Credit Score Classification

In this notebook we are going to classify the credit score of an individual with the data that we have with us. Data contains the person details such as annual income, credit utilization ratio etc., There are three classes**(Good, Standard, Poor)** to predict.

Dataset Link: https://www.kaggle.com/datasets/parisrohan/credit-score-classification (https://www.kaggle.com/datasets/parisrohan/credit-score-classification)

Imports

In [44]:
```
import warnings
import pandas as pd
from pandas.api.types import is_numeric_dtype
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder as le
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler as rbScaler
from sklearn.linear_model import LogisticRegression as lgrClassifier
from sklearn import metrics

from statsmodels.stats.outliers_influence import variance_inflation_factor

warnings.filterwarnings('ignore')
%matplotlib inline
```

Credit Score Classification

In [86]:
```
df = pd.read_csv('train.csv', low_memory=False)
df.shape
```

Out[86]:
```
(100000, 28)
```

In [87]:
```
df.head()
```

Out[87]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhar
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	182
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	182

5 rows × 28 columns

Our target column is **Credit_Score**

Answer the following

1.) What are the data types? (Only numeric and categorical)

In [88]:
```
df.dtypes
```

Out[88]:
```
ID                          object
Customer_ID                 object
Month                       object
Name                        object
Age                         object
SSN                         object
Occupation                  object
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
Credit_Score                object
dtype: object
```

Some of the columns are loaded as a objects by the pandas automatically, But we have to transform them to proper data types after the data analysis. I have listed them below after segregating them.

Numerical Columns:

1. Monthly_Inhand_Salary
2. Num_Bank_Accounts
3. Num_Credit_Card
4. Interest_Rate
5. Delay_from_due_date
6. Num_Credit_Inquiries
7. Credit_Utilization_Ratio
8. Total_EMI_per_month
9. Age
10. Annual_Income
11. Num_of_Loan
12. Num_of_Delayed_Payment
13. Changed_Credit_Limit
14. Outstanding_Debt

15. Amount_invested_monthly
16. Monthly_Balance

Categorical Columns:

1. Occupation
2. TypeofLoan
3. CreditMix
4. CreditHistoryAge
5. PaymentofMinAmount
6. PaymentBehaviour
7. CreditScore

Irrelavant columns for the problem:

1. ID
2. Customer_ID
3. Month
4. Name
5. SSN

2.) Are there missing values?

Yes there are missing values for about 8 columns in the whole dataset. Below code will show us the count of missing values.

In [89]:
```
null_count = df.isnull().sum().sort_values(ascending=False)
null_count
```

Out[89]:
```
Monthly_Inhand_Salary       15002
Type_of_Loan                11408
Name                         9985
Credit_History_Age           9030
Num_of_Delayed_Payment       7002
Amount_invested_monthly      4479
Num_Credit_Inquiries         1965
Monthly_Balance              1200
ID                              0
Changed_Credit_Limit            0
Payment_Behaviour               0
Total_EMI_per_month             0
Payment_of_Min_Amount           0
Credit_Utilization_Ratio        0
Outstanding_Debt                0
Credit_Mix                      0
Delay_from_due_date             0
Customer_ID                     0
Num_of_Loan                     0
Interest_Rate                   0
Num_Credit_Card                 0
Num_Bank_Accounts               0
Annual_Income                   0
Occupation                      0
SSN                             0
Age                             0
Month                           0
Credit_Score                    0
dtype: int64
```

From the above table, we can see that there are missing values for 8 columns. Highest being the **Monthly_Inhand_Salary** and **Type_of_Loan**

3.) What are the likely distributions of the numeric variables?

Before creating distribution plots, I am preprocessing the data, otherwise the distribution plots will not work because of the junk values in data.

In [90]:
```
num_cols = ['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Acco
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Lim
       'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Rati
       'Total_EMI_per_month', 'Amount_invested_monthly',
       'Monthly_Balance', 'Credit_History_Age']

categorical_cols = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount',
       'Payment_Behaviour', 'Credit_Score']
```

drop irrelavant columns

drop irrelavant columns

In [91]:
```
irrelavent_coulumns = ['ID', 'Customer_ID', 'Month', 'Name', 'SSN']
df.drop(columns=irrelavent_coulumns, inplace=True, axis=1)
```

Clean Data

In [92]:
```
df = df.applymap(
    lambda x: x if x is np.NaN or not \
        isinstance(x, str) else str(x).strip('_')).replace(
            ['', 'nan', '!@9#%8', '#F%$D@*&8'], np.NaN
        )
```

Change dtype of numerial columns

In [93]:
```
df.Age = df.Age.astype(int)
df.Annual_Income = df.Annual_Income.astype(float)
df.Num_of_Loan = df.Num_of_Loan.astype(int)
df.Num_of_Delayed_Payment = df.Num_of_Delayed_Payment.astype(float)
df.Changed_Credit_Limit = df.Changed_Credit_Limit.astype(float)
df.Outstanding_Debt = df.Outstanding_Debt.astype(float)
df.Amount_invested_monthly = df.Amount_invested_monthly.astype(float)
df.Monthly_Balance = df.Monthly_Balance.astype(float)
```

