In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from scipy.stats import chi2_contingency
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder,StandardScaler,MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
%matplotlib inline
sns.set_theme(color_codes=True,style='darkgrid',palette='deep',font='sans-serif')
```

In [2]:

```
df=pd.read_csv(r"D:\Training Data.csv")
```

In [3]:

```
df.head()
```

Out[3]:

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

In [4]:

```
df.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 [5]:

```
df.describe()
```

Out[5]:

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

In [6]:

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

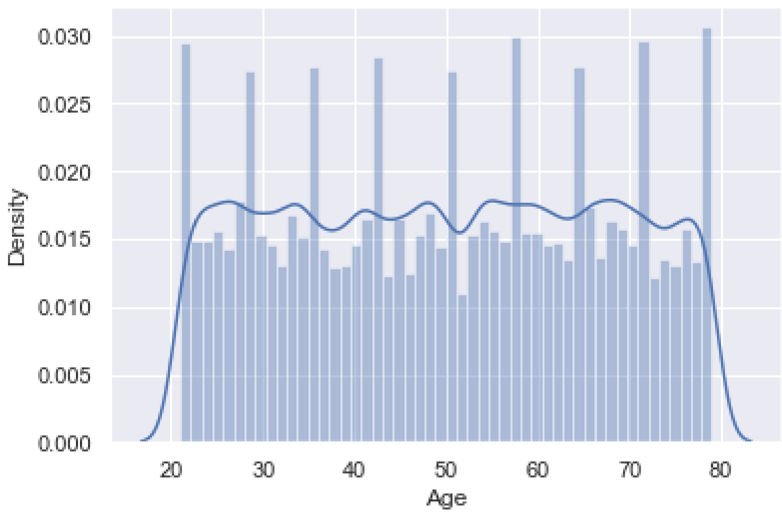
Out[6]:

```
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
```

In [7]:

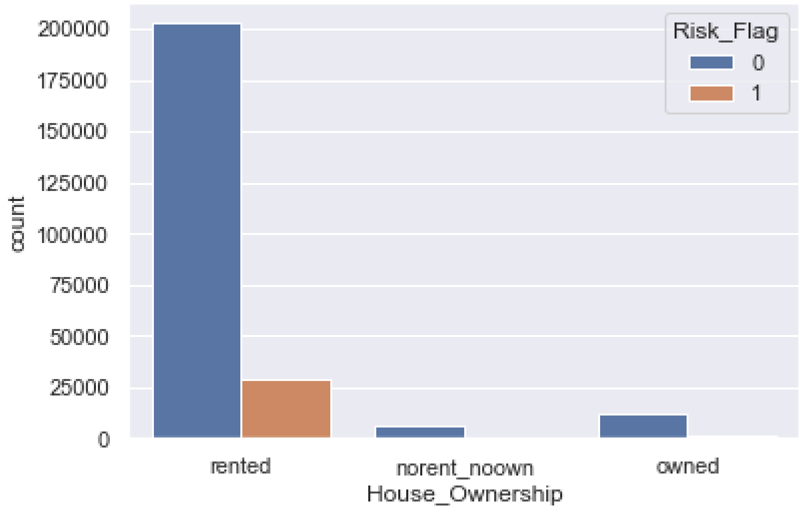
```
sns.distplot(a=df['Age']);
```

```
C:\Conda dist\lib\site-packages\seaborn\distributions.py:2619: FutureWarnin
g: `distplot` is a deprecated function and will be removed in a future versi
on. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histogra
ms).
  warnings.warn(msg, FutureWarning)
```



