Introduction

This Notebook focuses on the classification of credit scores. In this notebook, we will explore and implement a machine learning model to categorize credit scores based on various features. By leveraging powerful algorithms, we aim to create an efficient and accurate system for predicting creditworthiness.

Methodology

For this particular notebook, we are going to first impute our class column which is Credit_Mix. Credit Mix has four unique values, which are: Good, Standard, Bad and ' _ '. We are going to handle the ' _ ' values as they don't represent anything. They basically mean nan values. So, we are going to impute these ' _ ' values. But rather than using traditional imputing methods, we are going to drop the rows which have their class values as ' _ ' and keep them in a separate dataframe. Then we are going to work on the remaining rows, preprocess them and fit them into models. Then we are going to use our models to predict the class values of our previously saved dataframe which contains '_' values as their class. After predicting them, we are going to merge these two dataframes into one. The we are going to work on the cleaned dataset, train-test them in different models and evaluate them.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Initial Observations

In [2]:
```
data = pd.read_csv("https://raw.githubusercontent.com/rashakil-ds/Public-Datasets/m
```

In [3]:
```
data.head(5)
```

Out[3]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	M
0	0x160a	CUS_0xd40	September	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
1	0x160b	CUS_0xd40	October	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	
2	0x160c	CUS_0xd40	November	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	
3	0x160d	CUS_0xd40	December	Aaron Maashoh	24_	821-00-0265	Scientist	19114.12	
4	0x1616	CUS_0x21b1	September	Rick Rothackerj	28	004-07-5839	_______	34847.84	

5 rows × 27 columns

In [4]:
```
df = data.copy()
```

In [5]:
```
df["Credit_Mix"].unique()
```

Out[5]:
```
array(['Good', '_', 'Standard', 'Bad'], dtype=object)
```

In [6]:
```
df.shape
```

Out[6]:
```
(50000, 27)
```

From our initial obseravation, we can say:

```
- We have 27 columns in our dataset
- Credit_Mix is our class column
- We need to modify some columns to convert them into numeric
values. e.g: Credit History Age
```

Data Preparation & Preprocessing

Remove Unnecessary Features

In [7]:
```
# We remove some columns from our dataset which aren't having any significant impac
```

In [8]:
```
df.drop(["ID","Customer_ID","Month","Name","SSN","Age","Occupation"],axis = 1,inpla
```

In [9]:
```
df.isna().sum()
```

Out[9]:
```
Annual_Income                  0
Monthly_Inhand_Salary       7498
Num_Bank_Accounts              0
Num_Credit_Card                0
Interest_Rate                  0
Num_of_Loan                    0
Type_of_Loan                5704
Delay_from_due_date            0
Num_of_Delayed_Payment      3498
Changed_Credit_Limit           0
Num_Credit_Inquiries        1035
Credit_Mix                     0
Outstanding_Debt               0
Credit_Utilization_Ratio       0
Credit_History_Age          4470
Payment_of_Min_Amount          0
Total_EMI_per_month            0
Amount_invested_monthly     2271
Payment_Behaviour              0
Monthly_Balance              562
dtype: int64
```

In [10]:
```
df.dtypes
```

Out[10]:
```
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Type_of_Loan                 object
Delay_from_due_date           int64
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age           object
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly      object
Payment_Behaviour            object
Monthly_Balance              object
dtype: object
```

In [11]:
```
def impute_dataset(df):
    for col_name in df.columns:
        if df[col_name].isna().sum() > 0 and df[col_name].nunique() > 5 and df[col_
            df[col_name].fillna(df[col_name].mean(),inplace = True)
        elif df[col_name].isna().sum() > 0 and df[col_name].nunique() < 5 and df[co
            df[col_name].fillna(df[col_name].mode().iloc[0],inplace = True)
```

Handle Type of Loan

We need to modify our Type_of_Loan column as it has multiple loan types comma separated in a single string. To handle this, We are going to split our Type of loan column where there is an comma and we are going to remove 'and' from each row. We also going to handle any NAN value if there's any present in our column. Lastly we are going to use one-hot encoding.

In [12]:
```
# df["Type_of_Loan"].unique()
```

In [13]:
```
# df['Type_of_Loan'] = df['Type_of_Loan'].apply(lambda x: list(set(item.replace(" a
df['Type_of_Loan'] = df['Type_of_Loan'].apply(lambda x: ', '.join(set(item.replace(
```

In [14]:
```
df['Type_of_Loan']
```

Out[14]:
```
0        Home Equity Loan, Auto Loan, Personal Loan, Cr...
1        Home Equity Loan, Auto Loan, Personal Loan, Cr...
2        Home Equity Loan, Auto Loan, Personal Loan, Cr...
3        Home Equity Loan, Auto Loan, Personal Loan, Cr...
4                                      Credit-Builder Loan
                               ...
49995    Auto Loan, Mortgage Loan, Personal Loan, Stude...
49996                              Auto Loan, Student Loan
49997                              Auto Loan, Student Loan
49998                              Auto Loan, Student Loan
49999                              Auto Loan, Student Loan
Name: Type_of_Loan, Length: 50000, dtype: object
```

In [15]:
```
unique_values_set = set()

for value in df["Type_of_Loan"]:
    value_list = [item.replace(" and ","").strip() for item in str(value).split(","
    unique_values_set.update(value_list)

unique_values = list(unique_values_set)
```

In [16]:
```
print(unique_values_set)
```

```
{'Debt Consolidation Loan', 'Mortgage Loan', 'Student Loan', 'nan', 'Home Equity Loa
n', 'Personal Loan', 'Payday Loan', 'Not Specified', 'Auto Loan', 'Credit-Builder Lo
an'}
```

In [17]:
```
df['Type_of_Loan'] = df['Type_of_Loan'].str.replace('and','')
```

In [18]:
```
df['Type_of_Loan'] = df['Type_of_Loan'].str.strip('')
```

In [19]:
```
df['Type_of_Loan'][0]
```

Out[19]:
```
'Home Equity Loan, Auto Loan, Personal Loan, Credit-Builder Loan'
```

In [20]:
```python
dummies = df['Type_of_Loan'].str.get_dummies(", ")
```

In [21]:
```python
df = pd.concat([df, dummies], axis = 1)
```

In [22]:
```python
df.shape
```

Out[22]:
```
(50000, 30)
```

In [23]:
```python
df.drop("Type_of_Loan",axis=1,inplace = True)
```

In [24]:
```python
df.shape
```

Out[24]:
```
(50000, 29)
```

In [25]:
```python
df.nunique()
```

Out[25]:
```
Annual_Income               16121
Monthly_Inhand_Salary       12793
Num_Bank_Accounts             540
Num_Credit_Card               819
Interest_Rate                 945
Num_of_Loan                   263
Delay_from_due_date            73
Num_of_Delayed_Payment        443
Changed_Credit_Limit         3927
Num_Credit_Inquiries          750
Credit_Mix                      4
Outstanding_Debt            12685
Credit_Utilization_Ratio    50000
Credit_History_Age            399
Payment_of_Min_Amount           3
Total_EMI_per_month         13144
Amount_invested_monthly     45450
Payment_Behaviour               7
Monthly_Balance             49433
Auto Loan                       2
Credit-Builder Loan             2
Debt Consolidation Loan         2
Home Equity Loan                2
Mortgage Loan                   2
Not Specified                   2
Payday Loan                     2
Personal Loan                   2
Student Loan                    2
nan                             2
dtype: int64
```

We are dropping the nan column as we don't need it.If The other columns representing different loan types is zero '0', then we will automatically know if the user has any kind of loan or not.

