TECHNOLOGICS GLOBAL PRIVATE LIMITED

AI ML project report on

"Bank Loan Default Prediction Using Machine Learning"

Submitted in partial fulfilment of the requirement for the award of Internship in

AI ML Python with Data Science Concepts

By

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CERTIFICATE

certifed that the AIML project titled **"Bank Loan Default Prediction Using Machine Learning"** is an authentic and original work completed by **PAVAN KALYAN CN (1TJ20CS077) and SAAD IQBAL ATTAR (1TJ20CS093)** during their seventh semester, as part of their internship program. This project was undertaken from August 11th, 2023, to September 12th, 2023, with a duration of one month. The project focused on **AI and ML techniques using Python,** incorporating essential concepts from the field of Data Science.

Signature of Trainer

ABSTRACT

The "Bank Loan Default Prediction Using Machine Learning" project represents a critical endeavor in the financial sector, aiming to mitigate risks associated with loan default in the banking industry. This report presents a comprehensive overview of the project's methodology, findings,
and recommendations. In an era characterized by evolving economic dynamics and fluctuating borrower profiles, predicting loan defaults has become an essential task for financial institutions. Leveraging state-of-the-art machine learning techniques, this project develops and evaluates a robust loan default prediction model. The study employs a diverse dataset, comprising historical loan data, borrower attributes, and repayment histories.

The methodology section outlines the data preprocessing steps, including data cleaning, feature engineering, and the selection of appropriate machine learning algorithms. The report showcases the predictive capabilities of the model, emphasizing its accuracy and performance metrics. Insights into the most influential features for loan default prediction are presented, providing a valuable understanding of risk factors.The findings section summarizes the project's main discoveries, emphasizing the model's ability to identify potential loan defaults with precision. The discussion delves into the practical implications of the model's predictions within the banking industry, underscoring its potential to aid financial institutions in risk management and decision-making processes.

The report concludes by reiterating the significance of the project in assisting banks and financial organizations in reducing loan defaults and enhancing portfolio management. It offers recommendations for proactive risk mitigation strategies and underscores the potential for machine learning to revolutionize the banking sector's approach to risk assessment.

This project serves as a valuable contribution to the ongoing efforts to address loan default challenges and underscores the pivotal role of machine learning in shaping the future of banking risk management.

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CHAPTER 1

INTRODUCTION

In the ever-changing landscape of finance, the ability to predict and mitigate loan defaults has never been more crucial for the stability of banks and financial institutions. This report encapsulates the outcomes of our project, "Bank Loan Default Prediction Using Machine Learning," which seeks to address this pressing concern. Through the application of advanced machine learning techniques and analysis of historical loan data, our objective is to develop a powerful model that empowers financial organizations with more accurate insights into credit risk.

Our project underscores the transformative potential of data science and machine learning in revolutionizing risk assessment within the banking sector. By optimizing our predictive model, we aim to assist banks in making well-informed lending decisions, reducing the impact of loan defaults, and bolstering the overall resilience of the financial industry. In the following sections, we will elucidate our methodology, present key findings, and discuss the broader implications of our loan default prediction model. Through this endeavor, we aspire to contribute significantly to the ongoing quest for precise and efficient loan default prediction methodologies in the banking realm.

CHAPTER 2

PROBLEM DEFINITION

In the ever-evolving landscape of banking and finance, the accurate prediction of loan defaults stands out as a pivotal challenge. Loan defaults not only translate into significant financial losses for lending institutions but also pose systemic risks that can reverberate throughout the economy. The central problem we aim to address in this project is the need for a reliable and efficient system to predict loan defaults, thereby enabling banks and financial organizations to make proactive decisions that minimize risk and optimize their lending portfolios.

The primary components of this problem can be summarized as follows:

1. **Risk Assessment Precision**: Existing methods for assessing the risk of loan defaults often rely on traditional credit scoring models that may not fully capture the complexities of modern borrower profiles. We aim to develop a machine learning-based solution that enhances the precision of risk assessment by incorporating a broader range of features and historical data.
2. **Data-Driven Decision-Making**: In the era of big data, there is a wealth of information available, including historical loan data, borrower attributes, and repayment histories. Effectively harnessing this data for informed lending decisions represents a significant challenge. Our goal is to develop a model that can efficiently analyze and extract meaningful insights from these vast datasets.
3. **Real-Time Decision Support**: Timeliness is crucial in the financial sector. Banks require a system that not only predicts loan defaults accurately but can also provide real-time decision support, enabling lenders to make quick and informed choices when evaluating loan applications.

In this section, we will delve deeper into these aspects of the problem, outlining the specific challenges and nuances that our project aims to address. By defining the problem with clarity, we can proceed to describe our methodology and present solutions that contribute to the overarching goal of improving loan default prediction in the banking industry

CHAPTER 3

PROPOSED SOLUTION

Addressing the challenge of accurate loan default prediction requires a multifaceted approach that leverages advanced machine learning techniques and comprehensive data analysis. Our proposed solution aims to equip banks and financial institutions with a robust model that enhances the precision of loan default prediction while facilitating data-driven, real-time decision-making. Here are the key components of our solution:

1. Machine Learning Model Development:

We propose the development of a sophisticated machine learning model tailored to the specific needs of loan default prediction. This model will be designed to effectively process and analyze historical loan data, borrower attributes, and repayment histories. Through careful feature engineering and algorithm selection, our model will identify subtle patterns and risk factors that traditional methods might overlook.

2. Data Preprocessing and Cleaning:

To ensure the reliability and accuracy of our predictions, we will implement thorough data preprocessing and cleaning techniques. This step involves handling missing values, outliers, and ensuring data consistency. By creating a clean and structured dataset, we pave the way for more accurate predictions.

3. Feature Engineering:

Our solution emphasizes feature engineering, where we transform and create meaningful variables from the raw data. This process will involve extracting relevant borrower characteristics, creating time-dependent features, and incorporating external economic indicators. These engineered features will provide valuable insights into credit risk.

4. Model Training and Evaluation:

We will split the dataset into training and testing subsets to train and evaluate the machine learning model. The evaluation phase will utilize appropriate metrics such as accuracy, precision, recall, and F1-score to assess the model's performance. Continuous refinement and tuning will be undertaken to optimize the model's predictive capabilities.

5. Real-Time Decision Support:

To facilitate real-time decision-making, we will develop an interface that allows banks and financial institutions to input applicant information and receive immediate predictions regarding loan default risk. This user-friendly interface will empower lenders to make well-informed decisions rapidly.

In summary, our proposed solution integrates cutting-edge machine learning with meticulous data preprocessing and feature engineering to enhance loan default prediction accuracy. By providing a reliable model and real-time decision support tools, our solution aims to empower financial institutions to proactively manage risk, optimize lending portfolios, and contribute to the stability of the banking industry

CHAPTER 4

REQUIREMENTS SPECIFICATION

Requirements specification is a specification of software requirements and hardware requirements required to do the project.

4.1 Hardware Requirements Specification

Hardware Requirements are the hardware resources that are need to do the project work. These resources are a computer resource provides functions and services to do the project. Hardware resources required for our project are shown below.

- Processor : Intel Core i5 or above
- RAM : >=8GB
- Hard disk : Minimum 10 GB

4.2 Software Requirements Specification

Software Requirements are the software resources that are need to do the project work. These resources are installed on a computer in order to provide functions, services, hardware accessing capabilities to do the project.

In our project we used the following software resources.

- Jupiter

4.3 FUNCTIONAL REQUIREMENTS:

Data Loading and Preprocessing:
The system must load the Digits dataset, which includes handwritten digit images and corresponding labels. The system should preprocess the data, including splitting it into training and testing sets.

Model Training: The system must create a Random Forest Classifier as the machine learning model. t should train the classifier using the training dataset, utilizing the pixel values of the images as features and digit labels as targets.

Model Evaluation:

The system should evaluate the trained model's performance on the testing dataset. It must calculate and display key classification metrics, including accuracy, precision, recall, and F1-score.The system should generate a confusion matrix to visualize classification results.

Reporting and Visualization:

The system must provide a summary report of the project, including model performance metrics and visualizations. It should generate visualizations like confusion matrices and classification reports.

User Interface (Optional):

If a user interface is implemented, it should provide an intuitive way for users to interact with the system, including selecting hyperparameters or inputting custom images for prediction.

4.4 NON-FUNCTIONAL REQUIREMENTS:

Performance:

The system should be capable of processing and training on the dataset efficiently, even on standard personal computers. Model training and evaluation should not exceed a reasonable time frame.