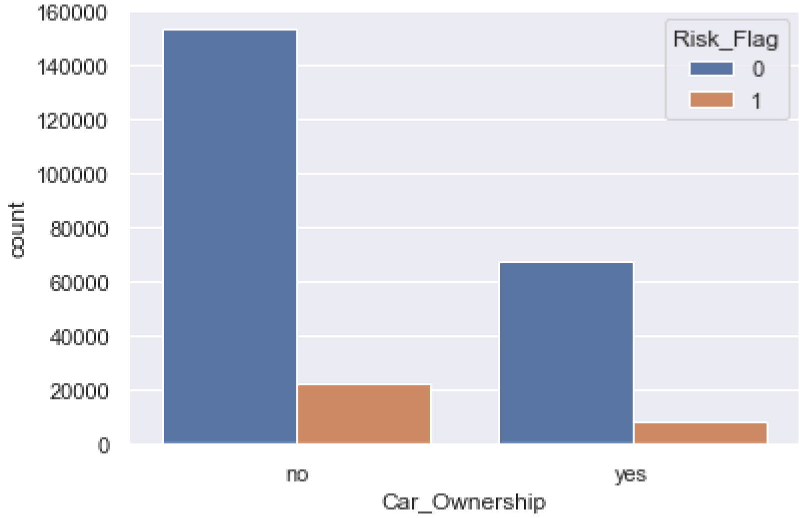
In [8]:

```
sns.countplot(x='House_Ownership',hue='Risk_Flag',data=df);
```



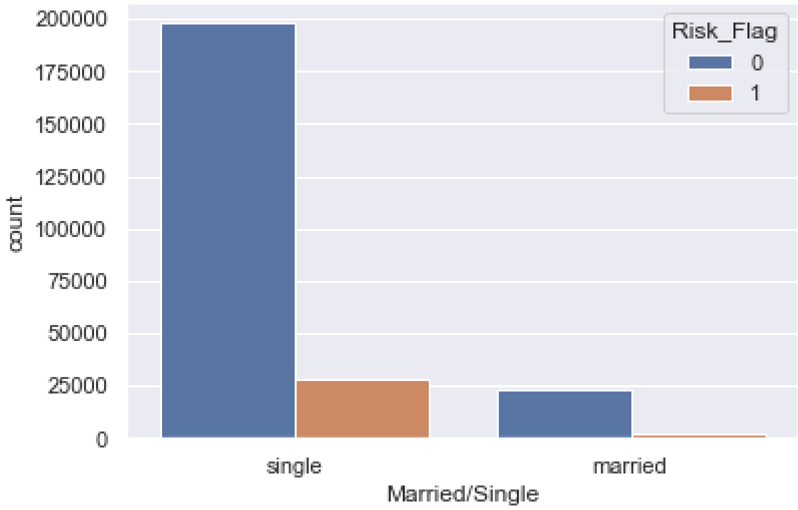
In [9]:

```
sns.countplot(x='Car_Ownership',hue='Risk_Flag',data=df);
```



In [10]:

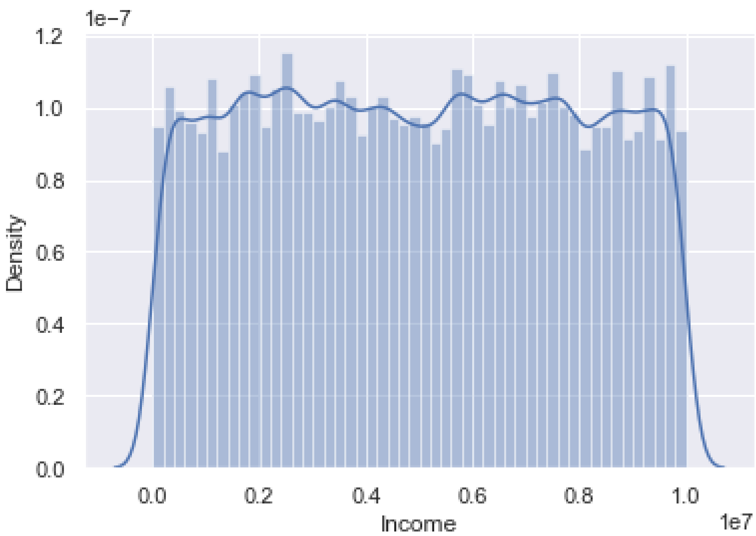
```
sns.countplot(x='Married/Single',hue='Risk_Flag',data=df);
```