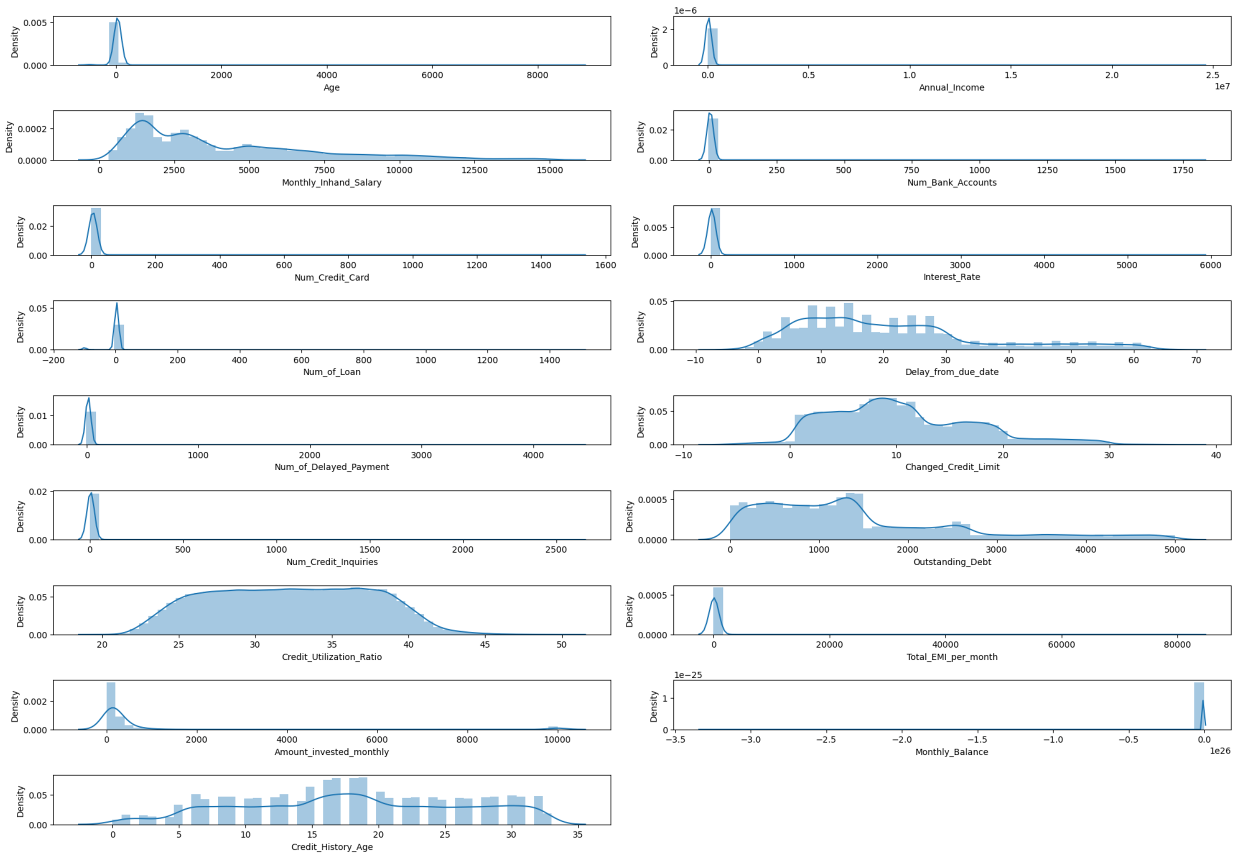
Credit History Age has years and month combined in the values like "22 years and 1 month". We are going to take only years from it.

In [94]:
```
def take_years(x):
    if x is not None:
        return str(x).strip()[0:2]

df.Credit_History_Age=df.Credit_History_Age.apply(take_years)
df['Credit_History_Age'] = df['Credit_History_Age'].replace({'na': np.NaN})
```

Distributions for the Numerical Columns

In [95]:
```python
rows=10
cols=2
counter=1
plt.rcParams['figure.figsize']=[20, 15]
for i in num_cols:
    plt.subplot(rows, cols, counter)
    sns.distplot(df[i])
    counter+=1
plt.tight_layout()
plt.show()
```



Credit_Utilization_Ratio follows normal distribution

Delay_from_due_data is right skewed

Changed_Credit_Limit distribution looks fine, close to normal distribution

Outstanding_Debt is right skewed

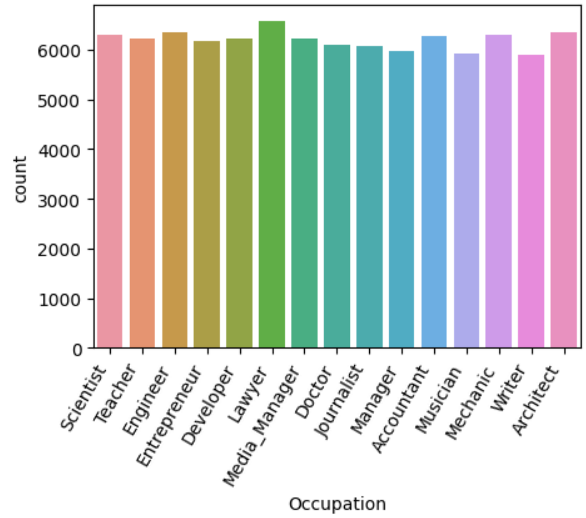
Monthly_Inhand_Salary is right skewed

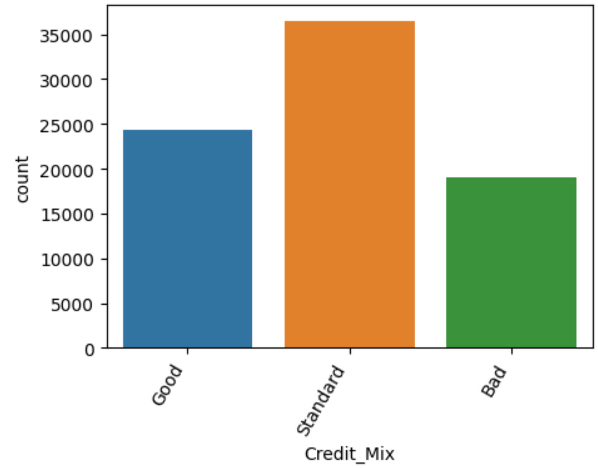
Credit_History_age is normally distributed

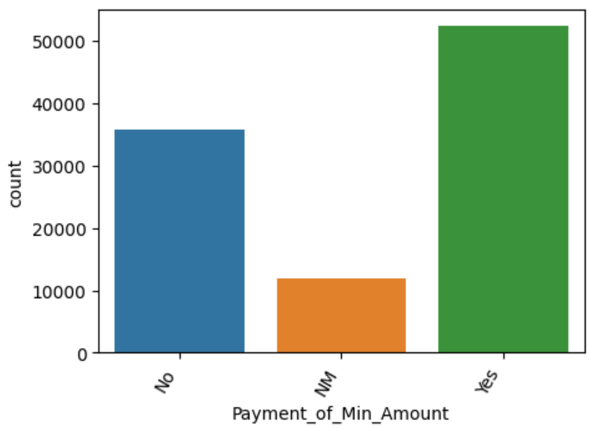
And all thre remaining fields contains outliers, because of that we are not able to properly distibute them with very less bins, lets try to remove outliers from those columns and replot them later.