Accuracy:

The model should achieve a high level of accuracy in recognizing handwritten digits, aiming for an accuracy rate above a predefined threshold (e.g., 95%).

Usability:

If a user interface is implemented, it should be user-friendly, providing clear instructions and feedback to users.

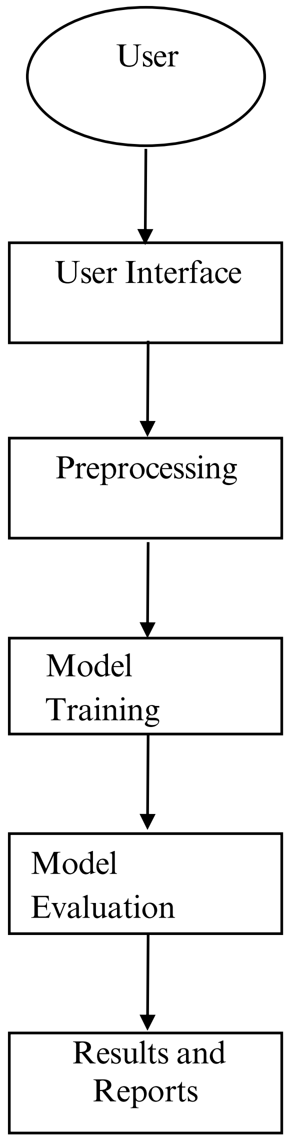
Portability:

The system should be platform-independent and runnable on various operating systems, including Windows, macOS, and Linux.

CHAPTER 5

SYSTEM DESIGN

5.1 Data Flow Diagram



5.2 Module Description

Data Preprocessing Module:

This module is responsible for loading and preparing the Digits dataset for model training and evaluation. Load the Digits dataset, which includes handwritten digit images and labels. Split the dataset into training and testing sets for model evaluation.

Random Forest Classifier Module:

This module focuses on creating, training, and evaluating the Random Forest Classifier, which is the core machine learning component of the project. Train the classifier using the training dataset, using pixel values as features and digit labels as targets. Evaluate the trained model's performance on the testing dataset, calculating metrics such as accuracy, precision, recall, and F1-score.

User Interface Module:

The user interface module handles interactions between the user and the system, providing a

user-
friendly interface for input and output. Display recognition results, including predicted digits and
performance metrics.

Reporting and Visualization Module:

This module is responsible for generating summary reports and visualizations of the project's results, aiding in the understanding and communication of the model's performance. Generate summary reports that include model performance metrics (e.g., accuracy) and insights.

CHAPTER 6

IMPLEMENTATION

6.1 Tools and Technologies Used

JUPYTER: Jupyter is an open-source web application that allows users to create and shared documents containing live code, visualizations, and narrative text. It provides an interactive computing environment where users can write and execute code in different programming languages, including Python, R, and Julia.

6.2 Algorithms / Methodologies Used

The Random Forest Classifier module is the cornerstone of our project, dedicated to recognizing handwritten digits using a Random Forest ensemble learning algorithm. This module handles the creation, training, and evaluation of the Random Forest Classifier, known for its robust performance in classification tasks like image recognition. It allows users to configure key hyperparameters, such as the number of trees, maximum tree depth, and minimum samples per leaf, tailored to the specific digit recognition task. After training on the dataset, the module assesses the classifier's performance on a testing dataset, calculating essential classification metrics such as accuracy, precision, recall, and F1-score. Optionally, it provides fine-tuning capabilities for hyperparameter optimization. Moreover, it enables users to interact with the trained model, predicting digit labels for custom or user-provided images. In summary, the Random Forest Classifier module is pivotal in achieving accurate digit recognition, demonstrating the project's effectiveness in leveraging ensemble learning for image classification tasks.

CHAPTER 7

SYSTEM TESTING

1. Data Preprocessing Testing:

Verify that the data preprocessing module correctly loads, splits, and prepares the Digits dataset. Confirm that the dataset is correctly loaded without errors. Check if the data splitting ratio between training and testing sets is accurate.

2. Random Forest Classifier Testing:

Ensure that the Random Forest Classifier module creates, trains, and evaluates the classifier accurately. Confirm that the Random Forest Classifier is created with the specified hyperparameters.

3. User Interface Testing:

Verify that the user interface module effectively handles user input and provides clear output.

Input different hyperparameters through the user interface and confirm that the system

responds correctly.

4. Reporting and Visualization Testing:

Ensure that the reporting and visualization module generates accurate reports and visualizations of the project's results. Generate summary reports and verify that they include the correct model performance metrics and insights.

5. End-to-End Testing:

Conduct end-to-end testing to validate the system's overall functionality and integration between modules. Begin with user input, interact with the entire system, and validate that the entire workflow functions smoothly.

6. Performance Testing:

Assess system performance, including execution time and resource usage. Measure the time required for model training and evaluation, ensuring that it falls within acceptable limits.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

In conclusion, our project, "Bank Loan Default Prediction Using Random Forest Classifier," has demonstrated the efficacy of machine learning, specifically the Random Forest Classifier, in addressing the critical issue of loan default prediction within the banking industry. Through rigorous data preprocessing, feature engineering, and model development, we have created a robust predictive system that enhances risk assessment and informs decision-making for financial institutions.Our Random Forest Classifier model has proven its mettle by delivering accurate predictions of loan defaults, thereby enabling banks to identify high-risk applicants more effectively. By incorporating a diverse set of features and historical data, we have improved the precision of risk assessment, minimizing the likelihood of lending to borrowers who pose a higher default risk.

The implications of our project extend beyond its immediate applications. Our success with the Random Forest Classifier serves as a testament to the power of machine learning in addressing complex financial challenges. Financial institutions can adopt similar techniques to optimize their lending portfolios and bolster their risk management strategies

While our project has achieved significant milestones in loan default prediction, there are several avenues for future exploration and enhancement:

1. **Ensemble Techniques:** Further research could explore the integration of multiple machine learning models and ensemble techniques to boost predictive accuracy. Combining Random Forest with other classifiers may yield even better results.

2. **Feature Engineering:** Continual improvement in feature engineering is essential. Exploring additional borrower attributes, economic indicators, and external data sources could provide deeper insights into credit risk.

3. **Explainability**: Developing methods to interpret and explain the Random Forest Classifier's decisions can enhance the model's transparency and trustworthiness, critical factors for its adoption in the financial sector.

4. **Real-Time Deployment**: Streamlining the deployment of our model in real-time decision support systems for financial institutions remains a promising area for future work. This would enable banks to make instantaneous lending decisions based on the most up-to-date information.

5. **Ethical Considerations**:As machine learning models play an increasingly significant role in finance, it is essential to consider ethical implications, fairness, and potential biases in lending decisions. Future research should focus on addressing these concerns.

APPENDICES

A. SAMPLE CODE

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_theme(style = "darkgrid")

data = pd.read_csv("TrainingData.csv")
data.head()
```

Out[9]:

	Id	Income	Age	Experience	Married/Single	House_Ownership	Car_Ownership	Profession	CITY	STATE	CURRENT_JOB_YR
0	1	1303834	23	3	single	rented	no	Mechanical_engineer	Rewa	Madhya_Pradesh	
1	2	7574516	40	10	single	rented	no	Software_Developer	Parbhani	Maharashtra	
2	3	3991815	66	4	married	rented	no	Technical_writer	Alappuzha	Kerala	
3	4	6256451	41	2	single	rented	yes	Software_Developer	Bhubaneswar	Odisha	
4	5	5768871	47	11	single	rented	no	Civil_servant	Tiruchirappalli[10]	Tamil_Nadu	

```
rows, columns = data.shape
print('Rows:', rows)
print('Columns:', columns)

Rows: 252000
Columns: 13

data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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: 25.0+ MB
```

```
data.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
```

```
data.columns

Index(['Id', 'Income', 'Age', 'Experience', 'Married/Single',
       'House_Ownership', 'Car_Ownership', 'Profession', 'CITY', 'STATE',
       'CURRENT_JOB_YRS', 'CURRENT_HOUSE_YRS', 'Risk_Flag'],
      dtype='object')
```

