```
import matplotlib.pyplot as plt

import seaborn as sns

import pandas as pd from sklearn.preprocessing

import power_transform

#Importing data and storing it in variable called 'data'
data = pd.read_excel('D:\Eshteyaque\Miscll\Personal\Project\AIML\ML\
Project\Project-Anamoly_Detection\Data_Set\AnomaData.xlsx')
data
```

```
<>:2: SyntaxWarning: invalid escape sequence '\A'
<>:2: SyntaxWarning: invalid escape sequence '\A'
C:\Users\Eshteyaque.Ahmad\AppData\Local\Temp\
ipykernel_16240\3623776104.py:2: SyntaxWarning: invalid escape
sequence '\A'
   data = pd.read_excel('D:\Eshteyaque.Ahmad\Eshteyaque\Miscll\Personal\
Project\AIML\ML\Project\Project-Anamoly_Detection\Data_Set\
AnomaData.xlsx')
```

```
                      time y        x1        x2        x3         x4  \
0      1999-05-01 00:00:00 0  0.376665 -4.596435 -4.095756  13.497687
1      1999-05-01 00:02:00 0  0.475720 -4.542502 -4.018359  16.230659
2      1999-05-01 00:04:00 0  0.363848 -4.681394 -4.353147  14.127997
3      1999-05-01 00:06:00 0  0.301590 -4.758934 -4.023612  13.161566
4      1999-05-01 00:08:00 0  0.265578 -4.749928 -4.333150  15.267340
...                    ... ..      ...       ...       ...        ...
18393 1999-05-28 23:58:00 0 -0.877441  0.786430  0.406426 135.301215
18394 1999-05-29 00:00:00 0 -0.843988  0.633086  0.561918 133.228949
18395 1999-05-29 00:02:00 0 -0.826547  0.450126  0.334582 134.977973
18396 1999-05-29 00:04:00 0 -0.822843  0.419383  0.387263 135.658942
18397 1999-05-29 00:06:00 0 -0.840981  0.582710  0.593416 136.339880


             x5         x6        x7        x8 ...       x51
x52   \
0     -0.118830 -20.669883 0.000732 -0.061114 ... ...  29.984624
10.091721
1     -0.128733 -18.758079 0.000732 -0.061114          29.984624
```

```
10.095871
2        -0.138636 -17.836632 0.010803 -0.061114          ...  ...    29.984624
10.100265                                                 ...  ...    29.984624
3        -0.148142 -18.517601 0.002075 -0.061114          ...  ...    29.984624
10.104660                                                 ...  ...          ...
4        -0.155314 -17.505913 0.000732 -0.061114          ...         29.984624
10.109054                                                             29.984624
... ... 18393    ...              ...            ...        ...       29.984624
                 0.112295 26.300392 -0.159185      0.058823           29.984624
                                                   0.058823          29.984624  -
0.773514                                           0.048752                     -
18394   0.141332 25.678597 -0.159185               0.048752                     -
0.773514                                          0.048752                      -
18395   0.170370 25.056801 -0.159185                                            -
0.773514
18396   0.199422 24.435005 -0.159185
0.773514
18397   0.228460 24.712960 -0.159185
0.773514

                x54            x55              x56          x57          x58          x59
x60    \
0            -4.936434 -24.590146 18.515436     3.473400   0.033444    0.953219
0.006076                                        2.682933   0.033536    1.090502
1        -4.937179 -32.413266 22.760065
0.006083                                        3.537487   0.033629    1.840540
2        -4.937924 -34.183774 27.004663
0.006090                                        3.986095   0.033721    2.554880
3        -4.938669 -35.954281 21.672449         3.601573   0.033777    1.410494
0.006097
4        -4.939414 -37.724789 21.907251                  ...          ...          ...
0.006105               6.944644 -37.795661 -0.860218   0.010220
...                     ...
...                    0.507755 -39.357199 -0.915698   0.010620
18393    2.682413
                       2.809146 -39.357199 -1.409596   0.013323 0.895685   -
0.011242
18394   2.683338       2.164859 -39.357199 -0.860218   0.012888 0.175348   -
0.011235              1.416690 -39.357199 -0.732044   0.012453 0.621020   -
18395   2.684263
0.011228                                                        1.390902   -
18396   2.685189                                                0.418993 -
0.011221
18397   2.686114
0.011214

          y.1
0          0
1          0
2          0
```

```
3   4  ...      0
18393           0
18394          ...
18395           0
18396           0
18397           0
                0
               0

[18398 rows x 62 columns]

# Converting the excel data into the dataframe
# Why ?
	#1. DataFrames are designed for easy handling of structured data
(rows and columns), Handling missing data, Sorting data etc.