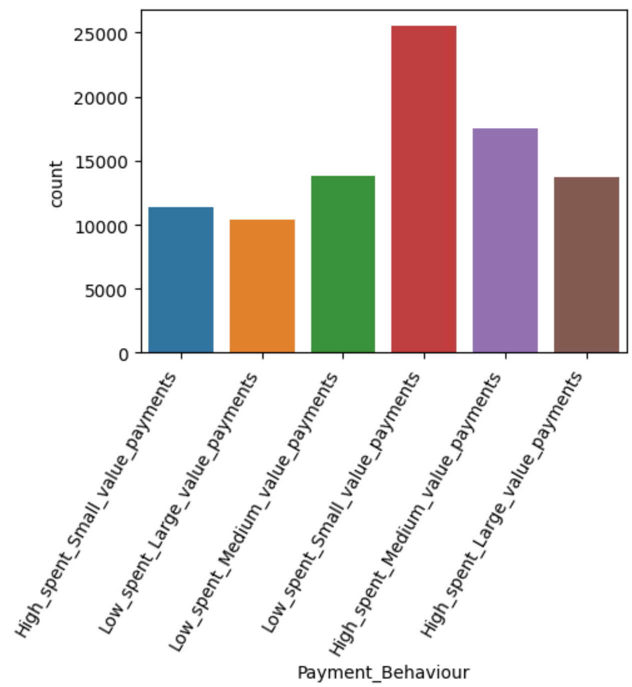
Distributions for the categorical columns

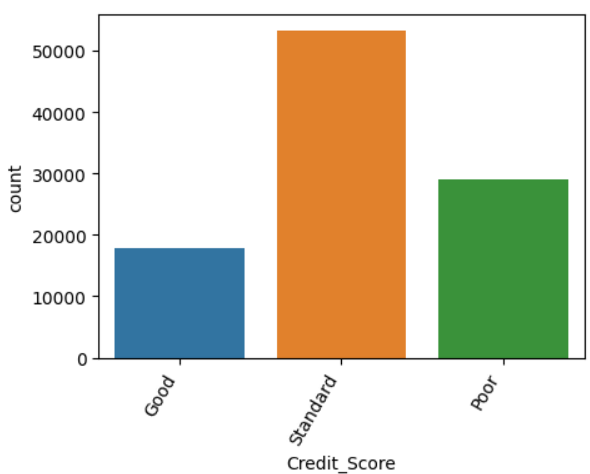
In [96]:
```
rows=3
cols=2
counter=1
plt.rcParams['figure.figsize']=[10,15]
for i in categorical_cols:
    plt.subplot(rows,cols,counter)
    sns.countplot(x=i,data=df)
    plt.xticks(rotation=60,ha='right')
    counter+=1
plt.tight_layout()
plt.show()
```











All the categorical columns have the equal distribution of data except **Payment_Behavious** and

Credit_Score

Occupation column has mix of rows from the various job roles

Credit_Mix column data is spreaded across three categories

Payment_of_Min_Amount column has data from both Yes and No categories, but there is one more category 'NM' which might need to be tranformed into 'No' as it might have been entered as a typo or pre-processing error in the upstream.

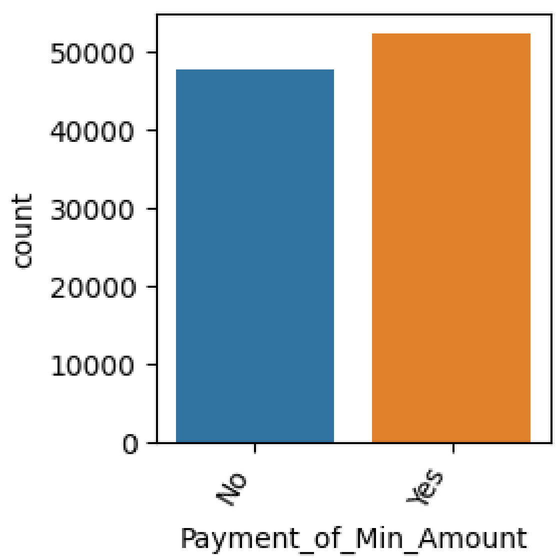
Payment_behaviour coulmn has more data with the "Low_spent_small_values" category

Credit_Score which is our target has a mix of good, bad and standard credit classification values

In [97]:
```
df['Payment_of_Min_Amount'] = df['Payment_of_Min_Amount'].replace({'NM': 'N
```

Plotting the **Payment_of_Min_Amount** after replacing it with proper value

In [99]:
```
plt.rcParams['figure.figsize'] = [3,3]
sns.countplot(x='Payment_of_Min_Amount', data=df)
plt.xticks(rotation=60, ha='right')
plt.tight_layout()
plt.show()
```



4.) Which independent variables are useful to predict a target (dependent variable)? (Use at least three methods)

Lets find out the correlation between all the variables. But before that, lets remove the outliers that are present in the dataset.

In [100]:
```
def remove_outlier(df):
    low = .05
    high = .95
    quant_df = df.quantile([low, high])
    print(quant_df)
    for name in list(df.columns):
        if is_numeric_dtype(df[name]):
            df = df[(df[name] > quant_df.loc[low, name]) & (df[name] < quan
    return df

df = remove_outlier(df)
```

```
       Age  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0.05  16.0        9743.51             836.125833                1.0
0.95  53.0      134533.32           10828.226500               10.0

      Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  \
0.05              3.0            2.0          0.0                  3.0
0.95             10.0           33.0          8.0                 54.0

      Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries
\
0.05                     2.0                  1.16                   0.0
0.95                    24.0                 23.60                  13.0

      Outstanding_Debt  Credit_Utilization_Ratio  Total_EMI_per_month  \
0.05          118.5465                 24.230834             0.000000
0.95         4073.7605                 40.220207           437.012753

      Amount_invested_monthly  Monthly_Balance
0.05                31.893067       174.599433
0.95              1149.405785       862.590861
```