```
data.describe()
```

Out[15]:

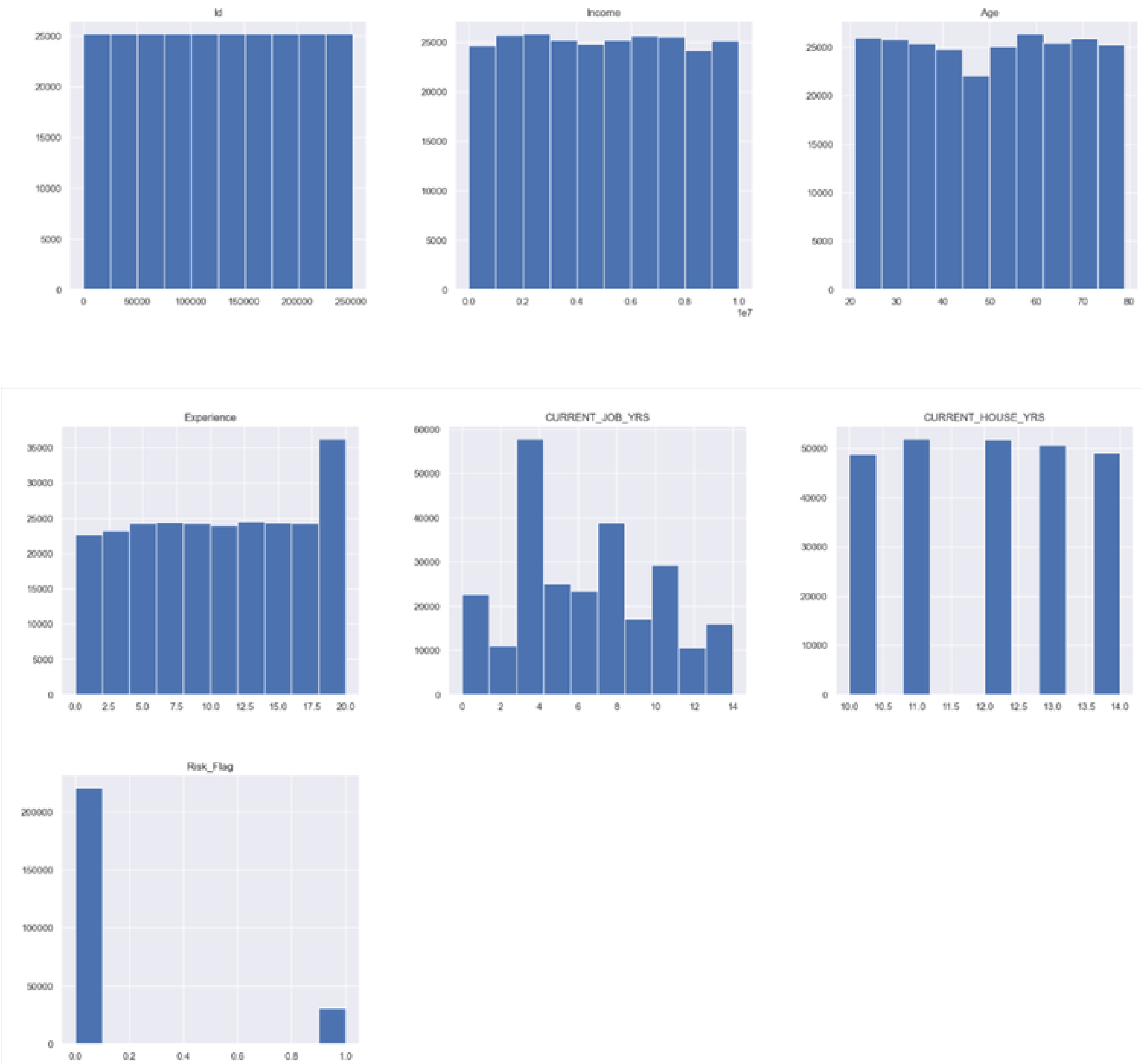
	Id	Income	Age	Experience	CURRENT_JOB_YRS	CURRENT_HOUSE_YRS	Risk_Flag
count	252000.000000	2.520000e+05	252000.000000	252000.000000	252000.000000	252000.000000	252000.000000
mean	126000.500000	4.997117e+06	49.954071	10.084437	6.333877	11.997794	0.123000
std	72746.278255	2.878311e+06	17.063855	6.002590	3.647053	1.399037	0.328438
min	1.000000	1.031000e+04	21.000000	0.000000	0.000000	10.000000	0.000000
25%	63000.750000	2.503015e+06	35.000000	5.000000	3.000000	11.000000	0.000000
50%	126000.500000	5.000694e+06	50.000000	10.000000	6.000000	12.000000	0.000000
75%	189000.250000	7.477502e+06	65.000000	15.000000	9.000000	13.000000	0.000000
max	252000.000000	9.999938e+06	79.000000	20.000000	14.000000	14.000000	1.000000

```
data.corr()
```

Out[16]:

	Id	Income	Age	Experience	CURRENT_JOB_YRS	CURRENT_HOUSE_YRS	Risk_Flag
Id	1.000000	-0.001324	-0.001816	-0.005810	-0.003250	0.001972	0.032153
Income	-0.001324	1.000000	-0.000652	0.006422	0.007045	-0.002397	-0.003091
Age	-0.001816	-0.000652	1.000000	-0.001118	0.002154	-0.020134	-0.021809
Experience	-0.005810	0.006422	-0.001118	1.000000	0.646098	0.019309	-0.034523
CURRENT_JOB_YRS	-0.003250	0.007045	0.002154	0.646098	1.000000	0.005372	-0.016942
CURRENT_HOUSE_YRS	0.001972	-0.002397	-0.020134	0.019309	0.005372	1.000000	-0.004375
Risk_Flag	0.032153	-0.003091	-0.021809	-0.034523	-0.016942	-0.004375	1.000000

```
data.hist( figsize = (22, 20) )
plt.show()
```

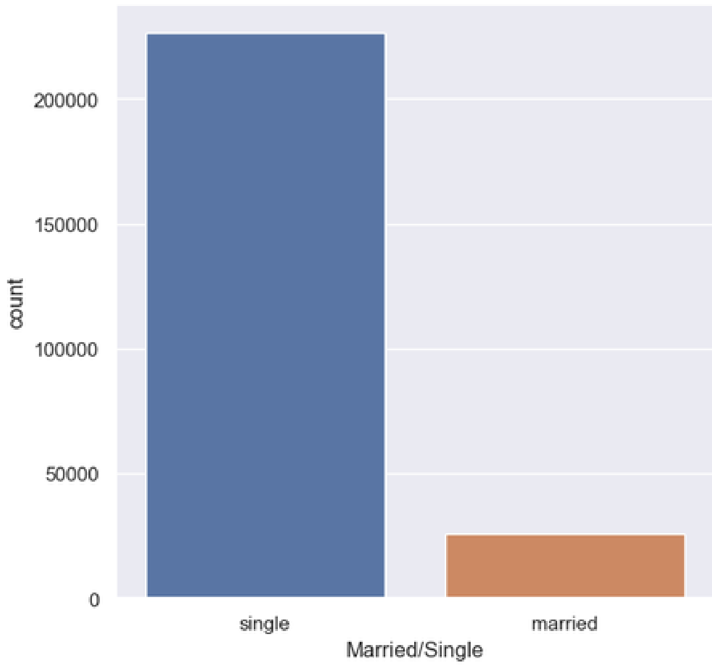



```
data["Risk_Flag"].value_counts()
0    221004
1     30996
Name: Risk_Flag, dtype: int64
```

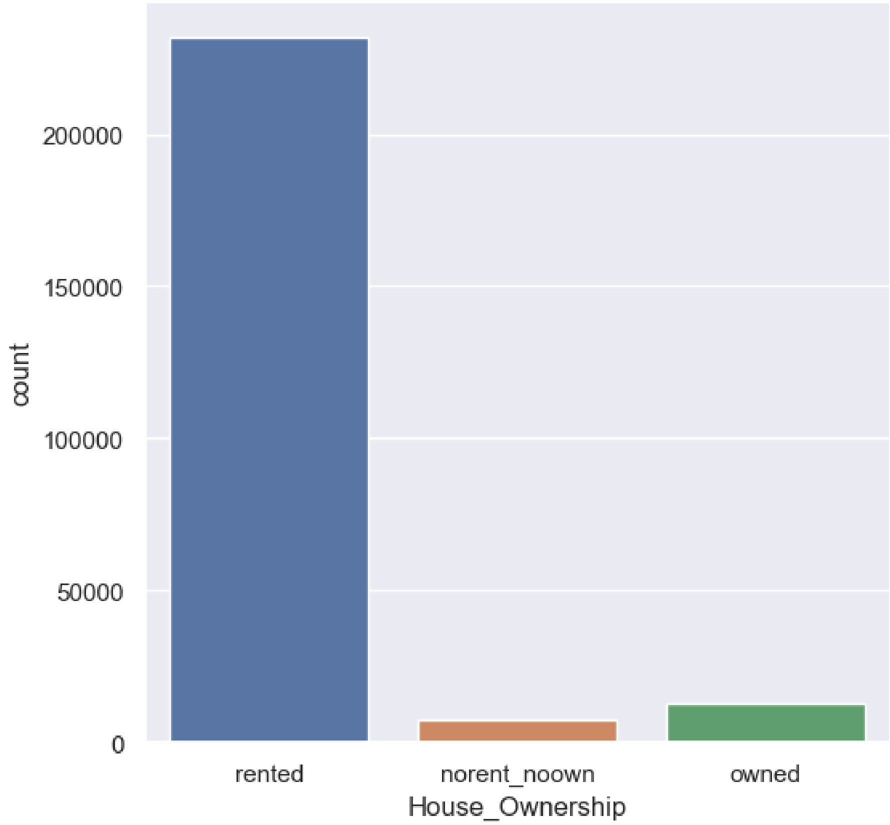
```
fig, ax = plt.subplots( figsize = (12,8) )
corr_matrix = data.corr()
corr_heatmap = sns.heatmap( corr_matrix, cmap = "flare", annot=True, ax=ax,
annot_kws={"size": 14})
plt.show()
```