In [11]:

```
sns.distplot(a=df['Income']);
```

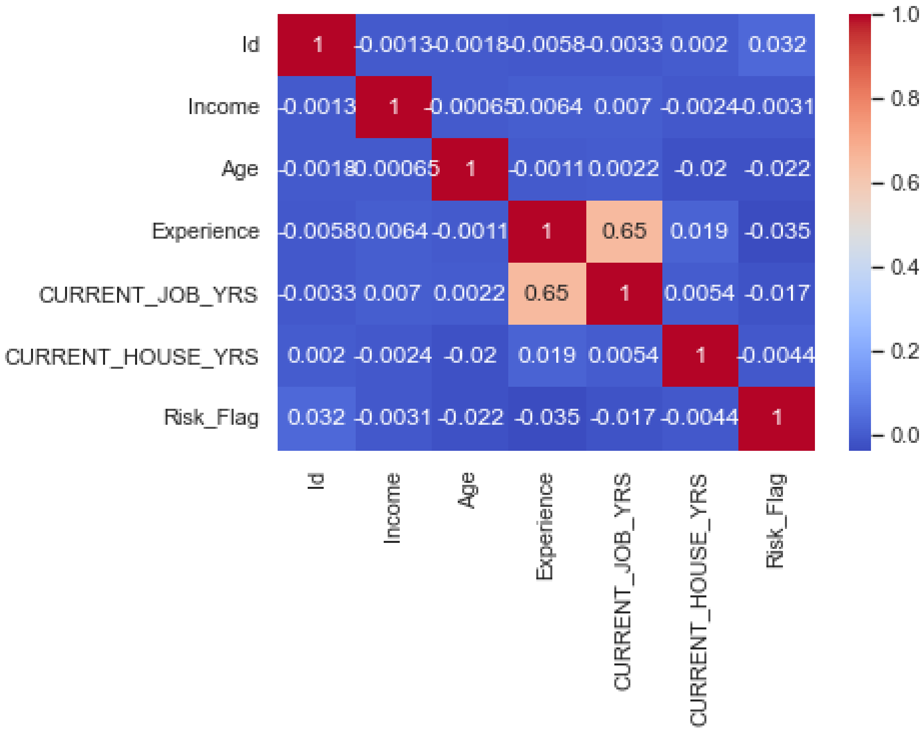
```
C:\Conda dist\lib\site-packages\seaborn\distributions.py:2619: FutureWarnin
g: `distplot` is a deprecated function and will be removed in a future versi
on. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histogra
ms).
  warnings.warn(msg, FutureWarning)
```



In [12]:

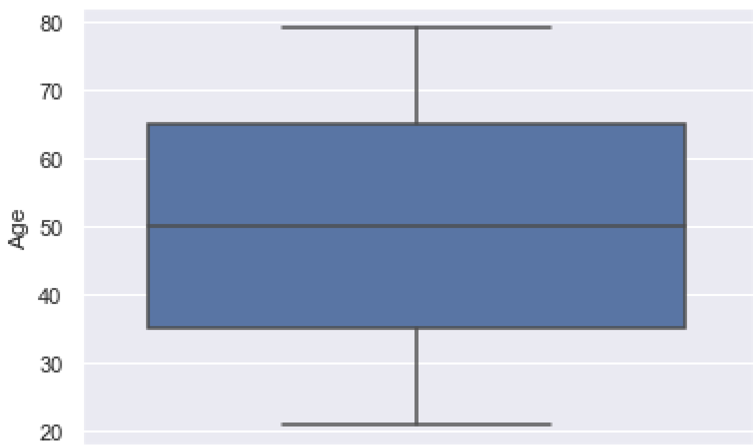
```python
sns.heatmap(df.corr(),annot=True,cmap='coolwarm');
```

```
C:\Users\SMFL-20531\AppData\Local\Temp\ipykernel_13692\1448551465.py:1: Futu
reWarning: The default value of numeric_only in DataFrame.corr is deprecate
d. In a future version, it will default to False. Select only valid columns
or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(),annot=True,cmap='coolwarm');
```