In [101]:
```
df.interpolate(method='linear', inplace=True)
```

Encoding the categorical columns

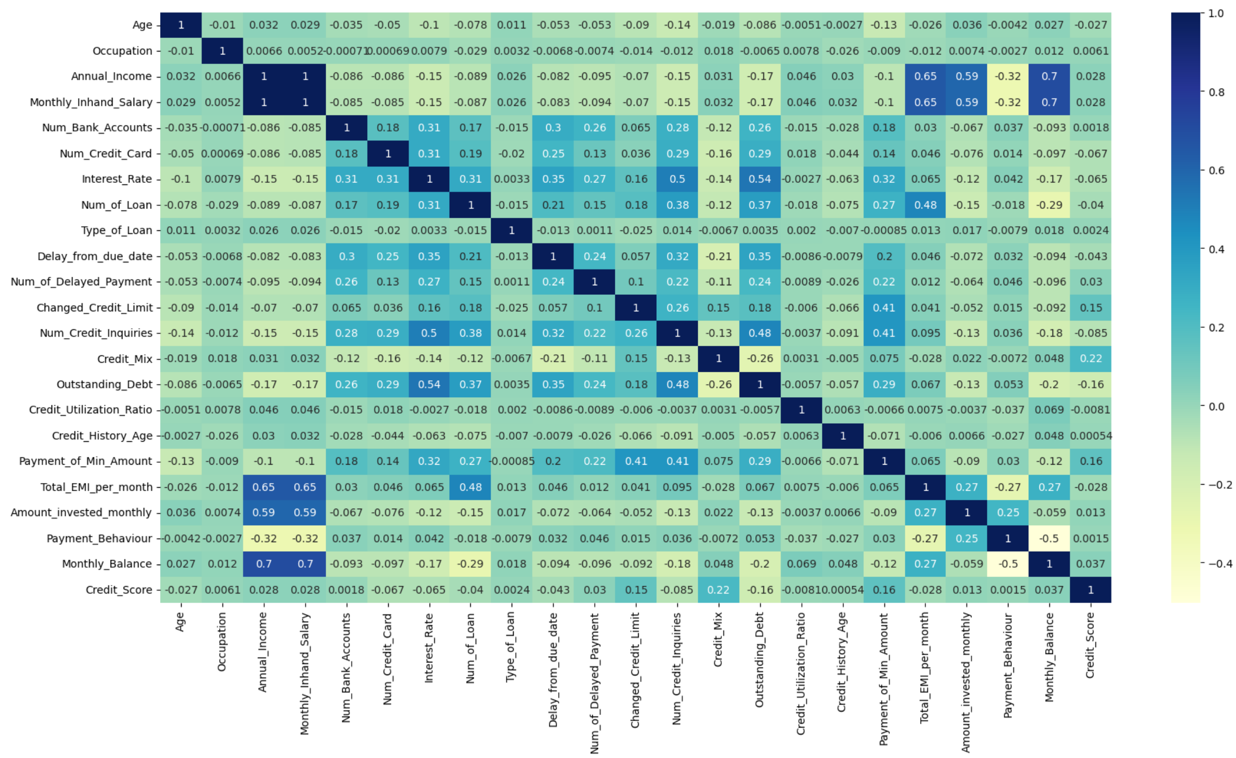
In [102]:
```
Occupation_le = le()
Type_of_Loan_le = le()
Credit_Mix_le = le()
Credit_History_Age_le = le()
Payment_of_Min_Amount_le = le()
Payment_Behaviour_le = le()
Credit_Score_le = le()

df['Occupation'] = Occupation_le.fit_transform(df['Occupation'])
df['Type_of_Loan'] = Type_of_Loan_le.fit_transform(df['Type_of_Loan'])
df['Credit_Mix'] = Credit_Mix_le.fit_transform(df['Credit_Mix'])
df['Credit_History_Age'] = Credit_History_Age_le.fit_transform(df['Credit_H
df['Payment_of_Min_Amount'] = Payment_of_Min_Amount_le.fit_transform(df['Pa
df['Payment_Behaviour'] = Payment_Behaviour_le.fit_transform(df['Payment_Be
df['Credit_Score'] = Credit_Score_le.fit_transform(df['Credit_Score'])
```

Correlation Heatmap

In [103]:
```
plt.figure(figsize = (20,10))
sns.heatmap(df.corr() , annot = True, cmap = "YlGnBu")
```

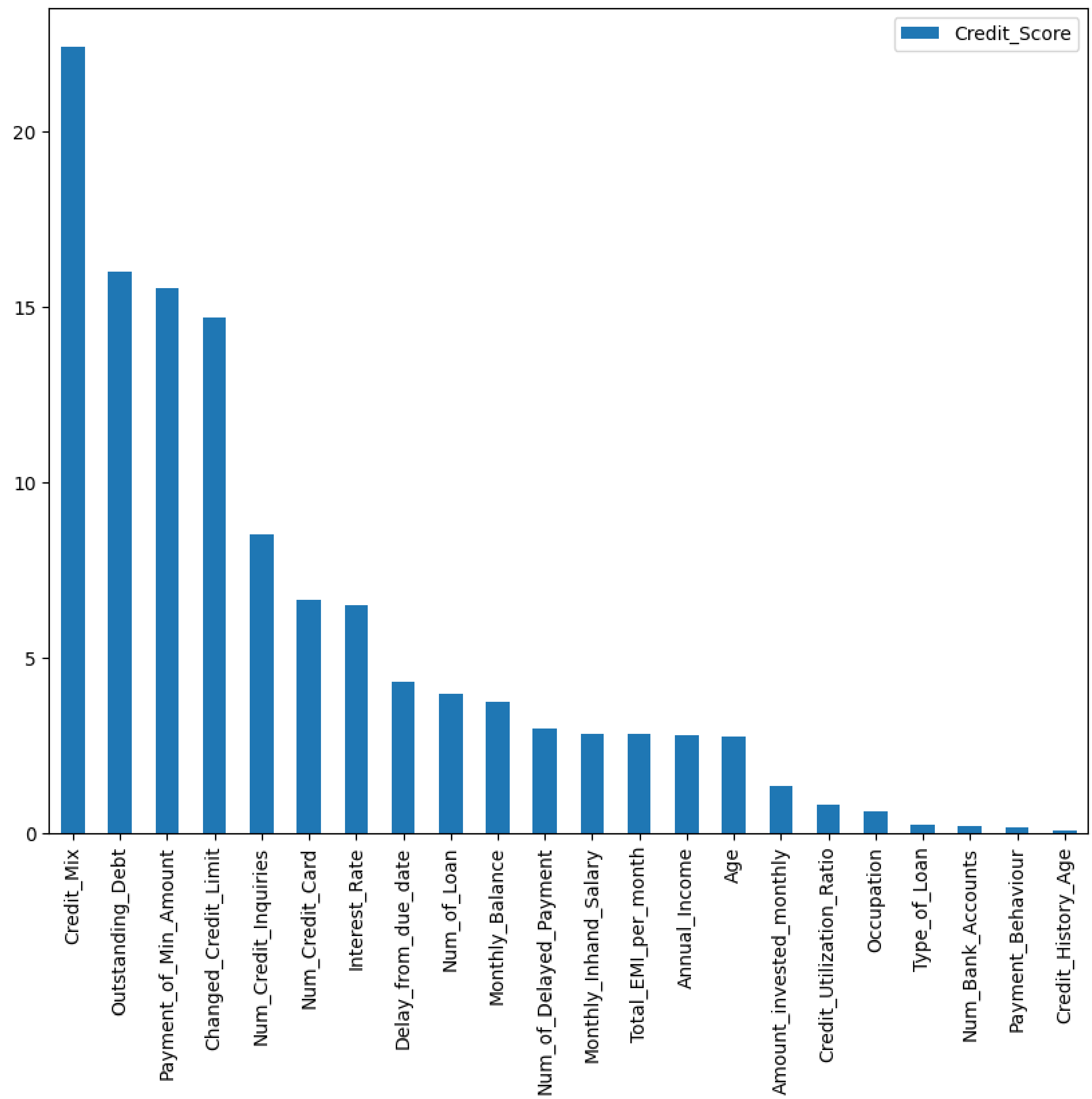
Out[103]: <AxesSubplot: >



Rank the columns based on the correlation

In [104]:
```
pd.DataFrame(abs(df.corr()['Credit_Score'].drop('Credit_Score')*100).sort_v
    ascending=False)).plot.bar(figsize = (10,8))
```