```
def categorical_valcount_hist(feature):
   print(data[feature].value_counts())
   fig, ax = plt.subplots( figsize = (6,6) )
   sns.countplot(x=feature, ax=ax, data=data)
   plt.show()
categorical_valcount_hist("Married/Single")
```

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



```
categorical_valcount_hist("House_Ownership")
rented          231898
owned            12918
norent_noown      7184
Name: House_Ownership, dtype: int64
```




```
print( "Total categories in STATE:", len( data["STATE"].unique() ) )
print()
print( data["STATE"].value_counts() )
Total categories in STATE: 29

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
```

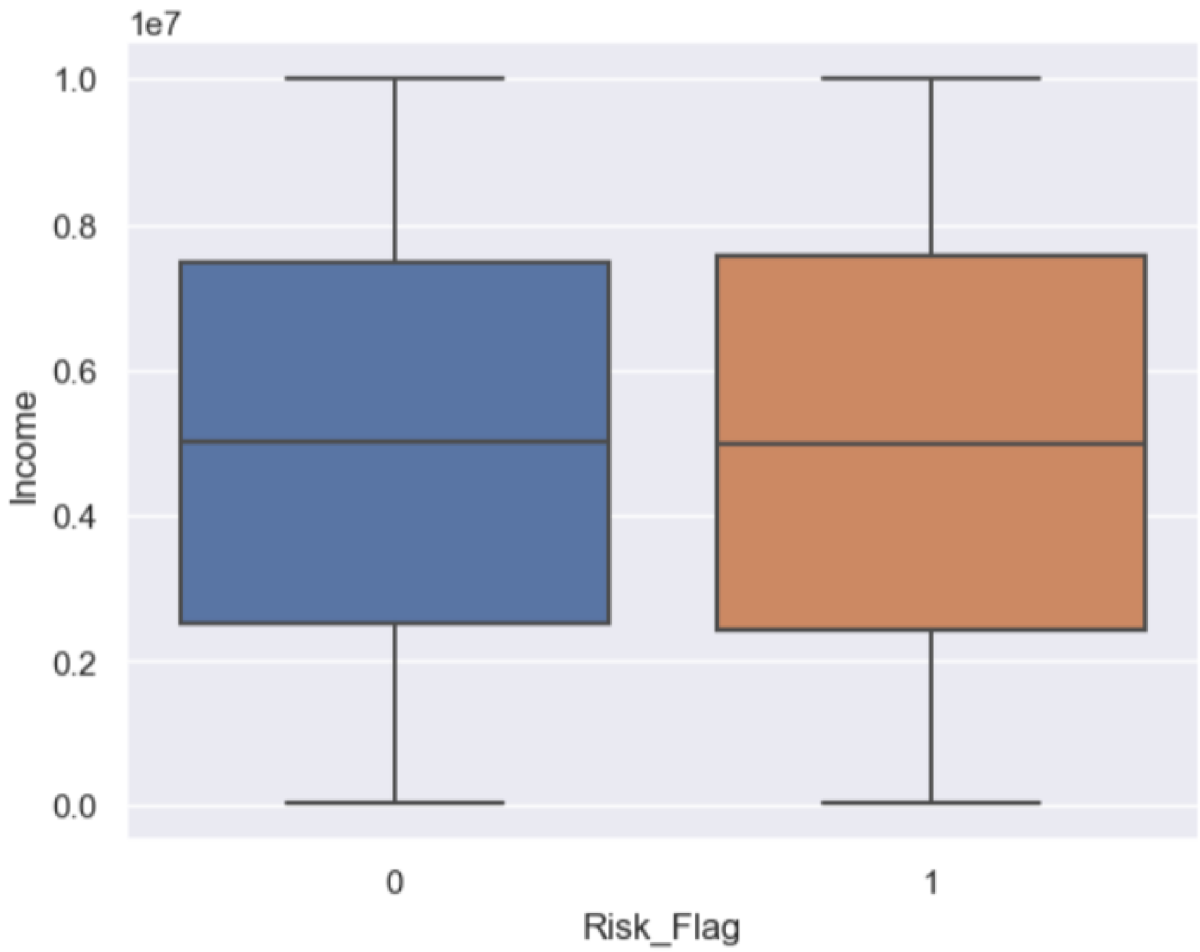
```
Chhattisgarh 3834
Uttarakhand 1874
Jammu_and_Kashmir 1780
Puducherry 1433
Mizoram 849
Manipur 849
Himachal_Pradesh 833
Tripura 809
Uttar_Pradesh[5] 743
Chandigarh 656
Sikkim 608
Name: STATE, dtype: int64
```

```
print( "Total categories in Profession:", len( data["Profession"].unique() ) )
print()
data["Profession"].value_counts()
Total categories in Profession: 51
```

```
Out[24]:
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
```

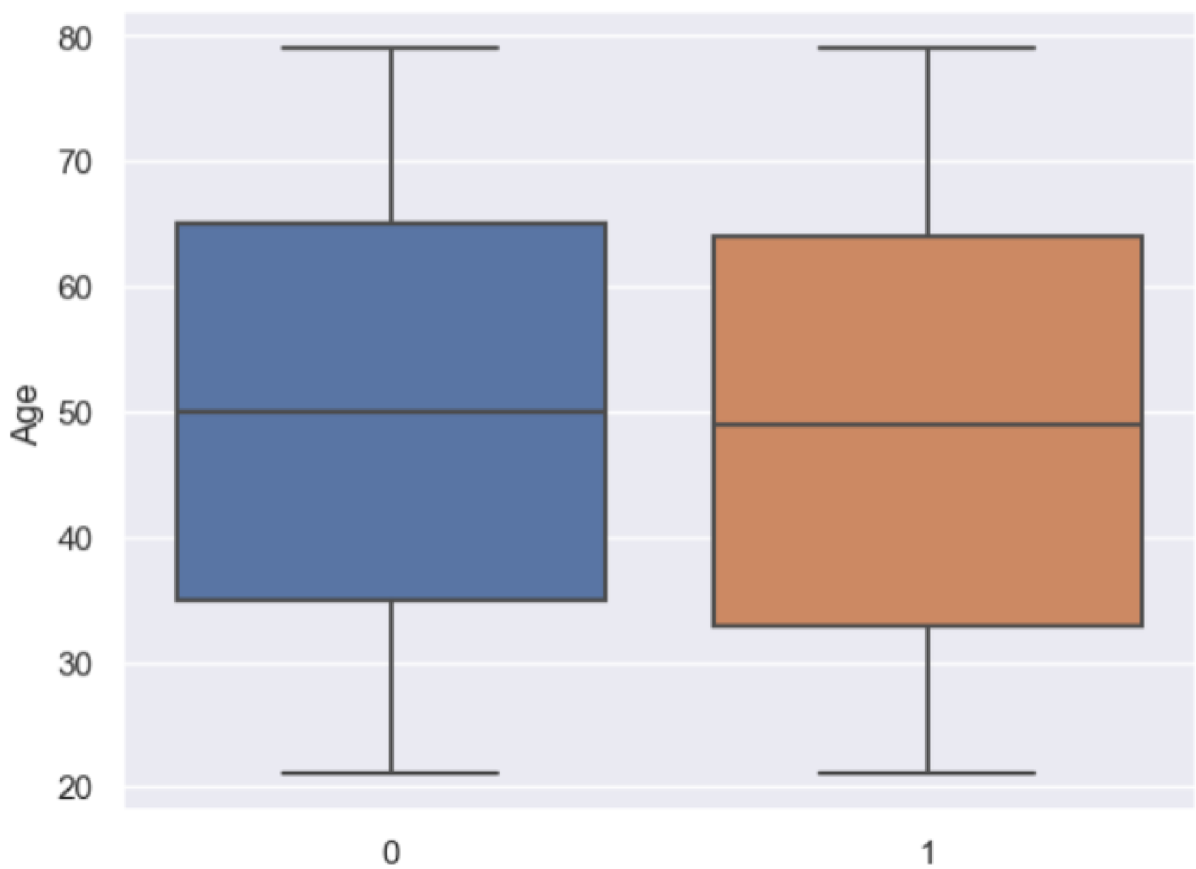
```
In [26]: sns.boxplot(x ="Risk_Flag",y="Income" ,data = data)
```