In [26]:
```python
df.drop("nan",axis=1,inplace=True)
```

In [27]:
```
df.describe()
```

Out[27]:

	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Delay_
count	42502.000000	50000.000000	50000.000000	50000.000000	
mean	4182.004291	16.838260	22.921480	68.772640	
std	3174.109304	116.396848	129.314804	451.602363	
min	303.645417	-1.000000	0.000000	1.000000	
25%	1625.188333	3.000000	4.000000	8.000000	
50%	3086.305000	6.000000	5.000000	13.000000	
75%	5934.189094	7.000000	7.000000	20.000000	
max	15204.633333	1798.000000	1499.000000	5799.000000	

In [28]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 28 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Annual_Income             50000 non-null  object 
 1   Monthly_Inhand_Salary     42502 non-null  float64
 2   Num_Bank_Accounts         50000 non-null  int64  
 3   Num_Credit_Card           50000 non-null  int64  
 4   Interest_Rate             50000 non-null  int64  
 5   Num_of_Loan               50000 non-null  object 
 6   Delay_from_due_date       50000 non-null  int64  
 7   Num_of_Delayed_Payment    46502 non-null  object 
 8   Changed_Credit_Limit      50000 non-null  object 
 9   Num_Credit_Inquiries      48965 non-null  float64
 10  Credit_Mix                50000 non-null  object 
 11  Outstanding_Debt          50000 non-null  object 
 12  Credit_Utilization_Ratio  50000 non-null  float64
 13  Credit_History_Age        45530 non-null  object 
 14  Payment_of_Min_Amount     50000 non-null  object 
 15  Total_EMI_per_month       50000 non-null  float64
 16  Amount_invested_monthly   47729 non-null  object 
 17  Payment_Behaviour         50000 non-null  object 
 18  Monthly_Balance           49438 non-null  object 
 19  Auto Loan                 50000 non-null  int64  
 20  Credit-Builder Loan       50000 non-null  int64  
 21  Debt Consolidation Loan   50000 non-null  int64  
 22  Home Equity Loan          50000 non-null  int64  
 23  Mortgage Loan             50000 non-null  int64  
 24  Not Specified             50000 non-null  int64  
 25  Payday Loan               50000 non-null  int64  
 26  Personal Loan             50000 non-null  int64  
 27  Student Loan              50000 non-null  int64  
dtypes: float64(4), int64(13), object(11)
memory usage: 10.7+ MB
```

In [29]:
```
df["Credit_Mix"].isna().sum()
```

Out[29]:
```
0
```

In [30]:
```
df["Payment_Behaviour"].nunique()
```

Out[30]:
```
7
```

In [31]:
```
df.head(5)
```

Out[31]:

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_
0	19114.12	1824.843333	3	4	
1	19114.12	1824.843333	3	4	
2	19114.12	1824.843333	3	4	
3	19114.12	NaN	3	4	
4	34847.84	3037.986667	2	4	

5 rows × 28 columns

Handle Credit History Age

Our credit history age has values like 'X Years and Y Months'. We are going to transform this column into numerical values by converting the month value of each row to year and add it up to the total years. For example, 22 Years and 9 months-> 22 Years + 0.75 Years -> 22.75 Years

In [32]:
```
for item in df["Credit_History_Age"].head(5):
    print(item)
```

```
22 Years and 9 Months
22 Years and 10 Months
nan
23 Years and 0 Months
27 Years and 3 Months
```

In [33]:
```
df["Credit_History_Age"] = df["Credit_History_Age"].apply(lambda x: float(x.split()

# df['Type_of_Loan'] = df['Type_of_Loan'].apply(lambda x: ', '.join(set(item.replac
```

In [34]:
```
df.head(5)
```

Out[34]:

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_
0	19114.12	1824.843333	3	4	
1	19114.12	1824.843333	3	4	
2	19114.12	1824.843333	3	4	
3	19114.12	NaN	3	4	
4	34847.84	3037.986667	2	4	

5 rows × 28 columns

In [35]:
```
df["Credit_History_Age"]
```

Out[35]:
```
0        22.750000
1        22.833333
2              NaN
3        23.000000
4        27.250000
           ...
49995          NaN
49996    31.916667
49997    32.000000
49998    32.083333
49999    32.166667
Name: Credit_History_Age, Length: 50000, dtype: float64
```

In [36]:
```
df.dtypes
```

Out[36]:
```
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Delay_from_due_date           int64
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age          float64
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly      object
Payment_Behaviour            object
Monthly_Balance              object
Auto Loan                     int64
Credit-Builder Loan           int64
Debt Consolidation Loan       int64
Home Equity Loan              int64
Mortgage Loan                 int64
Not Specified                 int64
Payday Loan                   int64
Personal Loan                 int64
Student Loan                  int64
dtype: object
```

Encoding Data

In [37]:
```
# Payment Behaviour, Payment of Min Amount
from sklearn.preprocessing import LabelEncoder
```

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

In [39]:
```
def encode_dataset(df):
    for col_name in df.columns:
        if df[col_name].dtypes == "object":
            df[col_name] = encoder.fit_transform(df[col_name])
```

In [40]:
```
df["Payment_Behaviour"] = encoder.fit_transform(df["Payment_Behaviour"])
```

In [41]:
```
df["Payment_of_Min_Amount"] = encoder.fit_transform(df["Payment_of_Min_Amount"])
```

In [42]:
```
df.dtypes
```

Out[42]:
```
Annual_Income                object
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                  object
Delay_from_due_date           int64
Num_of_Delayed_Payment       object
Changed_Credit_Limit         object
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt             object
Credit_Utilization_Ratio    float64
Credit_History_Age          float64
Payment_of_Min_Amount         int32
Total_EMI_per_month         float64
Amount_invested_monthly      object
Payment_Behaviour             int32
Monthly_Balance              object
Auto Loan                     int64
Credit-Builder Loan           int64
Debt Consolidation Loan       int64
Home Equity Loan              int64
Mortgage Loan                 int64
Not Specified                 int64
Payday Loan                   int64
Personal Loan                 int64
Student Loan                  int64
dtype: object
```

In [43]:
```
df.nunique()
```

Out[43]:
```
Annual_Income               16121
Monthly_Inhand_Salary       12793
Num_Bank_Accounts             540
Num_Credit_Card               819
Interest_Rate                 945
Num_of_Loan                   263
Delay_from_due_date            73
Num_of_Delayed_Payment        443
Changed_Credit_Limit         3927
Num_Credit_Inquiries          750
Credit_Mix                      4
Outstanding_Debt            12685
Credit_Utilization_Ratio    50000
Credit_History_Age            399
Payment_of_Min_Amount           3
Total_EMI_per_month         13144
Amount_invested_monthly     45450
Payment_Behaviour               7
Monthly_Balance             49433
Auto Loan                       2
Credit-Builder Loan             2
Debt Consolidation Loan         2
Home Equity Loan                2
Mortgage Loan                   2
Not Specified                   2
Payday Loan                     2
Personal Loan                   2
Student Loan                    2
dtype: int64
```

In [44]:
```
df["Num_of_Delayed_Payment"]
```

Out[44]:
```
0          7
1          9
2          4
3          5
4          1
        ...
49995     25
49996    NaN
49997      5
49998     6_
49999      5
Name: Num_of_Delayed_Payment, Length: 50000, dtype: object
```

In [45]:
```
df.dtypes
```