Out[104]: <AxesSubplot: >



Accoding to the heatmap and histogram, we can see that the following columns are correlated with the target variable "Credit score". Out of them **Outstanding_Debt** and **Credit_Mix** are highly correlated.

In [105]:
```
round(abs(df.corr()['Credit_Score']*100).sort_values(ascending=False), 2)
```

Out[105]:
```
Credit_Score                100.00
Credit_Mix                   22.41
Outstanding_Debt             16.01
Payment_of_Min_Amount        15.55
Changed_Credit_Limit         14.70
Num_Credit_Inquiries          8.52
Num_Credit_Card               6.66
Interest_Rate                 6.48
Delay_from_due_date           4.30
Num_of_Loan                   3.98
Monthly_Balance               3.74
Num_of_Delayed_Payment        2.97
Monthly_Inhand_Salary         2.84
Total_EMI_per_month           2.80
Annual_Income                 2.77
Age                           2.75
Amount_invested_monthly       1.34
Credit_Utilization_Ratio      0.81
Occupation                    0.61
Type_of_Loan                  0.24
Num_Bank_Accounts             0.18
Payment_Behaviour             0.15
Credit_History_Age            0.05
Name: Credit_Score, dtype: float64
```

Variance Inflation Factor(VIF)

In [106]:
```
numeric_cols = df.select_dtypes(exclude = "object").columns

vif_df = df[numeric_cols]
vif_data = pd.DataFrame()
vif_data["feature"] = vif_df.columns
vif_data["VIF"] = [variance_inflation_factor(vif_df.values ,i) for i in ran
vif_data.head(17)
```

Out[106]:

	feature	VIF
0	Age	13.054516
1	Occupation	3.639357
2	Annual_Income	692.661411
3	Monthly_Inhand_Salary	809.153941
4	Num_Bank_Accounts	12.314756
5	Num_Credit_Card	21.596890
6	Interest_Rate	8.780960
7	Num_of_Loan	11.686384
8	Type_of_Loan	3.951536
9	Delay_from_due_date	6.156857
10	Num_of_Delayed_Payment	12.170739
11	Changed_Credit_Limit	7.057102
12	Num_Credit_Inquiries	8.162455
13	Credit_Mix	7.548830
14	Outstanding_Debt	6.051092
15	Credit_Utilization_Ratio	45.331403
16	Credit_History_Age	3.698770

From the above table, we can see that the **Annual_Income**, **Monthly_Inhand_Salary**, **Credit_Utilization_Ratio**, **Num_of_Delayed_Payment** and **Num_of_Loan** are highly correlated.

We are going to remove the **Monthly_Inhand_Salary** and **Num_of_Delayed_Payment** from the list of independent columns because we can infer the same information from the **Annual_Income** and **Credit_Utilization_Ratio** respectively.

5.) Which independent variables have missing data? How much?

In [107]:
```
percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                 'percent_missing': percent_missing})

missing_value_df.sort_values('percent_missing', ascending=False, inplace=Tr
missing_value_df
```

Out[107]:

	column_name	percent_missing
Age	Age	0.0
Num_Credit_Inquiries	Num_Credit_Inquiries	0.0
Monthly_Balance	Monthly_Balance	0.0
Payment_Behaviour	Payment_Behaviour	0.0
Amount_invested_monthly	Amount_invested_monthly	0.0
Total_EMI_per_month	Total_EMI_per_month	0.0
Payment_of_Min_Amount	Payment_of_Min_Amount	0.0
Credit_History_Age	Credit_History_Age	0.0
Credit_Utilization_Ratio	Credit_Utilization_Ratio	0.0
Outstanding_Debt	Outstanding_Debt	0.0
Credit_Mix	Credit_Mix	0.0
Changed_Credit_Limit	Changed_Credit_Limit	0.0
Occupation	Occupation	0.0
Num_of_Delayed_Payment	Num_of_Delayed_Payment	0.0
Delay_from_due_date	Delay_from_due_date	0.0
Type_of_Loan	Type_of_Loan	0.0
Num_of_Loan	Num_of_Loan	0.0
Interest_Rate	Interest_Rate	0.0
Num_Credit_Card	Num_Credit_Card	0.0
Num_Bank_Accounts	Num_Bank_Accounts	0.0
Monthly_Inhand_Salary	Monthly_Inhand_Salary	0.0
Annual_Income	Annual_Income	0.0
Credit_Score	Credit_Score	0.0

There are no columns with the missing values as we have already taken care with the help of linear interpolation technique in the above steps.

6.) Do the training and test sets have the same data?

No, train and test splits will not have a same data. We are using a funtion **train_test_split** provided by the **sklearn** module. It will take care of train and test to have a completely different data with each other.

7.) In the predictor variables independent of all the other predictor variables?

In [108]:
```
numeric_cols = df.select_dtypes(exclude = "object").columns

vif_df = df[numeric_cols]
vif_data = pd.DataFrame()
vif_data["feature"] = vif_df.columns
vif_data["VIF"] = [variance_inflation_factor(vif_df.values ,i) for i in ran
vif_data.head(17)
```

Out[108]:

	feature	VIF
0	Age	13.054516
1	Occupation	3.639357
2	Annual_Income	692.661411
3	Monthly_Inhand_Salary	809.153941
4	Num_Bank_Accounts	12.314756
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6	Interest_Rate	8.780960
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8	Type_of_Loan	3.951536
9	Delay_from_due_date	6.156857
10	Num_of_Delayed_Payment	12.170739
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13	Credit_Mix	7.548830
14	Outstanding_Debt	6.051092
15	Credit_Utilization_Ratio	45.331403
16	Credit_History_Age	3.698770

From the above table, we can see that the **Annual_Income**, **Monthly_Inhand_Salary**, **Credit_Utilization_Ratio**, **Num_of_Delayed_Payment** and **Num_of_Loan** are highly correlated. We are going to remove 4 out of them from the independent variables list.