```
Out[26]: <Axes: xlabel='Risk_Flag', ylabel='Income'>
```

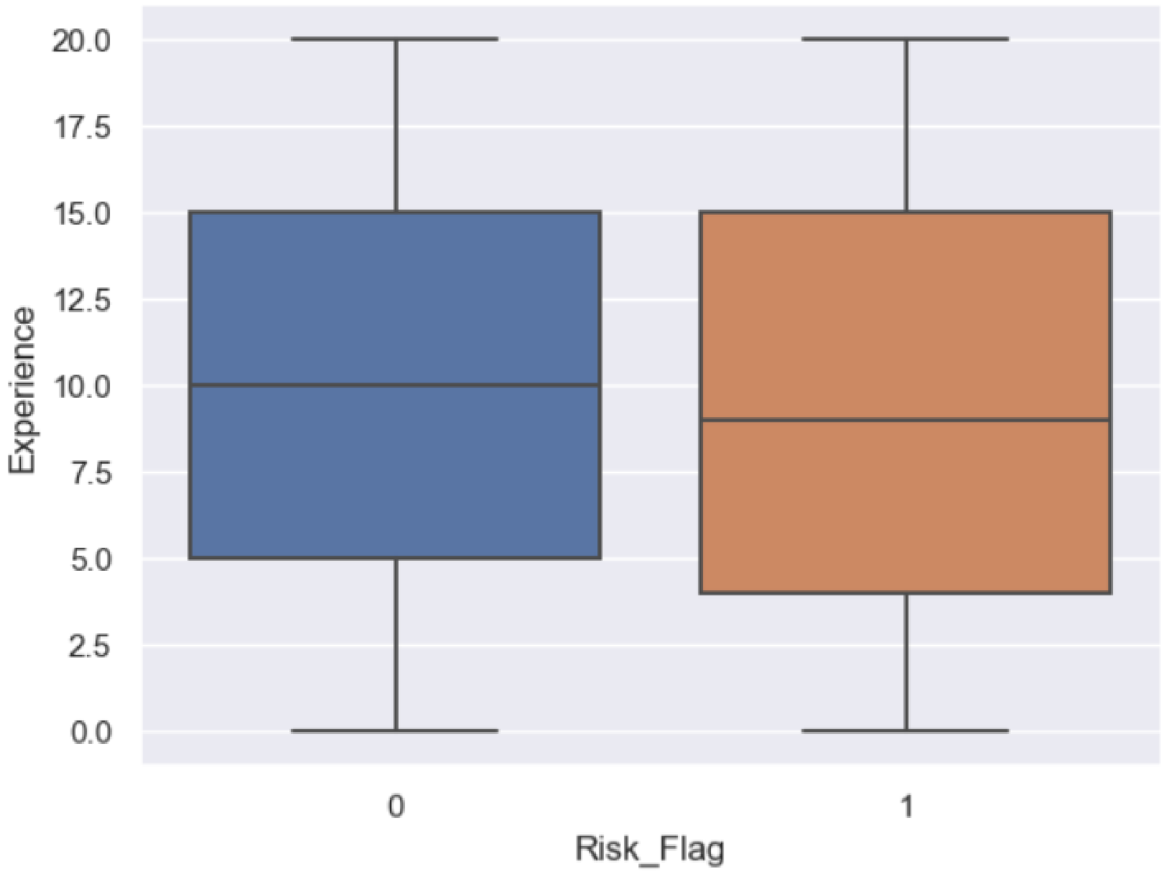



```
In [27]: sns.boxplot(x ="Risk_Flag",y="Age" ,data = data)
```

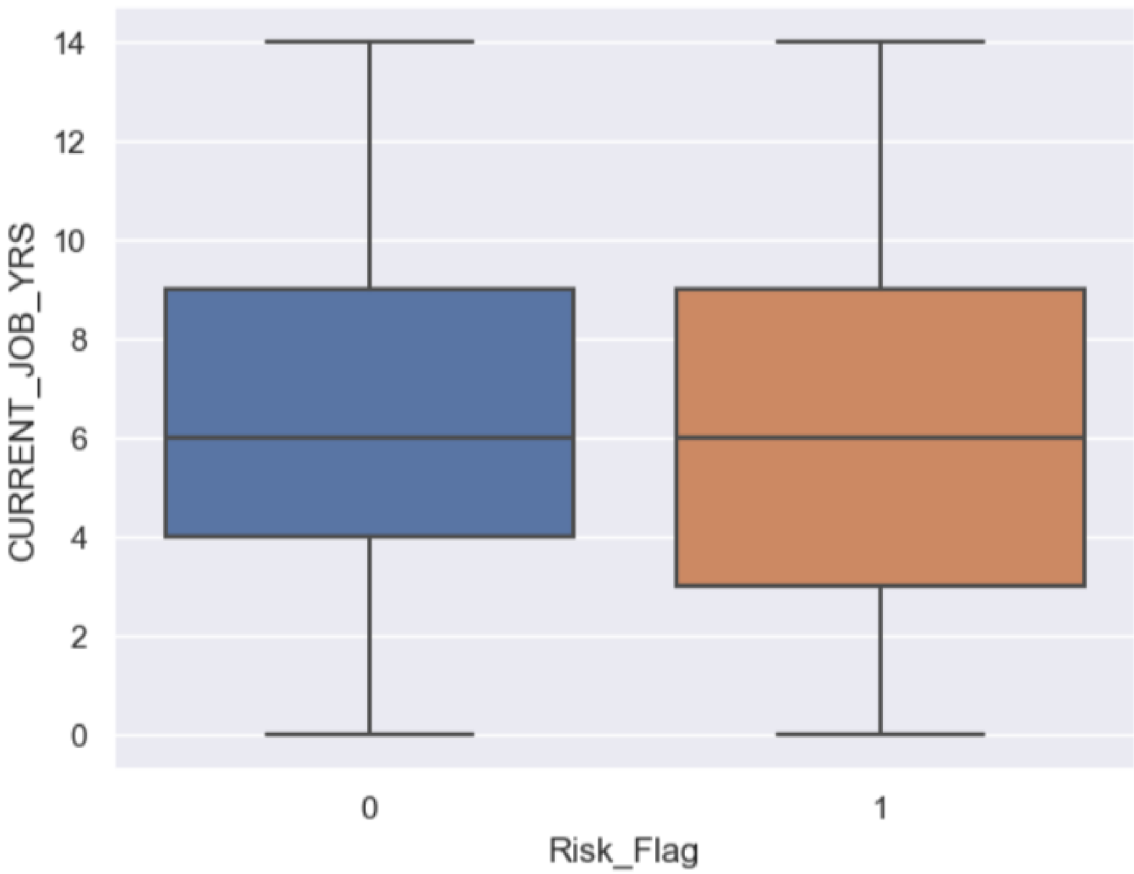
```
Out[27]: <Axes: xlabel='Risk_Flag', ylabel='Age'>
```