	#2. Pandas provides a wide range of built-in functions that are
optimized for DataFrame objects
df = pd.DataFrame(data)
df

                    time y        x1        x2        x3          x4
\
0       1999-05-01 00:00:00 0   0.376665 -4.596435 -4.095756   13.497687

1       1999-05-01 00:02:00 0   0.475720 -4.542502 -4.018359   16.230659

2       1999-05-01 00:04:00 0   0.363848 -4.681394 -4.353147   14.127997

3       1999-05-01 00:06:00 0   0.301590 -4.758934 -4.023612   13.161566

4       1999-05-01 00:08:00 0   0.265578 -4.749928 -4.333150   15.267340

...                      ... ..       ...       ...       ...         ...
18393 1999-05-28 23:58:00 0 -0.877441
                                    0.786430  0.406426  135.301215
18394 1999-05-29 00:00:00 0 -0.843988
                                    0.633086  0.561918  133.228949
18395 1999-05-29 00:02:00 0 -0.826547
                                    0.450126  0.334582  134.977973
18396 1999-05-29 00:04:00 0 -0.822843
                                    0.419383  0.387263  135.658942
18397 1999-05-29 00:06:00 0 -0.840981
                                    0.582710  0.593416  136.339880


           x5         x6        x7        x8 ...          x51
x52   \
0       -0.118830 -20.669883 0.000732 -0.061114 ... ...   29.984624
10.091721
                                                          29.984624
1     -0.128733 -18.758079 0.000732 -0.061114
10.095871
```

```
2        -0.138636 -17.836632 0.010803 -0.061114        ...  ...    29.984624
10.100265                                               ...  ...    29.984624
3        -0.148142 -18.517601 0.002075 -0.061114        ...  ...    29.984624
10.104660                                               ...  ...          ...
4        -0.155314 -17.505913 0.000732 -0.061114        ...         29.984624
10.109054                                                           29.984624
... ... 18393    ...          ...            ...         ...        29.984624
             0.112295 26.300392 -0.159185   0.058823                29.984624
                                            0.058823               29.984624  -
0.773514                                    0.048752                          -
18394   0.141332 25.678597 -0.159185        0.048752                          -
0.773514                                    0.048752                          -
18395   0.170370 25.056801 -0.159185                                          -
0.773514
18396   0.199422 24.435005 -0.159185
0.773514
18397   0.228460 24.712960 -0.159185
0.773514

              x54          x55          x56        x57       x58        x59
x60   \
0          -4.936434 -24.590146 18.515436    3.473400  0.033444   0.953219
0.006076                                     2.682933  0.033536   1.090502
1        -4.937179 -32.413266 22.760065
0.006083                                     3.537487  0.033629   1.840540
2        -4.937924 -34.183774 27.004663
0.006090                                     3.986095  0.033721   2.554880
3        -4.938669 -35.954281 21.672449      3.601573  0.033777   1.410494
0.006097
4        -4.939414 -37.724789 21.907251            ...        ...        ...
0.006105               6.944644 -37.795661 -0.860218  0.010220
...                ...
...                    0.507755 -39.357199 -0.915698  0.010620
18393    2.682413
                       2.809146 -39.357199 -1.409596  0.013323 0.895685  -
0.011242
18394   2.683338       2.164859 -39.357199 -0.860218  0.012888 0.175348  -
0.011235               1.416690 -39.357199 -0.732044  0.012453 0.621020  -
18395   2.684263
0.011228                                                       1.390902  -
18396   2.685189                                               0.418993 -
0.011221
18397   2.686114
0.011214

        y.1
0        0
1        0
2        0
3        0
```

```
4 0 ... ... 18393 0 18394 0 18395 0 18396 0
18397 0

[18398 rows x 62 columns]
```

Exploratory Data Analysis

```
#Analyzing Rows and Columns df.shape
```

```
(18398, 62)
```

```
#Information about non-null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18398 entries, 0 to 18397
Data columns (total 62 columns):

 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
0    time    18398 non-null  datetime64[ns]
 1   y       18398 non-null  int64
2    x1      18398 non-null  float64
3    x2      18398 non-null  float64
4    x3      18398 non-null  float64
5    x4      18398 non-null  float64
6    x5      18398 non-null  float64
7    x6      18398 non-null  float64
8    x7      18398 non-null  float64
9    x8      18398 non-null  float64
10   x9      18398 non-null  float64
11   x10     18398 non-null  float64
12   x11     18398 non-null  float64
13   x12     18398 non-null  float64
14   x13     18398 non-null  float64
15   x14     18398 non-null  float64
16   x15     18398 non-null  float64
17   x16     18398 non-null  float64
18   x17     18398 non-null  float64
19   x18     18398 non-null  float64
20   x19     18398 non-null  float64
21   x20     18398 non-null  float64
22   x21     18398 non-null  float64