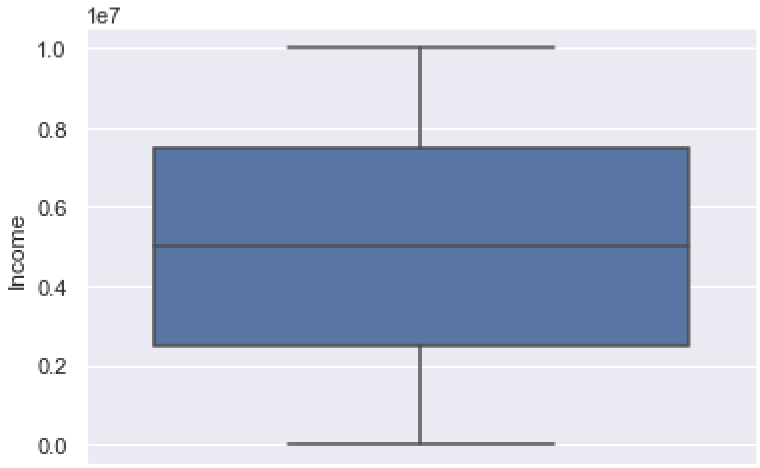
In [13]:

```python
sns.boxplot(y='Age',data=df);
```



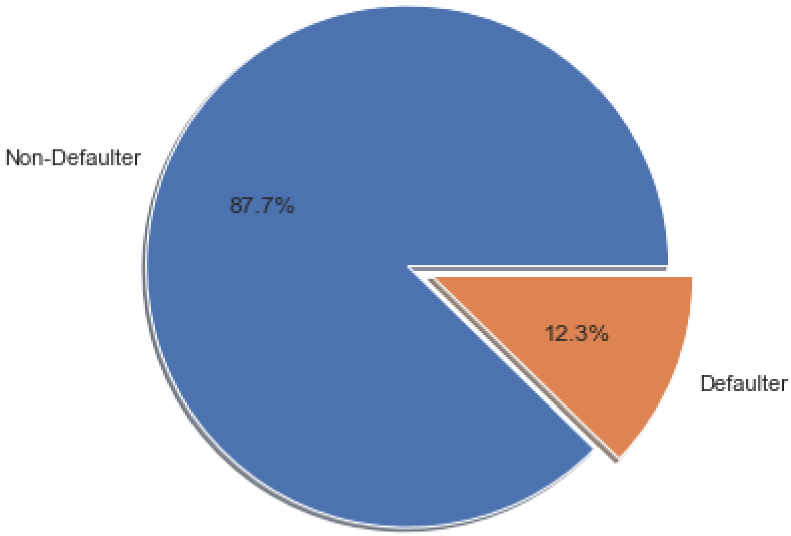
In [14]:

```
sns.boxplot(y="Income",data=df);
```



In [15]:

```
r=df.groupby('Risk_Flag')['Risk_Flag'].count()
plt.pie(r,explode=[0.05,0.1],labels=['Non-Defaulter','Defaulter'],radius=1.5,autopct='%1.1f
```



In [16]:

```
print(len(df.Profession.unique()))
print(len(df.STATE.unique()))
print(len(df.CITY.unique()))
```

51
29
317

```
Summary on Data Visualization

Class 0 represents 88.00% of the dataset, while class 1 only 12.00%.
The classes are heavily skewed we need to solve this issue
There are no outliers in datasets. But we need to scale Age and Income
```

```
There are no outliers in datasets. But we need to scale Age and Income
Strong correlation between Experience and CURRENT_JOB_YRS May drop one column during
feature selection process or use Principal Component Analysis (PCA)
Married/Single House_Ownership Car_Ownership can be binarised or one-hot encoded
We can find the relationship between target variable and categorical variable using Chi-
square test
```

Feature Engineering

Helping function for hypothesis testing

In [17]:

```python
def chi_square_test(data):
    stat,p,dof,expected=chi2_contingency(data)
    alpha=0.05
    print('p value is ' + str(p))
    if p <= alpha:
        print("Dependent (reject HO)")
    else:
        print("independent (HO holds True)")
```