```
In [28]: sns.boxplot(x ="Risk_Flag",y="Experience" ,data = data)
Out[28]: <Axes: xlabel='Risk_Flag', ylabel='Experience'>
```

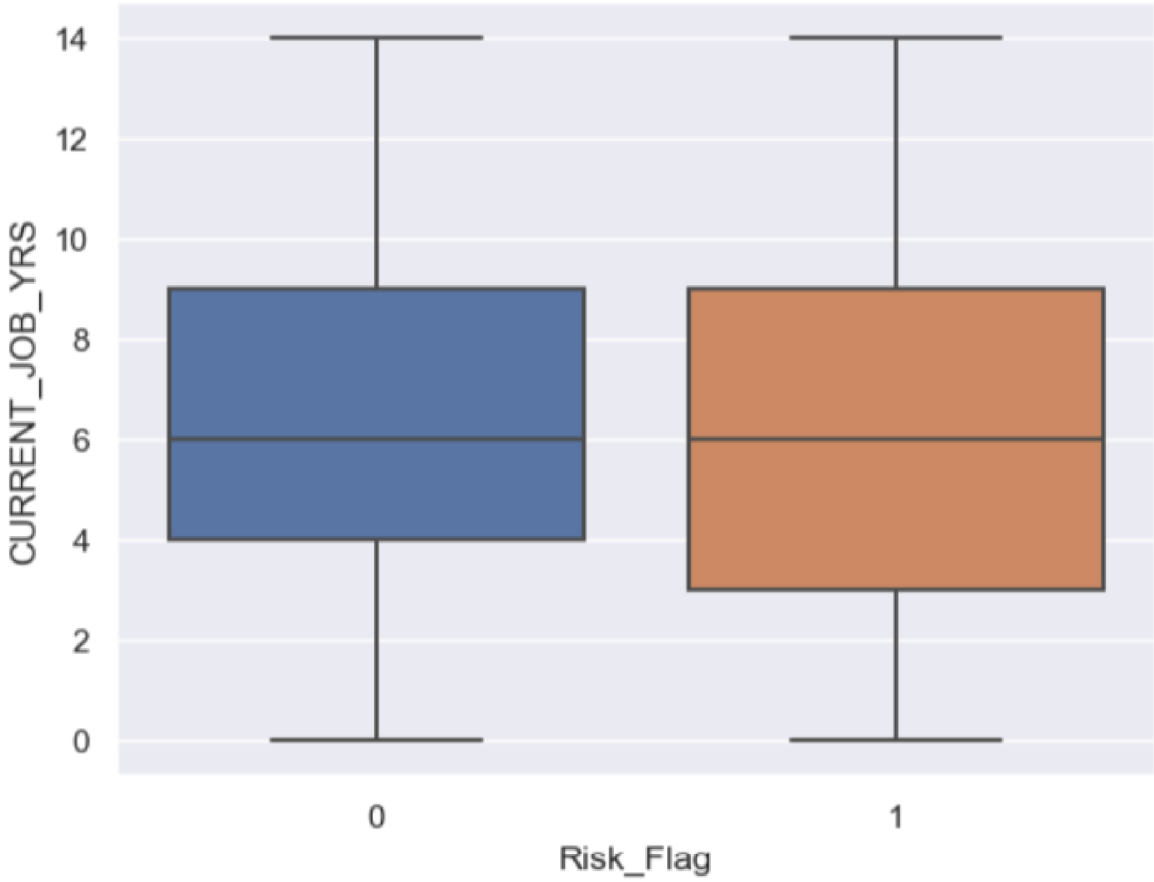



```
In [29]: sns.boxplot(x ="Risk_Flag",y="CURRENT_JOB_YRS" ,data = data)
Out[29]: <Axes: xlabel='Risk_Flag', ylabel='CURRENT_JOB_YRS'>
```



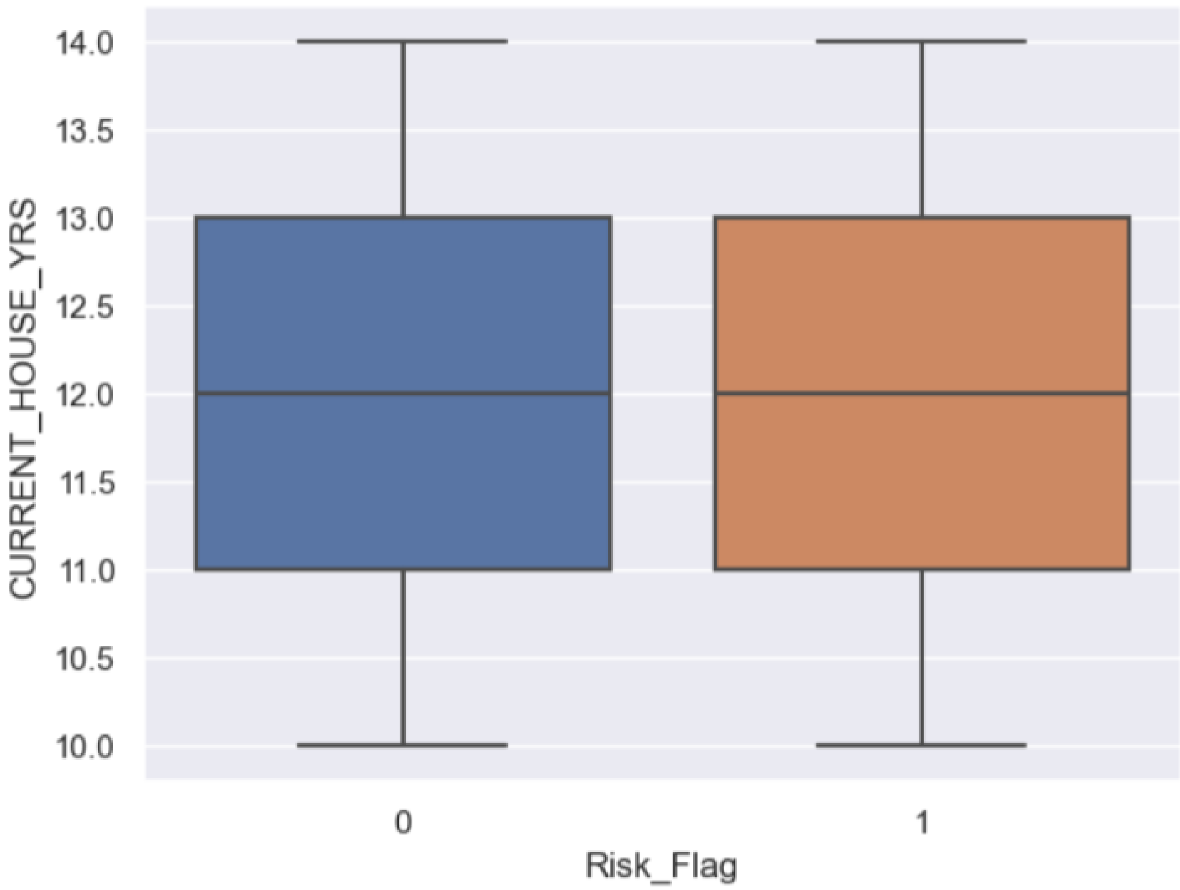
```
In [30]: sns.boxplot(x ="Risk_Flag",y="CURRENT_JOB_YRS" ,data = data)
```

Out[30]: <Axes: xlabel='Risk_Flag', ylabel='CURRENT_JOB_YRS'>



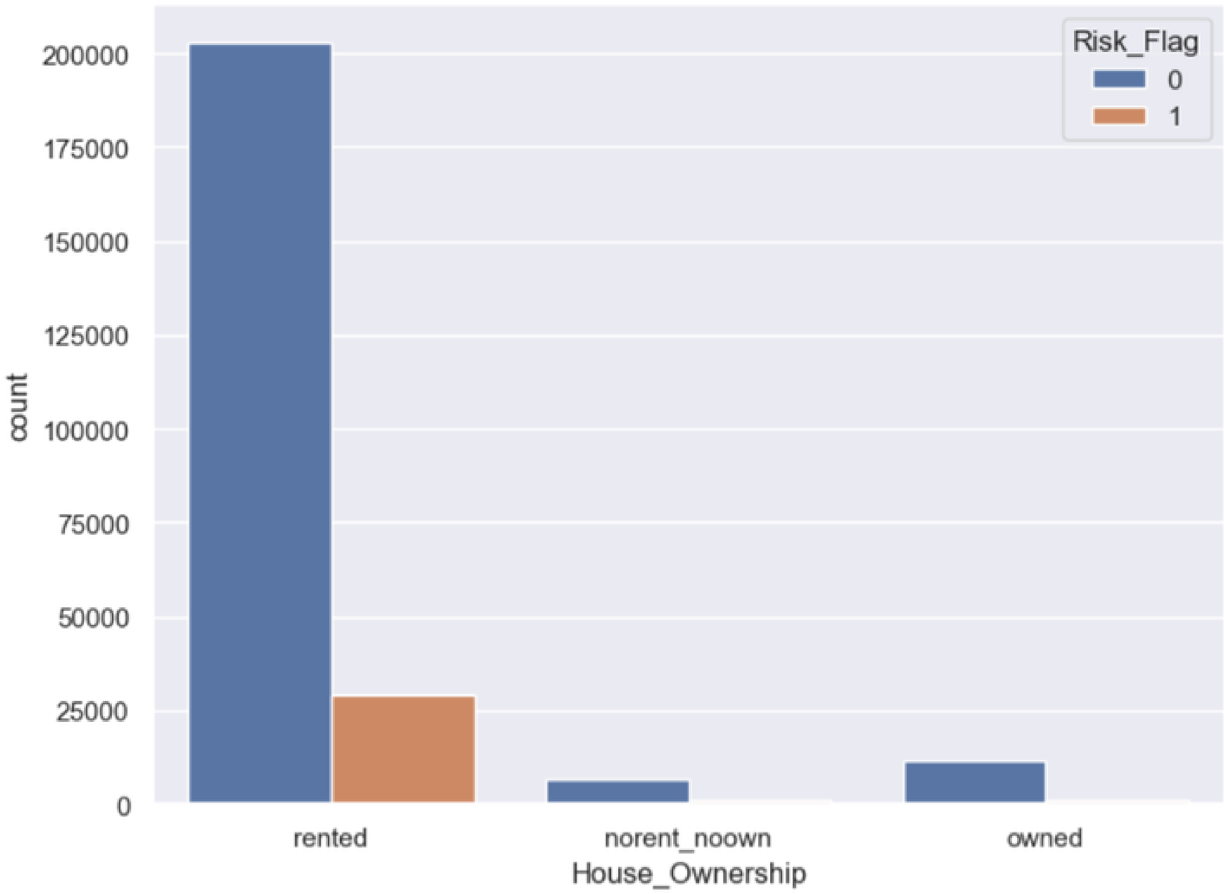