```
Out[45]: Annual_Income                 object
         Monthly_Inhand_Salary        float64
         Num_Bank_Accounts              int64
         Num_Credit_Card                int64
         Interest_Rate                  int64
         Num_of_Loan                   object
         Delay_from_due_date            int64
         Num_of_Delayed_Payment        object
         Changed_Credit_Limit          object
         Num_Credit_Inquiries         float64
         Credit_Mix                    object
         Outstanding_Debt              object
         Credit_Utilization_Ratio     float64
         Credit_History_Age           float64
         Payment_of_Min_Amount          int32
         Total_EMI_per_month          float64
         Amount_invested_monthly       object
         Payment_Behaviour              int32
         Monthly_Balance               object
         Auto Loan                      int64
         Credit-Builder Loan            int64
         Debt Consolidation Loan        int64
         Home Equity Loan               int64
         Mortgage Loan                  int64
         Not Specified                  int64
         Payday Loan                    int64
         Personal Loan                  int64
         Student Loan                   int64
         dtype: object
```

Data Cleaning & Type Conversion

In this subsection, we are going to iterate through each of the column and clean the values where it's need. e.g: Underscores '_'. We are also going to convert data types where it's needed

```
In [46]: for col_name in df.columns:
             if df[col_name].dtypes == "object" and col_name != "Credit_Mix":
                 df[col_name] = df[col_name].str.replace("_","")
                 df[col_name] = pd.to_numeric(df[col_name],errors='coerce')
```

```
In [47]: df.dtypes
```

Out[47]:
```
Annual_Income                float64
Monthly_Inhand_Salary        float64
Num_Bank_Accounts              int64
Num_Credit_Card                int64
Interest_Rate                  int64
Num_of_Loan                    int64
Delay_from_due_date            int64
Num_of_Delayed_Payment       float64
Changed_Credit_Limit         float64
Num_Credit_Inquiries         float64
Credit_Mix                    object
Outstanding_Debt             float64
Credit_Utilization_Ratio     float64
Credit_History_Age           float64
Payment_of_Min_Amount          int32
Total_EMI_per_month          float64
Amount_invested_monthly      float64
Payment_Behaviour              int32
Monthly_Balance              float64
Auto Loan                      int64
Credit-Builder Loan            int64
Debt Consolidation Loan        int64
Home Equity Loan               int64
Mortgage Loan                  int64
Not Specified                  int64
Payday Loan                    int64
Personal Loan                  int64
Student Loan                   int64
dtype: object
```

In [48]:
```
df.isna().sum()
```

Out[48]:
```
Annual_Income                0
Monthly_Inhand_Salary     7498
Num_Bank_Accounts            0
Num_Credit_Card              0
Interest_Rate                0
Num_of_Loan                  0
Delay_from_due_date          0
Num_of_Delayed_Payment    3498
Changed_Credit_Limit      1059
Num_Credit_Inquiries      1035
Credit_Mix                   0
Outstanding_Debt             0
Credit_Utilization_Ratio     0
Credit_History_Age        4470
Payment_of_Min_Amount        0
Total_EMI_per_month          0
Amount_invested_monthly   2271
Payment_Behaviour            0
Monthly_Balance            562
Auto Loan                    0
Credit-Builder Loan          0
Debt Consolidation Loan      0
Home Equity Loan             0
Mortgage Loan                0
Not Specified                0
Payday Loan                  0
Personal Loan                0
Student Loan                 0
dtype: int64
```

In [49]:
```
df.nunique()
```

```
Out[49]: Annual_Income                12989
         Monthly_Inhand_Salary        12793
         Num_Bank_Accounts              540
         Num_Credit_Card                819
         Interest_Rate                  945
         Num_of_Loan                    252
         Delay_from_due_date             73
         Num_of_Delayed_Payment         411
         Changed_Credit_Limit          3920
         Num_Credit_Inquiries           750
         Credit_Mix                       4
         Outstanding_Debt             12203
         Credit_Utilization_Ratio     50000
         Credit_History_Age             399
         Payment_of_Min_Amount            3
         Total_EMI_per_month          13144
         Amount_invested_monthly      45450
         Payment_Behaviour                7
         Monthly_Balance              49433
         Auto Loan                        2
         Credit-Builder Loan              2
         Debt Consolidation Loan          2
         Home Equity Loan                 2
         Mortgage Loan                    2
         Not Specified                    2
         Payday Loan                      2
         Personal Loan                    2
         Student Loan                     2
         dtype: int64
```

Handle Null Values

```
In [50]: for col_name in df.columns:
             if df[col_name].isna().sum() > 0 and df[col_name].nunique()>7:
                 df[col_name] = df[col_name].fillna(df[col_name].mean())
             elif df[col_name].isna().sum() > 0 and df[col_name].nunique()<=7:
                 df[col_name] = df[col_name].fillna(df[col_name].mode())
```

