
```

```
#Random forest with just train_scaled data
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train_scaled, y_train.values.ravel())
y_pred_val = clf.predict(X_val_scaled)
accuracy = accuracy_score(y_val, y_pred_val)
print(f'Validation Accuracy with just scaled data: {accuracy}')
```

```
Validation Accuracy with just scaled data: 0.8740079365079365
```

```
#using XGBoost
from xgboost import XGBClassifier
clf = XGBClassifier(random_state=42)
clf.fit(X_train_scaled, y_train.values.ravel())
y_pred_val = clf.predict(X_val_scaled)
accuracy = accuracy_score(y_val, y_pred_val)
y_pred_test = clf.predict(X_test_scaled)
accuracy1=accuracy_score(y_test,y_pred_test)
print(f'Validation Accuracy with XGBoost: {accuracy}')
print(f'Test Accuracy with XGBoost: {accuracy1}')
```

```
Validation Accuracy with XGBoost: 0.8649206349206349
Test Accuracy with XGBoost: 0.8686111111111111
```

```
#Using XGBoost with LDA
clf = XGBClassifier(random_state=42)
clf.fit(X_train_lda_df, y_train.values.ravel())
y_pred_val = clf.predict(X_val_lda_df)
accuracy = accuracy_score(y_val, y_pred_val)
y_pred_test = clf.predict(X_test_lda_df)
accuracy1=accuracy_score(y_test,y_pred_test)
print(f'Validation Accuracy with XGBoost and LDA: {accuracy}')
print(f'Test Accuracy with XGBoost and LDA: {accuracy1}')
```

```
Validation Accuracy with XGBoost and LDA: 0.8703571428571428
Test Accuracy with XGBoost and LDA: 0.8740476190476191
```

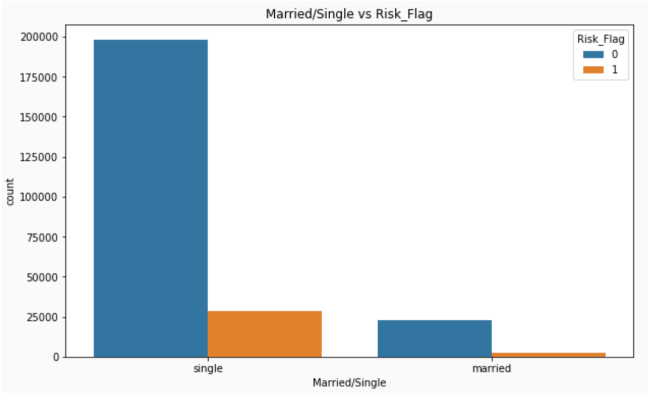
```
#Using logistic regression
from sklearn.linear_model import LogisticRegression
```

```
clf = LogisticRegression(random_state=42)
clf.fit(X_train_scaled, y_train.values.ravel())
y_pred_val = clf.predict(X_val_scaled)
accuracy = accuracy_score(y_val, y_pred_val)
y_pred_test = clf.predict(X_test_scaled)
accuracy1=accuracy_score(y_test,y_pred_test)
print(f'Validation Accuracy with Logistic Regression: {accuracy}')
print(f'Test Accuracy with Logistic Regression: {accuracy1}')
```

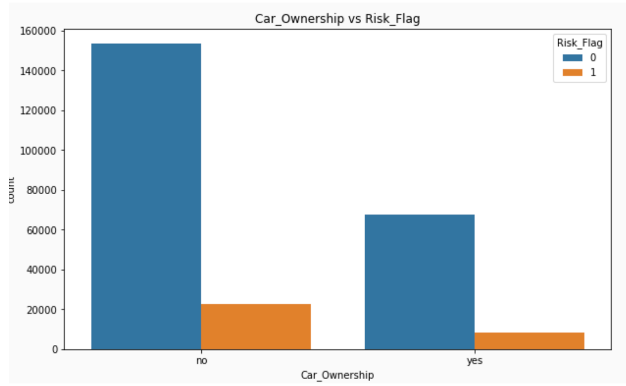
```
Validation Accuracy with Logistic Regression: 0.8740079365079365
Test Accuracy with Logistic Regression: 0.8778571428571429
```

After trying out various ML models Random Forest Classifier & Logisitic Regression got the highest accuracy result. I have got accuracy score of 87%

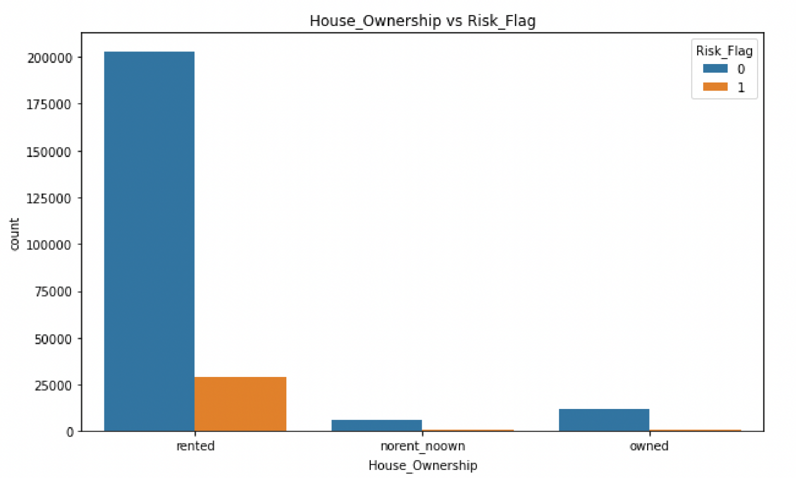
What are the main deciding factors associated with risk?



Single applicants exhibit a higher risk profile compared to married ones. This aligns with real-world observations, as factors like shared finances and stability often come with marriage.



Car ownership is associated with a lower risk of loan default. This suggests potential borrowers with cars might have better financial stability or a stronger ability to repay loans.



Individuals renting a house exhibit a higher risk profile compared to homeowners. This aligns with the potential for greater financial stability and asset ownership associated with homeownership.

In conclusion, our analysis reveals several key factors influencing loan risk. Marital status, car ownership, and homeownership all play a significant role. Single applicants, individuals without car ownership, and renters tend to be associated with higher risk profiles. These findings likely reflect factors like shared finances, financial stability, and asset ownership, which can influence a borrower's ability to repay loans.

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