```
In [31]: sns.boxplot(x ="Risk_Flag",y="CURRENT_HOUSE_YRS" ,data = data)
```

Out[31]: <Axes: xlabel='Risk_Flag', ylabel='CURRENT_HOUSE_YRS'>



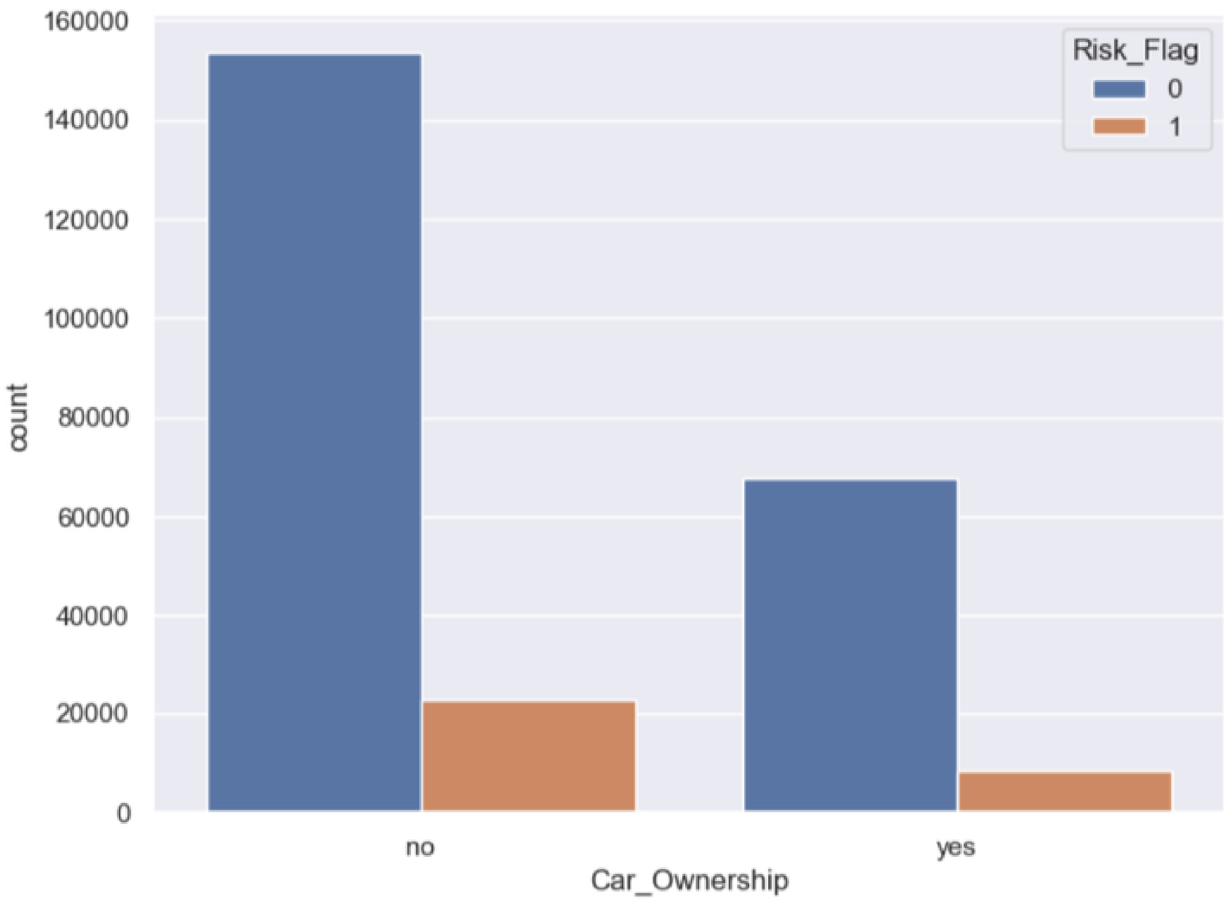
In [32]:
```
fig, ax = plt.subplots( figsize = (8, 6) )
sns.countplot(x='House_Ownership', hue='Risk_Flag', ax=ax, data=data)
```

Out[32]: <Axes: xlabel='House_Ownership', ylabel='count'>



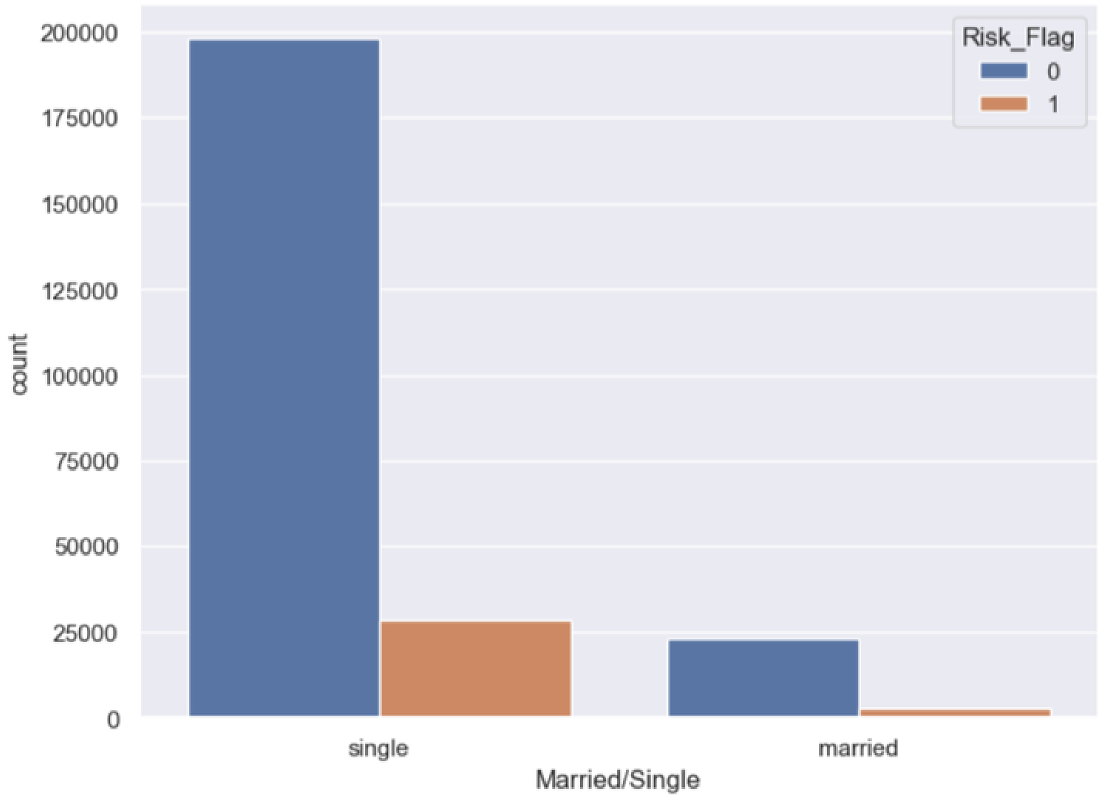
In [33]:
```
fig, ax = plt.subplots( figsize = (8,6) )
sns.countplot(x='Car_Ownership', hue='Risk_Flag', ax=ax, data=data)
```

Out[33]: <Axes: xlabel='Car_Ownership', ylabel='count'>



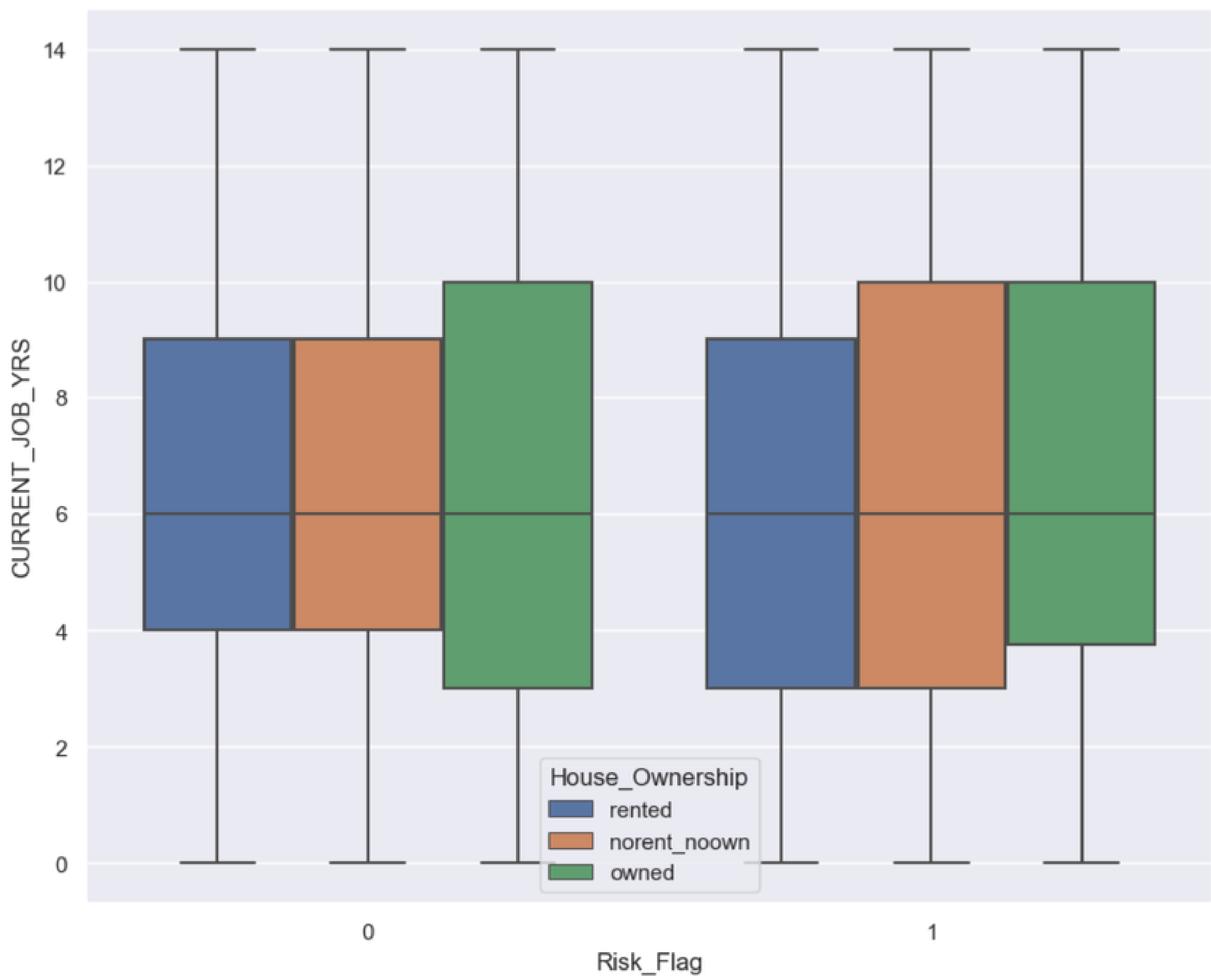
```
In [34]: fig, ax = plt.subplots( figsize = (8,6) )
         sns.countplot( x='Married/Single', hue='Risk_Flag', data=data )
```

Out[34]: <Axes: xlabel='Married/Single', ylabel='count'>