```
In [51]: df.isna().sum()
```

Out[51]:
```
Annual_Income              0
Monthly_Inhand_Salary      0
Num_Bank_Accounts          0
Num_Credit_Card            0
Interest_Rate              0
Num_of_Loan                0
Delay_from_due_date        0
Num_of_Delayed_Payment     0
Changed_Credit_Limit       0
Num_Credit_Inquiries       0
Credit_Mix                 0
Outstanding_Debt           0
Credit_Utilization_Ratio   0
Credit_History_Age         0
Payment_of_Min_Amount      0
Total_EMI_per_month        0
Amount_invested_monthly    0
Payment_Behaviour          0
Monthly_Balance            0
Auto Loan                  0
Credit-Builder Loan        0
Debt Consolidation Loan    0
Home Equity Loan           0
Mortgage Loan              0
Not Specified              0
Payday Loan                0
Personal Loan              0
Student Loan               0
dtype: int64
```

Handling Credit Mix

In this section, we separate the rows containing credit mix value "_" and keep then in a separate variable

In [52]:
```
df["Credit_Mix"]
```

Out[52]:
```
0         Good
1         Good
2         Good
3         Good
4         Good
          ...
49995        _
49996     Good
49997     Good
49998     Good
49999        _
Name: Credit_Mix, Length: 50000, dtype: object
```

In [53]:
```
df_test = df[df["Credit_Mix"] == "_"]
```

In [54]:
```
df.drop(df[df["Credit_Mix"] == "_"].index,inplace=True)
```

In [55]:
```
df.dtypes
```

Out[55]:
```
Annual_Income                 float64
Monthly_Inhand_Salary         float64
Num_Bank_Accounts               int64
Num_Credit_Card                 int64
Interest_Rate                   int64
Num_of_Loan                     int64
Delay_from_due_date             int64
Num_of_Delayed_Payment        float64
Changed_Credit_Limit          float64
Num_Credit_Inquiries          float64
Credit_Mix                     object
Outstanding_Debt              float64
Credit_Utilization_Ratio      float64
Credit_History_Age            float64
Payment_of_Min_Amount           int32
Total_EMI_per_month           float64
Amount_invested_monthly       float64
Payment_Behaviour               int32
Monthly_Balance               float64
Auto Loan                       int64
Credit-Builder Loan             int64
Debt Consolidation Loan         int64
Home Equity Loan                int64
Mortgage Loan                   int64
Not Specified                   int64
Payday Loan                     int64
Personal Loan                   int64
Student Loan                    int64
dtype: object
```

In [56]:
```
df["Credit_Mix"].unique()
```

Out[56]:
```
array(['Good', 'Standard', 'Bad'], dtype=object)
```

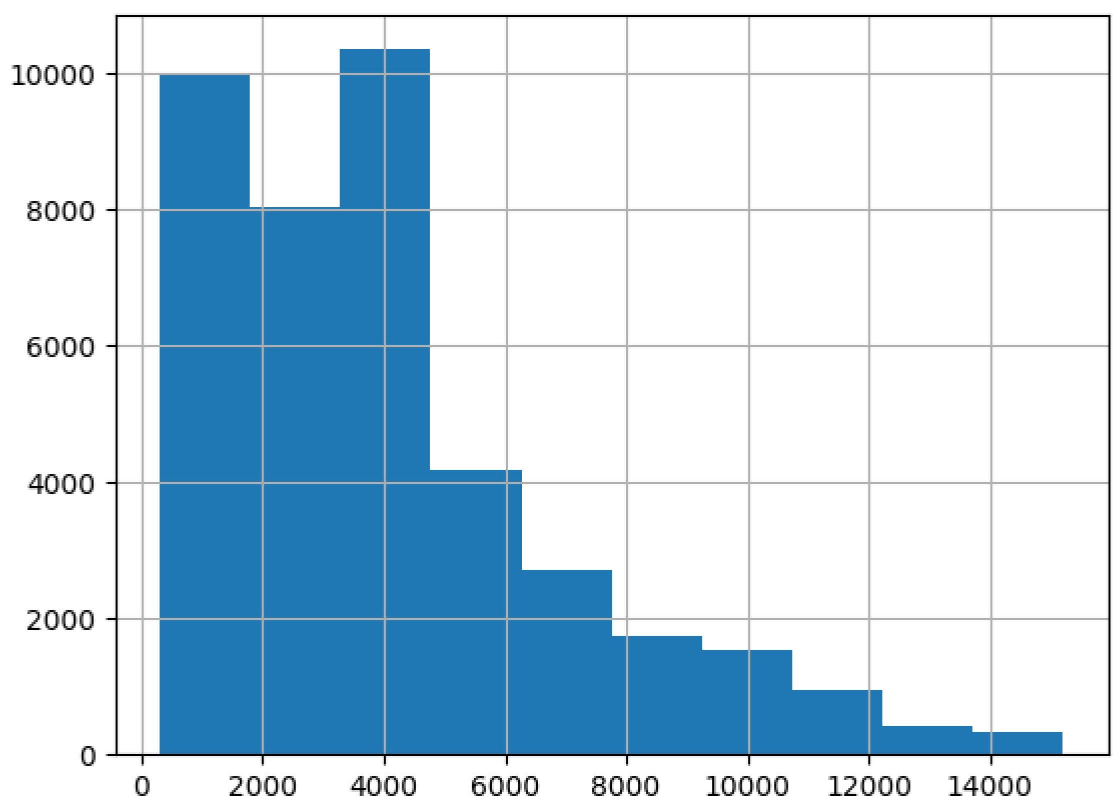
In [57]:
```
df["Credit_Mix"]= encoder.fit_transform(df["Credit_Mix"])
```

Exploratory Data Analysis

In [58]:
```
# Histogram
df.hist(bins=50, figsize = [20,15])
plt.show()
```

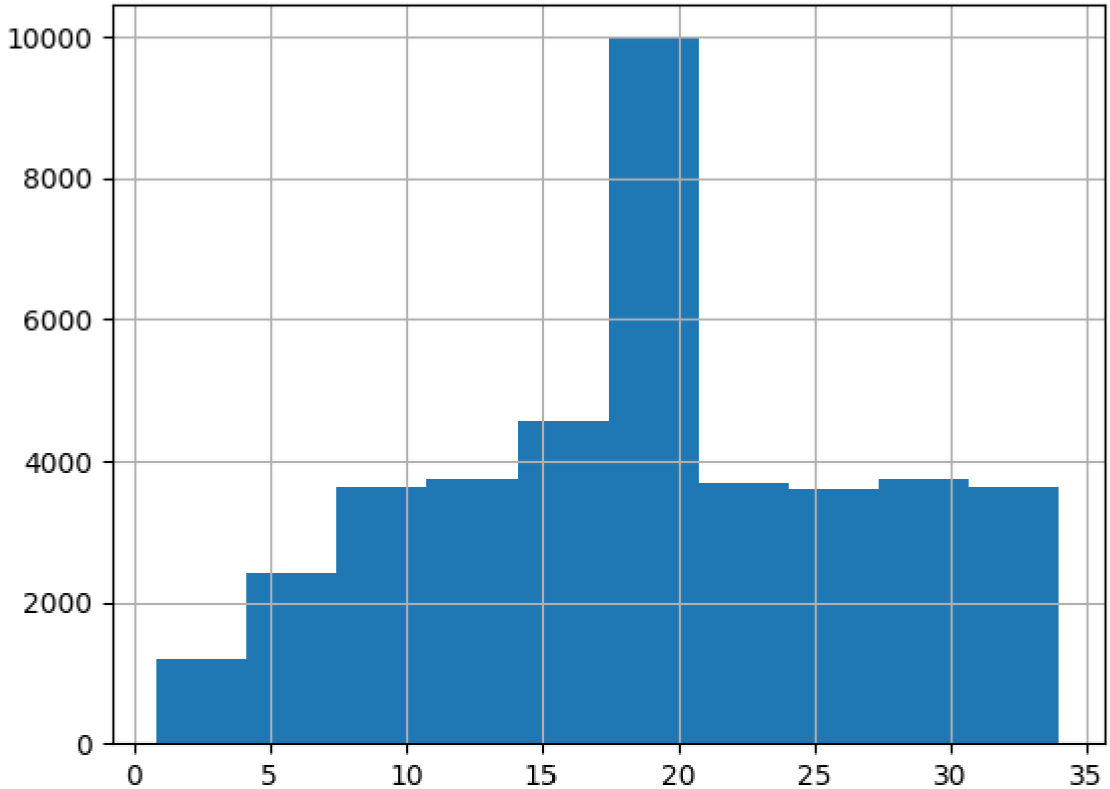