8.) Which predictor variables are the most important?

The following columns are having the high correlation value.

The following columns are having the high correlation value:

Credit_Mix 22.41

Outstanding_Debt 16.01

Payment_of_Min_Amount 15.55

Changed_Credit_Limit 14.70

Num_Credit_Inquiries 8.52

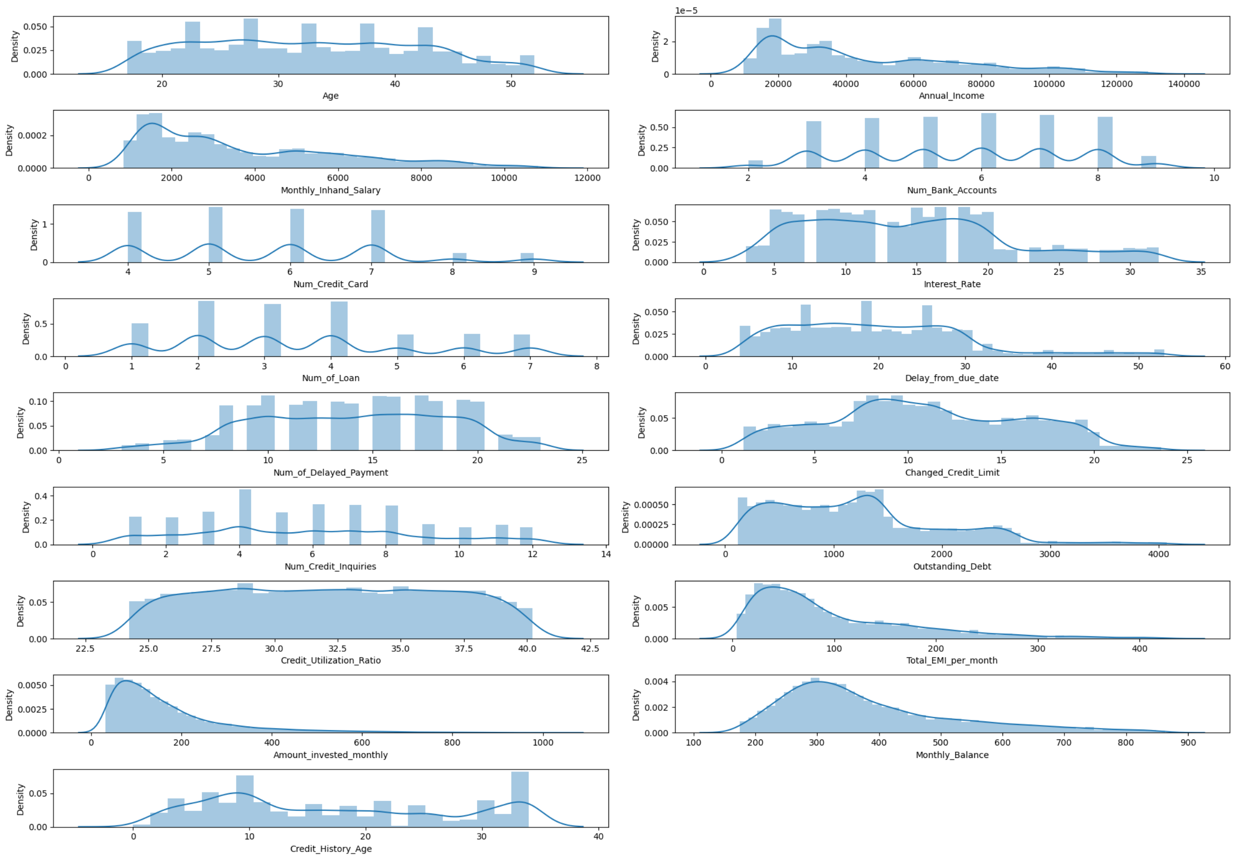
The above four columns are the important one because they are highly correlated with the target variable.

9.) Do the ranges of the predictor variables make sense?

Ranges are not as per the expectations, so we have removed the outliers with the help of *remove_outliers* funtion.

10.) What are the distributions of the predictor variables?

In [109]:
```
rows=10
cols=2
counter=1
plt.rcParams['figure.figsize']=[20, 15]
for i in num_cols:
    plt.subplot(rows, cols, counter)
    sns.distplot(df[i])
    counter+=1
plt.tight_layout()
plt.show()
```



After removing the outliers, the distributions are changed.

Most of the columns are distributed across all the ranges, but still we can observe some of them are right skewed.

11.) Remove outliers and keep outliers (does if have an effect of the final predictive model)?