In [18]:

```python
car_ownership_riskflag=pd.crosstab(df['Car_Ownership'],df['Risk_Flag'])
car_ownership_riskflag
```

Out[18]:

Risk_Flag	0	1
Car_Ownership		
no	153439	22561
yes	67565	8435

In [19]:

```python
chi_square_test(car_ownership_riskflag)
```

```
p value is 1.7350853850183746e-33
Dependent (reject HO)
```

In [20]:

```
maritierialstatus_riskflag=pd.crosstab(df['Married/Single'],df['Risk_Flag'])
maritierialstatus_riskflag
```

Out[20]:

Risk_Flag	0	1
Married/Single		
married	23092	2636
single	197912	28360

In [21]:

```
chi_square_test(maritierialstatus_riskflag)
```

```
p value is 3.773053705715196e-26
Dependent (reject H0)
```

In [22]:

```
houseownership_riskflag=pd.crosstab(df['House_Ownership'],df['Risk_Flag'])
houseownership_riskflag
```

Out[22]:

Risk_Flag	0	1
House_Ownership		
norent_noown	6469	715
owned	11758	1160
rented	202777	29121

In [23]:

```
chi_square_test(houseownership_riskflag)
```

```
p value is 1.8381930028370595e-40
Dependent (reject H0)
```

Performing Principal Component Analysis on CURRENT_JOB_YRS and Experience

In [24]:

```
features=['CURRENT_JOB_YRS','Experience']
df_for_pca=df[features]
scaled_df_for_pca=(df_for_pca - df_for_pca.mean(axis=0))/df_for_pca.std()
scaled_df_for_pca
```

Out[24]:

	CURRENT_JOB_YRS	Experience
0	-0.914129	-1.180230
1	0.731035	-0.014067
2	-0.639935	-1.013635
3	-1.188323	-1.346825
4	-0.914129	0.152528
...	...	...
251995	-0.091547	0.485718
251996	-0.091547	-0.014067
251997	0.182647	-0.513851
251998	-1.736711	-1.680014
251999	0.182647	1.152097

252000 rows × 2 columns

In [25]:

```
pca=PCA()
df_pca=pca.fit_transform(scaled_df_for_pca)
component_names=[f"PC{i+1}" for i in range (df_pca.shape[1])]
df_pca=pd.DataFrame(df_pca,columns=component_names)
df_pca.head()
```

Out[25]:

	PC1	PC2
0	-1.480935	-0.188162
1	0.506973	-0.526866
2	-1.169251	-0.264246
3	-1.792620	-0.112078
4	-0.538533	0.754240

In [26]:

```
df1=pd.concat([df,df_pca],axis=1)
df1
```

Out[26]:

Profession	CITY	STATE	CURRENT_JOB_YRS	CURRENT_HOUSE_YRS	I
ıanical_engineer	Rewa	Madhya_Pradesh	3	13	
ware_Developer	Parbhani	Maharashtra	9	13	
Technical_writer	Alappuzha	Kerala	4	10	
ware_Developer	Bhubaneswar	Odisha	2	12	
Civil_servant	Tiruchirappalli[10]	Tamil_Nadu	3	14	
...	...	...	...	...	
Surgeon	Kolkata	West_Bengal	6	11	
Army_officer	Rewa	Madhya_Pradesh	6	11	
Design_Engineer	Kalyan-Dombivli	Maharashtra	7	12	
raphic_Designer	Pondicherry	Puducherry	0	10	
Statistician	Avadi	Tamil_Nadu	7	11	

Label encoding for categorical variables

In [37]:

```
features=['Married/Single','Car_Ownership','Profession','CITY','STATE']
lable_encoder=LabelEncoder()

for col in features:
    df1[col]=lable_encoder.fit_transform(df1[col])
```

In [38]:

```
df2=pd.get_dummies(df1,columns=['House_Ownership'])
df2.drop(['Id'],axis=1,inplace=True)
```