```
In [59]: df["Monthly_Inhand_Salary"].hist()
```

Out[59]: <Axes: >



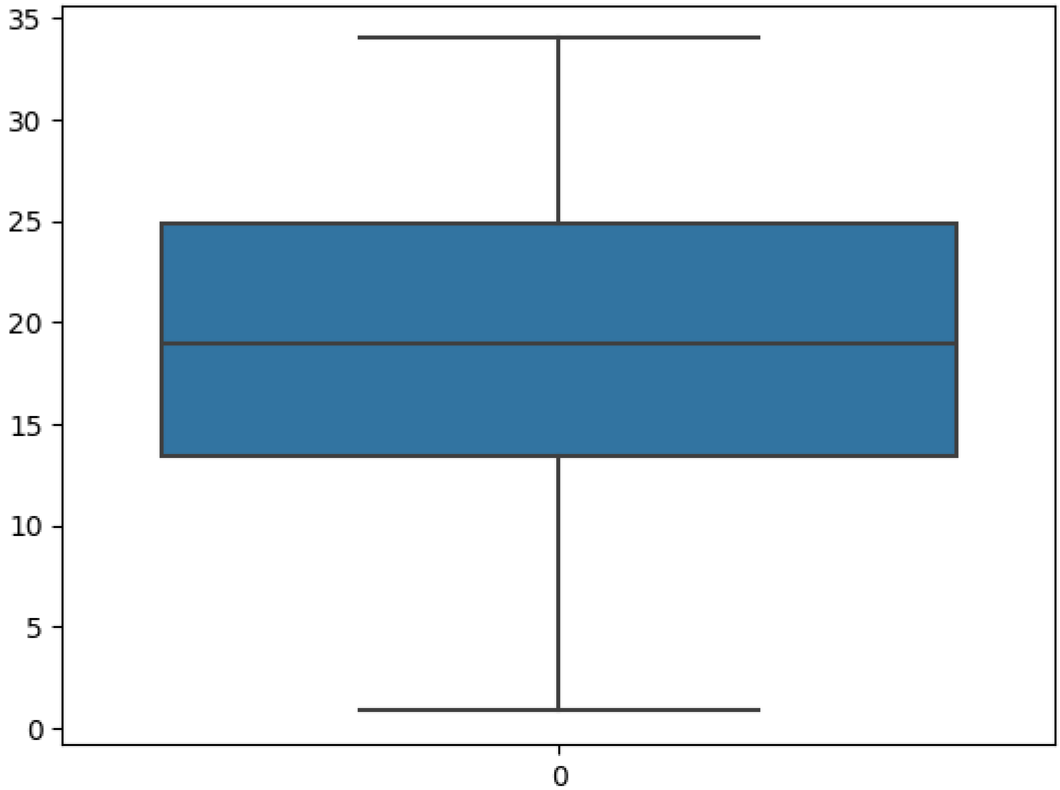
In [60]:
```
df["Credit_History_Age"].hist()
```

Out[60]: <Axes: >



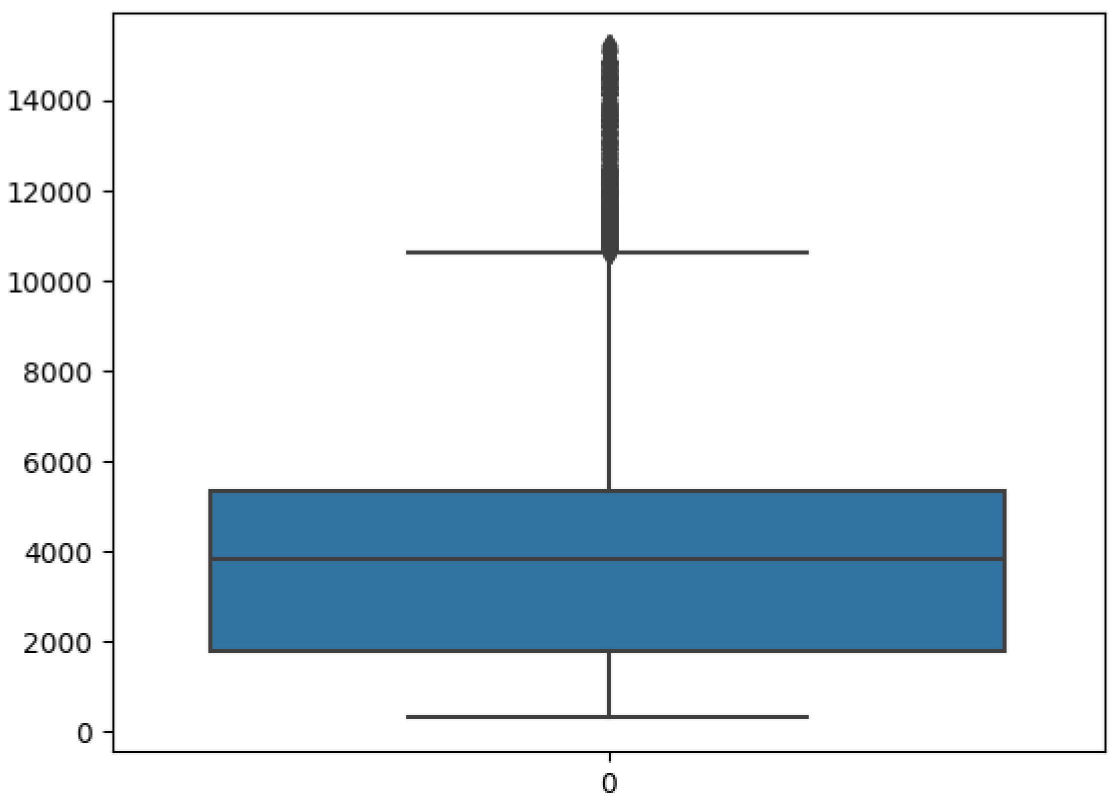
In [61]:
```
sns.boxplot(df["Credit_History_Age"])
```

Out[61]: <Axes: >



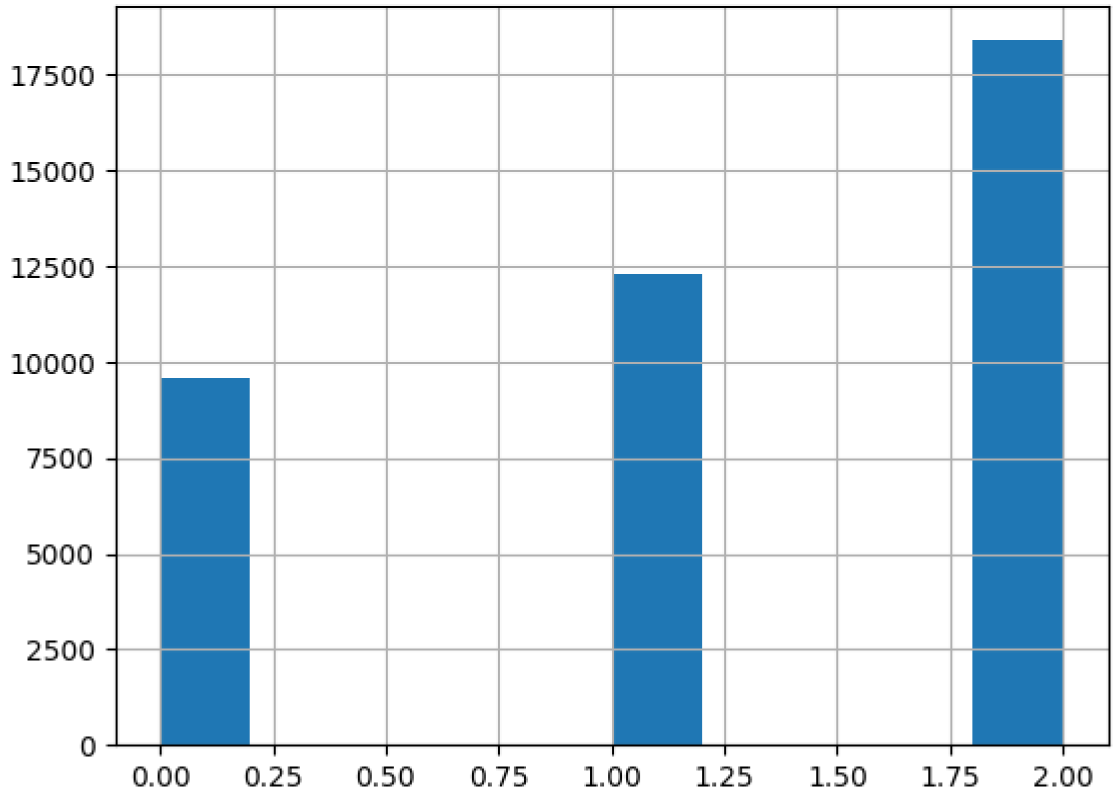
In [62]:
```
sns.boxplot(df["Monthly_Inhand_Salary"])
```

Out[62]: <Axes: >



In [63]:
```
df[df["Credit_Mix"]!= "_"]["Credit_Mix"].hist()
```

Out[63]: <Axes: >



There is visible class imbalance in our dataset

Data Scaling

In [64]:
```
from sklearn.preprocessing import StandardScaler
```

In [65]:
```
scaler = StandardScaler()
```

In [66]:
```
for col_name in df.columns:
    if df[col_name].dtypes == "float64":
        df[col_name] = scaler.fit_transform(df[[col_name]])
```

Model Training & Evaluation(1st Phase)

In [67]:
```
from sklearn.model_selection import train_test_split