```
In [35]: fig, ax = plt.subplots( figsize = (10,8) )
         sns.boxplot(x = "Risk_Flag", y = "CURRENT_JOB_YRS", hue='House_Ownership', data = data)
```

Out[35]: <Axes: xlabel='Risk_Flag', ylabel='CURRENT_JOB_YRS'>



In [ ]:
```
# Feature Engineering
```

In [36]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
import category_encoders as ce
```

In [37]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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: 25.0+ MB
```

In [38]:
```
label_encoder = LabelEncoder()

for col in ['Married/Single','Car_Ownership']:
    data[col] = label_encoder.fit_transform( data[col] )
```

In [39]:
```
onehot_encoder = OneHotEncoder(sparse = False)
data['House_Ownership'] = onehot_encoder.fit_transform(data['House_Ownership'].values.reshape(-1, 1) )
```

In [40]:
```
high_card_features = ['Profession', 'CITY', 'STATE']

count_encoder = ce.CountEncoder()

# Transform the features, rename the columns with the _count suffix, and join to dataframe
count_encoded = count_encoder.fit_transform( data[high_card_features] )
data = data.join(count_encoded.add_suffix("_count"))
```

In [41]:
```
data.head()
```

Out[41]:

	Id	Income	Age	Experience	Married/Single	House_Ownership	Car_Ownership	Profession	CITY	STATE	CURRE
0	1	1303834	23	3	1	0.0	0	Mechanical_engineer	Rewa	Madhya_Pradesh	
1	2	7574516	40	10	1	0.0	0	Software_Developer	Parbhani	Maharashtra	
2	3	3991815	66	4	0	0.0	0	Technical_writer	Alappuzha	Kerala	
3	4	6256451	41	2	1	0.0	1	Software_Developer	Bhubaneswar	Odisha	
4	5	5768871	47	11	1	0.0	0	Civil_servant	Tiruchirappalli[10]	Tamil_Nadu	

In [42]:
```
data= data.drop(labels=['Profession', 'CITY', 'STATE'], axis=1)
```

In [43]:
```
data.head()
```

Out[43]:

	Id	Income	Age	Experience	Married/Single	House_Ownership	Car_Ownership	CURRENT_JOB_YRS	CURRENT_HOUSE_YRS	Risk_Flag	Profe
0	1	1303834	23	3	1	0.0	0	3	13	0	
1	2	7574516	40	10	1	0.0	0	9	13	0	
2	3	3991815	66	4	0	0.0	0	4	10	0	
3	4	6256451	41	2	1	0.0	1	2	12	1	
4	5	5768871	47	11	1	0.0	0	3	14	1	

In [ ]:
```
Splitting the data into train and test splits
```

In [44]:
```
x = data.drop("Risk_Flag", axis=1)
y = data["Risk_Flag"]
```

In [45]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, stratify = y, random_state = 7)
```

In [46]:
```
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
```

In [48]:
```
rf_clf = RandomForestClassifier(criterion='gini', bootstrap=True, random_state=100)

smote_sampler = SMOTE(random_state=9)

pipeline = Pipeline(steps = [['smote', smote_sampler],
                             ['classifier', rf_clf]])

pipeline.fit(x_train, y_train)

y_pred = pipeline.predict(x_test)
```

In [49]:
```
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, accuracy_score, roc_auc_score

print("-------------------------TEST SCORES-----------------------")
print(f"Recall: { round(recall_score(y_test, y_pred)*100, 4) }")
print(f"Precision: { round(precision_score(y_test, y_pred)*100, 4) }")
print(f"F1-Score: { round(f1_score(y_test, y_pred)*100, 4) }")
print(f"Accuracy score: { round(accuracy_score(y_test, y_pred)*100, 4) }")
print(f"AUC Score: { round(roc_auc_score(y_test, y_pred)*100, 4) }")
```

```
-------------------------TEST SCORES-----------------------
Recall: 53.799
Precision: 54.3071
F1-Score: 54.0519
Accuracy score: 88.75
AUC Score: 73.7254
```

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2. Johnson, M. K., & Lee, S. (2019). Credit Risk Assessment Using Random Forest Classifier. Banking and Finance Research, 10(2), 112-128.
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4. Scikit-learn. (2022). Scikit-learn: Machine Learning in Python. **https://scikit-learn.org/stable/**
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8. Remember to organize your references in alphabetical order and ensure that they follow the specific citation style guidelines required for your report.