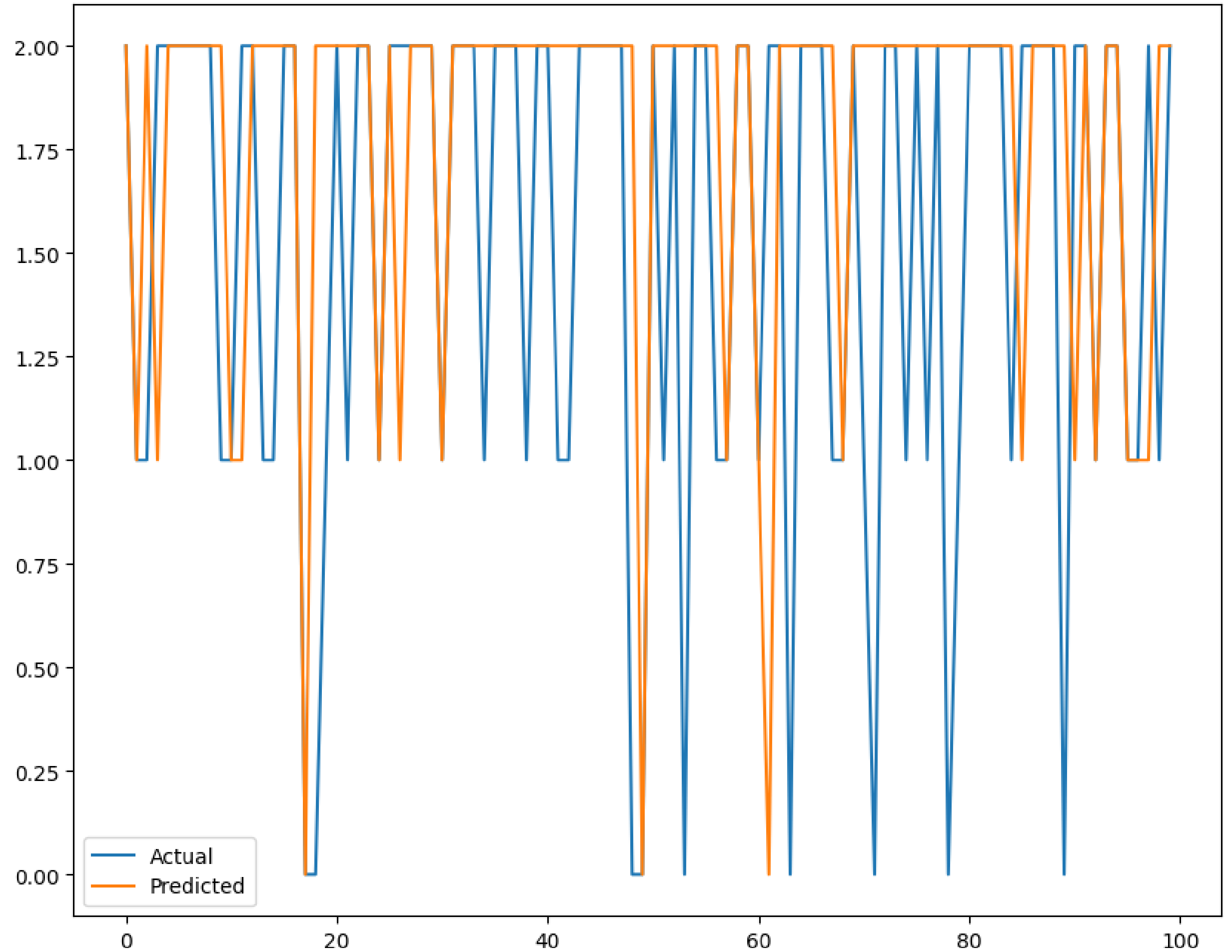
In [110]:
```
mdf = df[
    ['Credit_Score','Changed_Credit_Limit',
      'Payment_of_Min_Amount', 'Credit_Mix',
      'Delay_from_due_date', 'Annual_Income',
      'Age', 'Monthly_Balance', 'Outstanding_Debt',
      'Payment_Behaviour', 'Credit_History_Age',
      'Num_Bank_Accounts'
    ]
]
```

In [111]:
```
x = mdf.drop(['Credit_Score'] , axis = 1).values
y = mdf['Credit_Score' ].values
```

Remove Outliers and calculate Train Test Scores

In [112]:
```
# Data Split
x_train , x_test , y_train , y_test = train_test_split(x,y , test_size= 0.2
print([x_train.shape, y_train.shape, x_test.shape, y_test.shape])

# Data Scaling using Robust Scaler
ro_scaler = rbScaler()
x_train = ro_scaler.fit_transform(x_train)
x_test = ro_scaler.fit_transform(x_test)
[x_train.shape, x_test.shape]

# logistic Regression
lgr = lgrClassifier(C = 100)
lgr.fit(x_train , y_train)

lgr_score = lgr.score(x_train , y_train)
lgr_score_t = lgr.score(x_test , y_test)

y_pred1 = lgr.predict(x_test)
dd = pd.DataFrame({"Y_test" : y_test , "y_pred1": y_pred1})
plt.figure(figsize=(10,8))
plt.plot(dd[:100])
plt.legend(["Actual" , "Predicted"])

print(f"Train Score: {lgr_score}")
print(f"Test Score: {lgr_score_t}")
```

```
[(10455, 11), (10455,), (2614, 11), (2614,)]
Train Score: 0.6983261597321856
Test Score: 0.6866870696250956
```



Train and test Scores with outliers

Wrote a script to pass the "include outliers" parameter. This script will be available in the github under the URL https://github.com/aiskunks/Skunks_Skool/tree/main/INFO_6105/ML_Data_Cleaning_and_Feature_S (https://github.com/aiskunks/Skunks_Skool/tree/main/INFO_6105/ML_Data_Cleaning_and_Feature_S

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py -h
usage: train.py [-h] [--exclude-outliers] [--include-outliers] [-r REMOVE_PERCENT] [-n FILLNA_METHOD] [--normal-process]

optional arguments:
  -h, --help            show this help message and exit
  --exclude-outliers    Pass this variable to exclude outliers in the data
  --include-outliers    Pass this variable to include outliers in the data
  -r REMOVE_PERCENT, --remove-percent REMOVE_PERCENT
                        Pass the number of percentage that you want to remove from the data
  -n FILLNA_METHOD, --fillna-method FILLNA_METHOD
                        Pass the method that you want to use to fill the missing values
  --normal-process      Pass this variable to check the scores in the usual process
(py39) Nagas-Air:learn nagavenkateshgavini$
(py39) Nagas-Air:learn nagavenkateshgavini$
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --include-outliers --remove-percent 0 --fillna-method None --normal-process
Train Score: 0.17845882352941175
Test Score: 0.17726666666666666
(py39) Nagas-Air:learn nagavenkateshgavini$
```

As we can see in the above screenshot, the train and test scores were really bad in case of outliers.

Final Table with the scores

Train Score	Test Score	Outliers in data?
0.698	0.686	No
0.178	0.177	Yes

12.) Remove 1%, 5%, and 10% of your data randomly and impute the values back using at least 3 imputation methods. How well did the methods recover the missing values? That is remove some data, check the % error on residuals for numeric data and check for bias and variance of the error.

1 percent data removed and imputed with bfill approach

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 1 --fillna-method bfill
Train Score: 0.6965250270075621
Test Score: 0.6970933197348291
(py39) Nagas-Air:learn nagavenkateshgavini$
(py39) Nagas-Air:learn nagavenkateshgavini$
```

5 percent removed and imputed with bfill approach

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 5 --fillna-method bfill
Train Score: 0.6938242707958229
Test Score: 0.7001529831718512
(py39) Nagas-Air:learn nagavenkateshgavini$
```

10 percent removed and imputed with bfill approach

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 10 --fillna-method bfill
Train Score: 0.6799603889088945
Test Score: 0.6965833758286588
(py39) Nagas-Air:learn nagavenkateshgavini$
```

1 percent removed and imputed with mode

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 1 --fillna-method mode
Train Score: 0.6974252790781419
Test Score: 0.7042325344212137
(py39) Nagas-Air:learn nagavenkateshgavini$
```

5 percent removed and imputed with mode

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 5 --fillna-method mode
Train Score: 0.6943644220381707
Test Score: 0.6950535441101479
(py39) Nagas-Air:learn nagavenkateshgavini$
```