# Logistic Regression
from sklearn.linear_model import LogisticRegression

# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

# Support Vector Machine (SVM)
from sklearn.svm import SVC
```

```
# Gradient Boosting Classifier (XGBoost)
import xgboost as xgb
from xgboost import XGBClassifier
```

In [68]:
```
X_train, X_test, y_train, y_test = train_test_split(df.drop("Credit_Mix",axis=1), d
```

In [69]:
```
# Initialize models
lr = LogisticRegression()
rf = RandomForestClassifier()
svm = SVC()
xg = XGBClassifier()
```

Logistic Regression

In [138…
```
lr.fit(X_train,y_train)
```

Out[138…
```
▾ LogisticRegression
LogisticRegression()
```

In [71]:
```
predicted = lr.predict(X_test)
```

In [72]:
```
import sklearn.metrics as mt
```

In [73]:
```
print(mt.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

           0       0.82      0.81      0.82      1937
           1       0.66      0.71      0.69      2434
           2       0.71      0.67      0.69      3668

    accuracy                           0.72      8039
   macro avg       0.73      0.73      0.73      8039
weighted avg       0.72      0.72      0.72      8039
```

In [74]:
```
predicted_train = lr.predict(X_train)
```

In [75]:
```
print(mt.classification_report(y_train, predicted_train))
```

```
              precision    recall  f1-score   support

           0       0.81      0.82      0.81      7619
           1       0.68      0.72      0.70      9826
           2       0.71      0.68      0.70     14711

    accuracy                           0.73     32156
   macro avg       0.73      0.74      0.74     32156
weighted avg       0.73      0.73      0.73     32156
```

Random Forest Classifier

In [77]:
```
rf.fit(X_train,y_train)
```

Out[77]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [78]:
```
predicted = rf.predict(X_test)
```

In [79]:
```
print(mt.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      1937
           1       0.97      0.98      0.97      2434
           2       0.97      0.96      0.97      3668

    accuracy                           0.97      8039
   macro avg       0.97      0.97      0.97      8039
weighted avg       0.97      0.97      0.97      8039
```

SVM

In [81]:
```
svm.fit(X_train,y_train)
```

Out[81]:
```
▾ SVC
SVC()
```

In [82]:
```
predicted = svm.predict(X_test)
```

In [83]:
```
print(mt.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

           0       0.83      0.69      0.76      1937
           1       0.82      0.79      0.80      2434
           2       0.73      0.81      0.77      3668

    accuracy                           0.78      8039
   macro avg       0.79      0.76      0.78      8039
weighted avg       0.78      0.78      0.78      8039
```

XGboost Classifier

In [85]:
```
xg.fit(X_train,y_train)
```

Out[85]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric=None, feature_types=
None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

In [86]:
```
predicted = xg.predict(X_test)
```

In [87]:
```
print(mt.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1937
           1       0.97      0.97      0.97      2434
           2       0.97      0.97      0.97      3668

    accuracy                           0.97      8039
   macro avg       0.97      0.97      0.97      8039
weighted avg       0.97      0.97      0.97      8039
```

In [139…
```
## Random forest and XG boost performed the best. For now, we use random forest for
```

Data Finalization

In [89]:
```
for col_name in df_test.columns:
    if df_test[col_name].dtypes == "float64":
        df_test[col_name] = scaler.fit_transform(df_test[[col_name]])
```

In [90]:
```
predicted_credit_mix = rf.predict(df_test.drop("Credit_Mix",axis=1))
```

In [91]:
```
predicted_credit_mix
```

Out[91]:
```
array([1, 1, 1, ..., 1, 0, 1])
```

In [92]:
```
df_test.drop("Credit_Mix",axis=1,inplace=True)
```

In [93]:
```
df_test['Credit_Mix'] = predicted_credit_mix
```

In [94]:
```
df_test.tail(5)
```

Out[94]:

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Int
49983	-0.088032	0.000506	0	4	
49987	-0.108243	0.000506	1	1	
49991	-0.092437	-0.365054	1	4	
49995	-0.105682	-0.758278	10	8	
49999	-0.090556	-0.276643	4	6	

5 rows × 28 columns

In [95]:
```
df2 = pd.concat([df, df_test])
```

In [96]:
```
df2.head(5)
```

Out[96]:

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_
0	-0.109508	-0.808431	3	4	
1	-0.109508	-0.808431	3	4	
2	-0.109508	-0.808431	3	4	
3	-0.109508	-0.000126	3	4	
4	-0.097980	-0.392426	2	4	

5 rows × 28 columns

In [97]:
```
df2["Credit_Mix"].nunique()
```

Out[97]: 3

Model Training(2nd Phase)

In [98]:
```
X_train, X_test, y_train, y_test = train_test_split(df2.drop("Credit_Mix",axis=1),
```

In [99]:
```
lr.fit(X_train,y_train)
```

Out[99]:
```
▾ LogisticRegression
LogisticRegression()
```

In [100…
```
rf.fit(X_train,y_train)
```
Out[100…
```
▾ RandomForestClassifier
RandomForestClassifier()
```
In [101…
```
svm.fit(X_train,y_train)
```
Out[101…
```
▾ SVC
SVC()
```
In [102…
```
xg.fit(X_train,y_train)
```
Out[102…
```
▾ XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric=None, feature_types=
None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

Model Evaluation

Logistic Regression

In [104…
```
predicted_lr_train= lr.predict(X_train)
```
In [105…
```
predicted_lr_test= lr.predict(X_test)
```
In [106…
```
print(mt.classification_report(y_train,predicted_lr_train))
```
```
              precision    recall  f1-score   support

           0       0.83      0.79      0.81      9598
           1       0.69      0.70      0.69     12141
           2       0.70      0.72      0.71     18261

    accuracy                           0.73     40000
   macro avg       0.74      0.73      0.74     40000
weighted avg       0.73      0.73      0.73     40000
```

In [107…
```
print(mt.classification_report(y_test,predicted_lr_test))
```

```
              precision    recall  f1-score   support

           0       0.85      0.79      0.81      2374
           1       0.69      0.72      0.70      3051
           2       0.71      0.71      0.71      4575

    accuracy                           0.73     10000
   macro avg       0.75      0.74      0.74     10000
weighted avg       0.73      0.73      0.73     10000
```

Random Forest Classifier

In [109…
```
predicted_rf_train = rf.predict(X_train)
```

In [110…
```
predicted_rf_test= rf.predict(X_test)
```

In [111…
```
print(mt.classification_report(y_train,predicted_rf_train))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9598
           1       1.00      1.00      1.00     12141
           2       1.00      1.00      1.00     18261

    accuracy                           1.00     40000
   macro avg       1.00      1.00      1.00     40000
weighted avg       1.00      1.00      1.00     40000
```

In [112…
```
print(mt.classification_report(y_test,predicted_rf_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      2374
           1       0.96      0.98      0.97      3051
           2       0.98      0.96      0.97      4575

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000
```

SVM

In [114…
```
predicted_svm_train= svm.predict(X_train)
```

In [115…
```
predicted_svm_test= svm.predict(X_test)
```

In [116…
```
print(mt.classification_report(y_train,predicted_svm_train))
```

```
              precision    recall  f1-score   support

           0       0.84      0.73      0.78      9598
           1       0.84      0.79      0.81     12141
           2       0.75      0.82      0.78     18261

    accuracy                           0.79     40000
   macro avg       0.81      0.78      0.79     40000
weighted avg       0.80      0.79      0.79     40000
```

In [117…

```
print(mt.classification_report(y_test,predicted_svm_test))
```

```
              precision    recall  f1-score   support

           0       0.83      0.72      0.77      2374
           1       0.82      0.81      0.81      3051
           2       0.75      0.81      0.78      4575

    accuracy                           0.79     10000
   macro avg       0.80      0.78      0.79     10000
weighted avg       0.79      0.79      0.79     10000
```