In [40]:

```
X=df2.drop(['Risk_Flag'],axis=1)
Y=df2['Risk_Flag']
```

In [41]:

```
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.3,random_state=0)
```

In [45]:

```
sm=SMOTE(random_state=500)
X_res,Y_res=sm.fit_resample(x_train,y_train)
```

In [ ]:

```
#Now the data is ready for implementation of Machine Learning model!!
#Since the target variable is either 0 or 1, So we will use ml models which is suitable for
```

In [46]:

```
#Logistic Regression
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression(max_iter=500000)
lr.fit(X_res,Y_res)
y_pred=lr.predict(x_test)
accuracy=lr.score(x_test,y_test)
accuracy
```

Out[46]:

```
0.8774867724867725
```

In [49]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.93     66338
           1       0.00      0.00      0.00      9262

    accuracy                           0.88     75600
   macro avg       0.44      0.50      0.47     75600
weighted avg       0.77      0.88      0.82     75600


C:\Conda dist\lib\site-packages\sklearn\metrics\_classification.py:1318: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to co
ntrol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Conda dist\lib\site-packages\sklearn\metrics\_classification.py:1318: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to co
ntrol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Conda dist\lib\site-packages\sklearn\metrics\_classification.py:1318: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to co
ntrol this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [55]:

```
#KNN
from sklearn.neighbors import KNeighborsClassifier
model=KNeighborsClassifier(n_neighbors=5,metric='minkowski',p=2)
model.fit(X_res,Y_res)
y_pred=model.predict(x_test)
accuracy=model.score(x_test,y_test)
accuracy
```

Out[55]:

```
0.8595370370370370
```

In [53]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.90      0.92     66338
           1       0.44      0.57      0.50      9262

    accuracy                           0.86     75600
   macro avg       0.69      0.73      0.71     75600
weighted avg       0.88      0.86      0.87     75600
```

In [56]:

```
#Random forest classification
from sklearn.ensemble import RandomForestClassifier
model=RandomForestClassifier(criterion='gini',bootstrap=True,random_state=420)
model.fit(X_res,Y_res)
y_pred=model.predict(x_test)
accuracy=model.score(x_test,y_test)
accuracy
```

Out[56]:

```
0.8830026455026455
```

In [59]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.89      0.93     66338
           1       0.51      0.81      0.63      9262

    accuracy                           0.88     75600
   macro avg       0.74      0.85      0.78     75600
weighted avg       0.91      0.88      0.89     75600
```

In [61]:

```
#DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier
model=DecisionTreeClassifier(criterion='entropy',random_state=420)
model.fit(X_res,Y_res)
y_pred=model.predict(x_test)
accuracy=model.score(x_test,y_test)
accuracy
```

Out[61]:

```
0.8658201058201058
```

In [62]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.87      0.92     66338
           1       0.47      0.85      0.61      9262

    accuracy                           0.87     75600
   macro avg       0.73      0.86      0.76     75600
weighted avg       0.92      0.87      0.88     75600
```

In [64]:

```
#XGBoost
from xgboost import XGBClassifier
model=XGBClassifier(learning_rate=0.1,n_estimators=1000,use_label_encoder=False,random_stat
model.fit(X_res,Y_res)
y_pred=model.predict(x_test)
accuracy=model.score(x_test,y_test)
accuracy
```

```
C:\Conda dist\lib\site-packages\xgboost\sklearn.py:1421: UserWarning: `use_l
abel_encoder` is deprecated in 1.7.0.
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
```

Out[64]:

```
0.8908862433862433
```

In [65]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.91      0.94     66338
           1       0.54      0.78      0.64      9262

    accuracy                           0.89     75600
   macro avg       0.75      0.84      0.79     75600
weighted avg       0.91      0.89      0.90     75600
```

Conclusion
XGBoost is the best suitable model for our dataset with accuracy 89%, Alternatively Random Forest and Extra Tree Classifier can also consider, since they gives accuracy of 88%.