10 percent removed and imputed with mode

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 10 --fillna-method mode
Train Score: 0.6991357580122435
Test Score: 0.6909739928607853
(py39) Nagas-Air:learn nagavenkateshgavini$
```

1 percent removed and imputed with ffill

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 1 --fillna-method ffill
Train Score: 0.6956247749369824
Test Score: 0.7011728709841918
(py39) Nagas-Air:learn nagavenkateshgavini$
```

5 percent removed and imputed with ffill

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 5 --fillna-method ffill
Train Score: 0.6901332373064458
Test Score: 0.6935237123916369
(py39) Nagas-Air:learn nagavenkateshgavini$
```

10 percent removed and imputed with ffill

```
(py39) Nagas-Air:learn nagavenkateshgavini$ python train.py --exclude-outliers --remove-percent 10 --fillna-method ffill
Train Score: 0.6922938422758372
Test Score: 0.6909739928607853
(py39) Nagas-Air:learn nagavenkateshgavini$
```

Remove and imputation technique doesn't help much with the current data set that we have.

13.) For categorical data, calculate the accuracy and a confusion matrix.

Final Train and Test Score

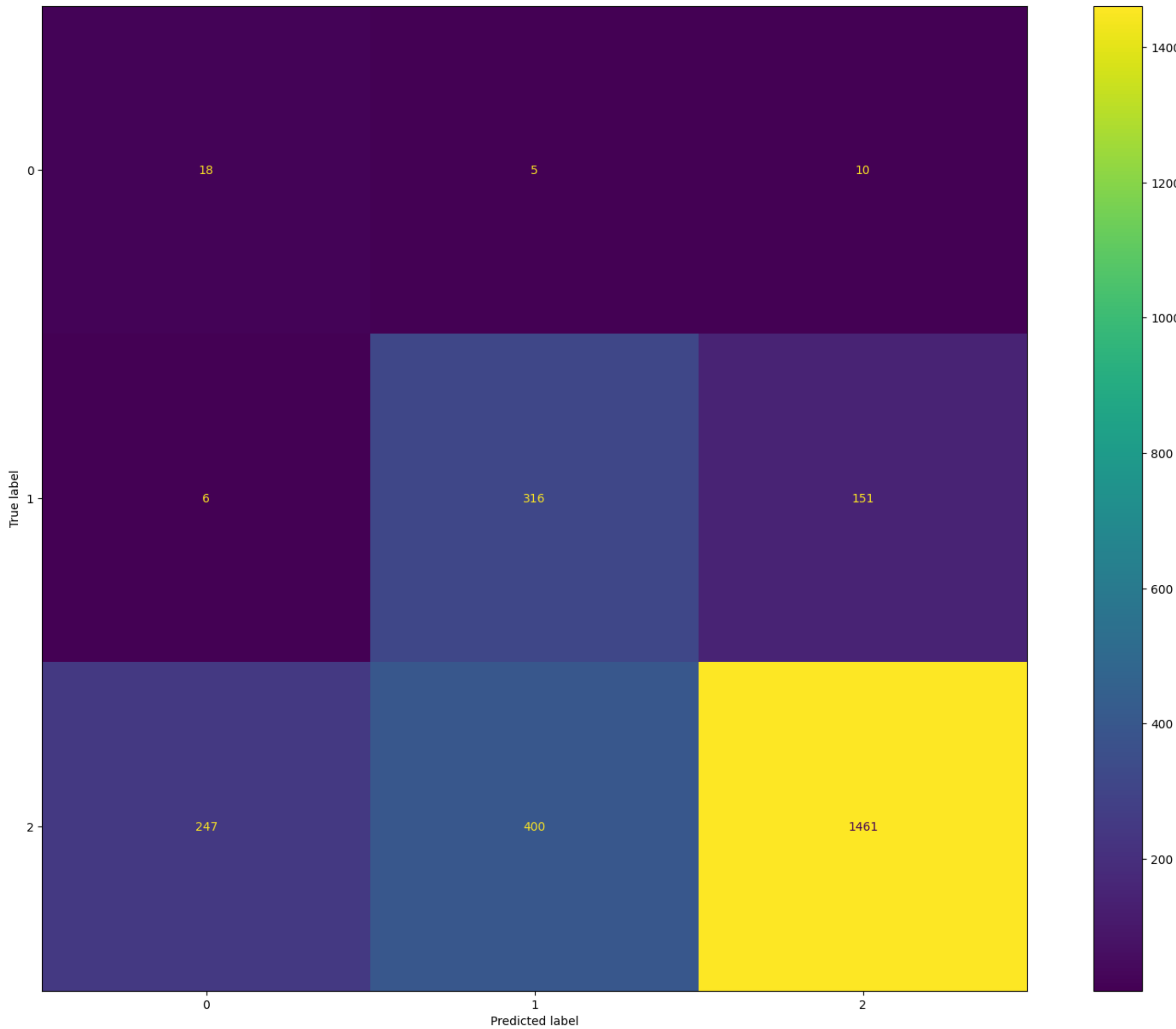
In [82]:
```python
print(f"Train Score: {lgr_score}")
print(f"Test Score: {lgr_score_t}")
```

```
Train Score: 0.6983261597321856
Test Score: 0.6866870696250956
```

Confusion Matrix

In [83]:
```
y_pred = lgr.predict(x_test)
cm = metrics.confusion_matrix(y_pred, y_test)
cmd = metrics.ConfusionMatrixDisplay(cm)
cmd.plot()
```

Out[83]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fae1
0eed8e0>
```



From the confusion matrix we can observe that there are still so many errors for the class **Poor**

Conclusion

After data analysis, cleaning and training, we were able to get the test score of **68.66** with the help of logistic regression algorithm.

We can improve the score by integrating better imputation techniques and different classification algorithms later.

References

Refered the following links to understand the functions or the processes that are going to be required during the problem analysis.

1. `Scikit-learn Documentation`

2. `Pandas Official Documentation`

3. `Analytics Vidya`

4. `medium: towardsdatascience`

5. `Seaborn: statistical data visualization`

All the visualization code was referred form the **seaborn** and **scikit-learn** official documentations. **Data frame** functions and usage was referred from the **Pandas** official documentation. All the concepts and doubts in the machine learning cleared with the help of **medium(towardsdatascience)** and **analytics vidya** articles. Rest of the code is written individually.