XGB Classifier

In [119…

```
predicted_xg_train= xg.predict(X_train)
```

In [120…

```
predicted_xg_test= xg.predict(X_test)
```

In [121…

```
print(mt.classification_report(y_train,predicted_xg_train))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9598
           1       1.00      1.00      1.00     12141
           2       1.00      0.99      1.00     18261

    accuracy                           1.00     40000
   macro avg       1.00      1.00      1.00     40000
weighted avg       1.00      1.00      1.00     40000
```

In [122…

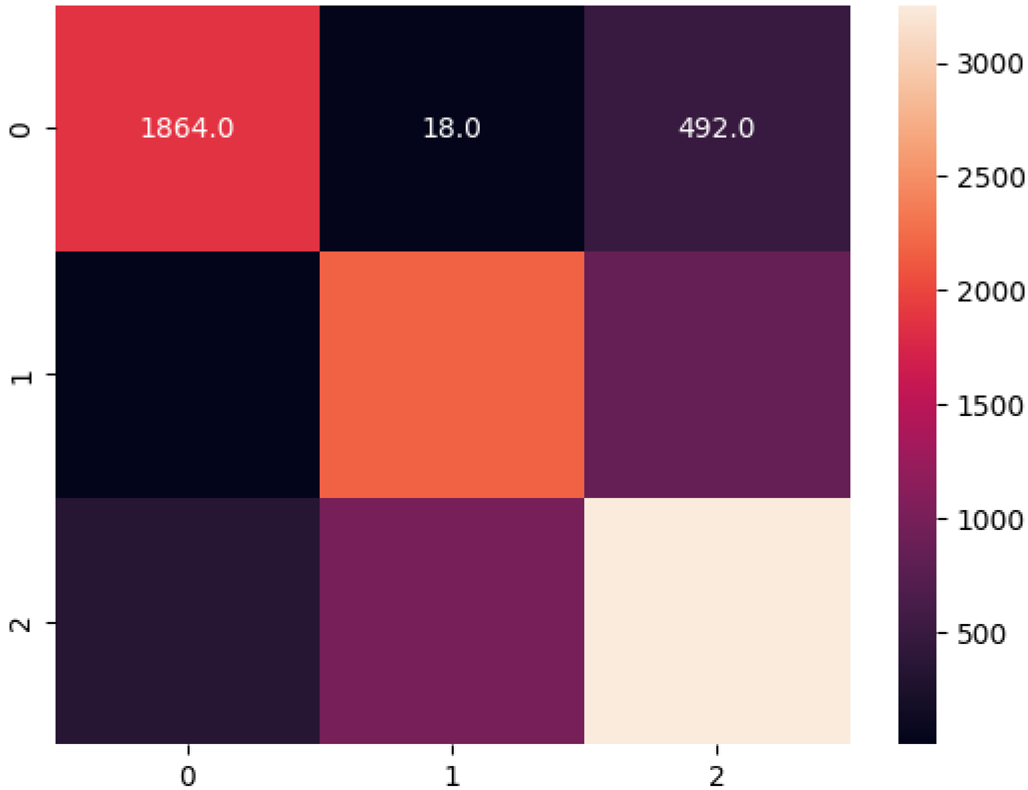
```
print(mt.classification_report(y_test,predicted_xg_test))
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      2374
           1       0.96      0.97      0.97      3051
           2       0.97      0.96      0.97      4575

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000
```

Confusion Matrix

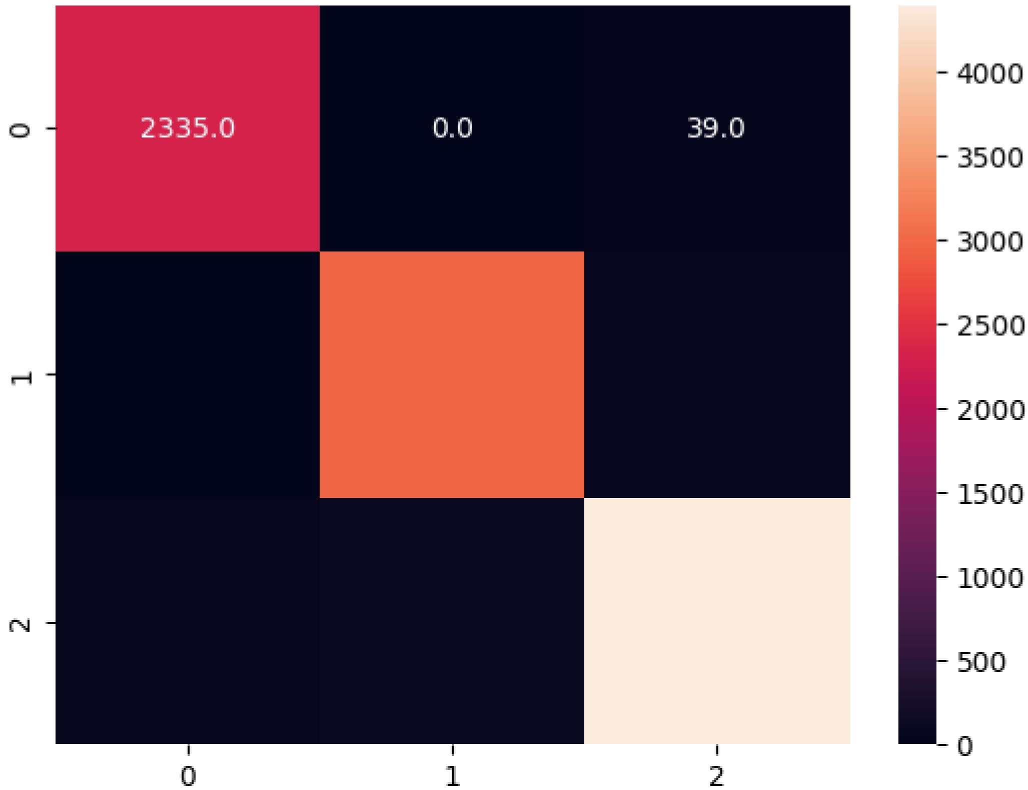
In [124…
```
sns.heatmap(mt.confusion_matrix(y_test,predicted_lr_test), annot=True,fmt=".1f")
```

Out[124… <Axes: >



In [125…
```
sns.heatmap(mt.confusion_matrix(y_test,predicted_rf_test), annot=True,fmt=".1f")
```

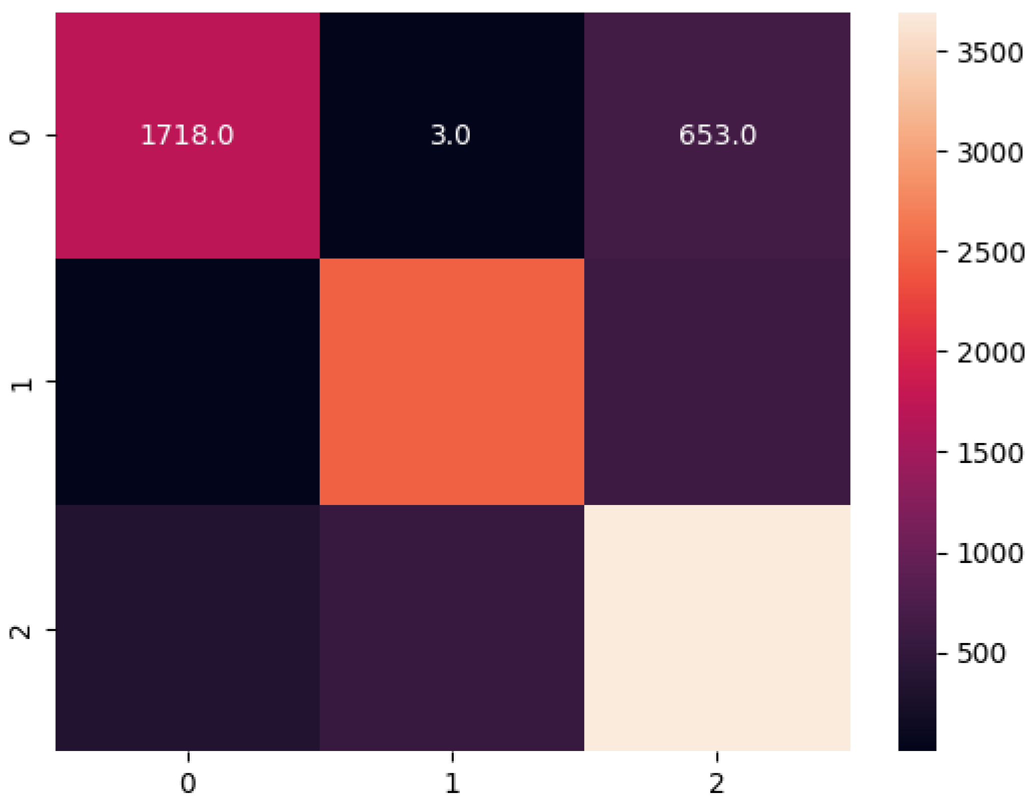
Out[125… <Axes: >



In [126…

```
sns.heatmap(mt.confusion_matrix(y_test,predicted_svm_test), annot=True,fmt=".1f")
```

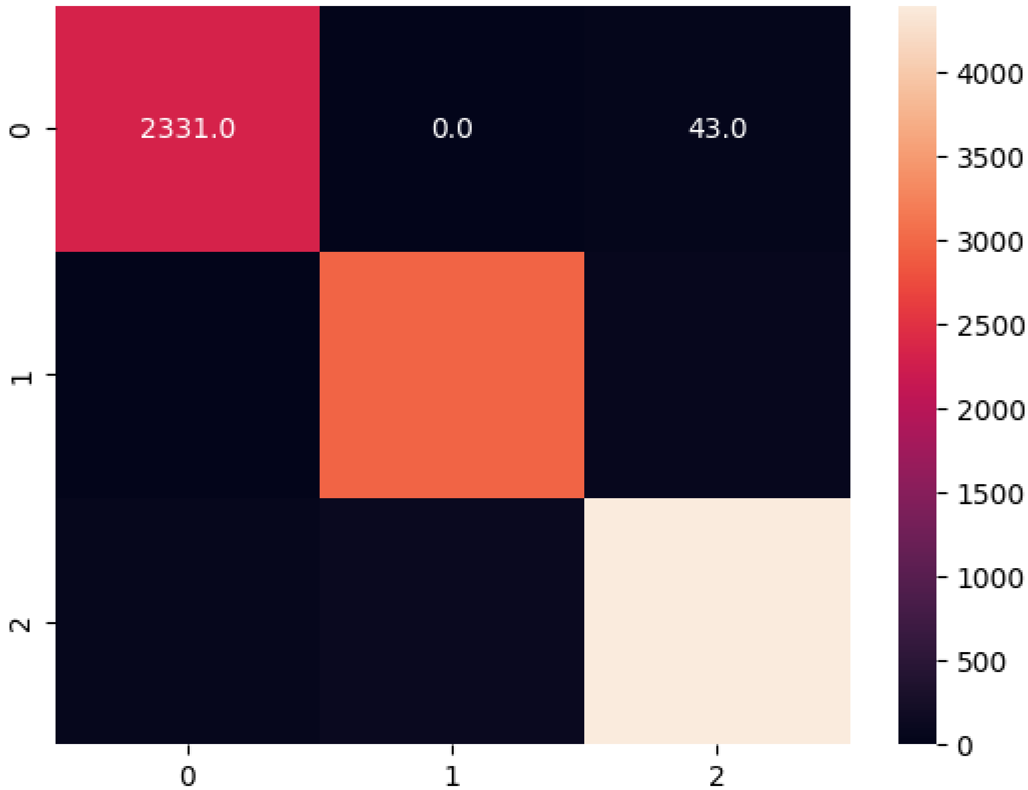
Out[126… <Axes: >



In [127…

```
sns.heatmap(mt.confusion_matrix(y_test,predicted_xg_test), annot=True,fmt=".1f")
```

Out[127… <Axes: >



Model Evaluation Interpretation

Logistic Regression:

- **Precision:** The model performs reasonably well in identifying class 0 and class 2, but less accurately for class 1.
- **Recall:** Good recall for class 1, but slightly lower for classes 0 and 2.
- **F1-score:** Balanced F1-scores, indicating a fair trade-off between precision and recall for each class.
- **Overall Accuracy:** 73%, with a balanced performance across classes.

Random Forest Classifier:

- **Precision:** High precision for all classes, indicating low false positive rates.
- **Recall:** High recall for all classes, indicating low false negative rates.
- **F1-score:** Excellent balance between precision and recall for each class.
- **Overall Accuracy:** 97%, demonstrating a highly accurate model across all classes.

Support Vector Machine (SVM):

- **Precision:** Slightly lower precision for class 0, but relatively balanced for other classes.
- **Recall:** Lower recall for class 0, affecting the ability to identify all instances of this class.
- **F1-score:** Reasonable balance between precision and recall for each class.
- **Overall Accuracy:** 79%, with room for improvement, especially in identifying instances of class 0.

XGBoost:

- **Precision:** High precision for all classes, indicating low false positive rates.
- **Recall:** High recall for all classes, indicating low false negative rates.
- **F1-score:** Excellent balance between precision and recall for each class.
- **Overall Accuracy:** 97%, showing a highly accurate model across all classes.

General Insights:

- Random Forest and XGBoost outperform Logistic Regression and SVM in terms of overall accuracy and class-specific metrics.
- Random Forest and XGBoost show robustness with high precision and recall, indicating a well-balanced model.
- Logistic Regression and SVM, while not as accurate, still provide reasonable performance, and their weaknesses may be addressed through further tuning or feature engineering.

Hyperparameter Tuning

Both Random Forest Classifier and XGBoost classifier performed exceptionally well. We choose XGBoost for hypertuning it's parameters and potentially improve it's performance even more

In [128…

```
from sklearn.model_selection import GridSearchCV
```

In [129…

```
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
}
```

In [130…

```
grid_search = GridSearchCV(estimator=xg, param_grid=param_grid, cv=5, scoring='accu
grid_search.fit(X_train, y_train)
```

Out[130…

```
▸ GridSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

In [131...
```python
best_params = grid_search.best_params_
```

In [132...
```python
# Retrain XGB
```

In [133...
```python
best_xgb_classifier = XGBClassifier(**best_params)
```

In [134...
```python
best_xgb_classifier.fit(X_train,y_train)
```

Out[134...

```
▾ XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric=None, feature_types=
None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.2, max_bin=N
one,
```

In [135...
```python
predicted = best_xgb_classifier.predict(X_test)
```

In [136...
```python
print(mt.classification_report(y_test,predicted))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      2374
           1       0.97      0.98      0.98      3051
           2       0.98      0.97      0.98      4575

    accuracy                           0.98     10000
   macro avg       0.98      0.98      0.98     10000
weighted avg       0.98      0.98      0.98     10000
```

Conclusion

Random Forest Classifier and XGBoostClassifier perform extremely well(around 97% accurracy) with good precision and recall scores. We further tuned the hyperparameters of XGBoost to improve performance. After using Grid Search on some important parameters, our performance increased by 1%, around 98%.

Recommendations:

- We can tune Random Forest Classifier also to see how much improvement it can gain and compare it to XGBoost

- Even though our ensemble techniques performed well even with imbalance class, rest of out models performed quite average. We can use Feature Selection techniques and sampling methods to see how much improvement we can gain on these models.

In [ ]:

```

```