23   x22     18398 non-null  float64
24   x23     18398 non-null  float64
```

```
  25  x24        18398     non-null  float64
  26  x25        18398     non-null  float64
  27  x26        18398     non-null  float64
  28  x27        18398     non-null  float64
  29  x28        18398     non-null  int64
  30  x29        18398     non-null  float64
  31  x30        18398     non-null  float64
  32  x31        18398     non-null  float64
  33  x32        18398     non-null  float64
  34  x33        18398     non-null  float64
  35  x34        18398     non-null  float64
  36  x35        18398     non-null  float64
  37  x36        18398     non-null  float64
  38  x37        18398     non-null  float64
  39  x38        18398     non-null  float64
  40  x39        18398     non-null  float64
  41  x40        18398     non-null  float64
  42  x41        18398     non-null  float64
  43  x42        18398     non-null  float64
  44  x43        18398     non-null  float64
  45  x44        18398     non-null  float64
  46  x45        18398     non-null  float64
  47  x46        18398     non-null  float64
  48  x47        18398     non-null  float64
  49  x48        18398     non-null  float64
  50  x49        18398     non-null  float64
  51  x50        18398     non-null  float64
  52  x51        18398     non-null  float64
  53  x52        18398     non-null  float64
  54  x54        18398     non-null  float64
  55  x55        18398     non-null  float64
  56  x56        18398     non-null  float64
  57  x57        18398     non-null  float64
  58  x58        18398     non-null  float64
  59  x59        18398     non-null  float64
  60  x60        18398     non-null  float64
 61   y.1        18398 non-null      int64
dtypes: datetime64[ns](1), float64(58), int64(3)
memory usage: 8.7 MB
```

```python
#Counting the no. of Null values for each column
df.isnull().sum()
```

```
time    0
y       0
x1      0
x2      0
x3      0
..
x57     0
```

```
x58      0
x59      0
x60      0
y.1      0
Length: 62, dtype: int64
```

```python
#Finding Duplicate values
print(df.duplicated())
```

```
0        False
1        False
2        False
3        False
4        False
         ...
18393    False
18394    False
18395    False
18396    False
18397    False
Length: 18398, dtype: bool
```

```python
#Dropping any duplicate values
df.drop_duplicates()
```

```
                     time y        x1        x2        x3          x4  \
0     1999-05-01 00:00:00 0  0.376665 -4.596435 -4.095756   13.497687
1     1999-05-01 00:02:00 0  0.475720 -4.542502 -4.018359   16.230659
2     1999-05-01 00:04:00 0  0.363848 -4.681394 -4.353147   14.127997
3     1999-05-01 00:06:00 0  0.301590 -4.758934 -4.023612   13.161566
4     1999-05-01 00:08:00 0  0.265578 -4.749928 -4.333150   15.267340
...                   ... ..       ...       ...       ...         ...
18393 1999-05-28 23:58:00 0 -0.877441  0.786430  0.406426  135.301215
18394 1999-05-29 00:00:00 0 -0.843988  0.633086  0.561918  133.228949
18395 1999-05-29 00:02:00 0 -0.826547  0.450126  0.334582  134.977973
18396 1999-05-29 00:04:00 0 -0.822843  0.419383  0.387263  135.658942
18397 1999-05-29 00:06:00 0 -0.840981  0.582710  0.593416  136.339880

            x5          x6        x7        x8  ...       x51
```

```
x52  \
0        -0.118830 -20.669883 0.000732 -0.061114          ...  ...    29.984624
10.091721                                                 ...  ...    29.984624
1        -0.128733 -18.758079 0.000732 -0.061114          ...  ...    29.984624
10.095871                                                 ...  ...    29.984624
2        -0.138636 -17.836632 0.010803 -0.061114          ...  ...    29.984624
10.100265                                                 ...               ...
3        -0.148142 -18.517601 0.002075 -0.061114                      29.984624
10.104660                                                             29.984624
4        -0.155314 -17.505913 0.000732 -0.061114                      29.984624
10.109054                                                             29.984624
... ... 18393    ...          ...          ...          ...          29.984624
               0.112295 26.300392 -0.159185    0.058823
                                               0.058823                       -
0.773514                                       0.048752                       -
18394   0.141332 25.678597 -0.159185           0.048752                       -
0.773514                                       0.048752                       -
18395   0.170370 25.056801 -0.159185                                          -
0.773514
18396   0.199422 24.435005 -0.159185
0.773514
18397   0.228460 24.712960 -0.159185
0.773514

              x54          x55            x56          x57          x58          x59
x60  \
0           -4.936434 -24.590146 18.515436    3.473400   0.033444   0.953219
0.006076                                      2.682933   0.033536   1.090502
1        -4.937179 -32.413266 22.760065
0.006083                                      3.537487   0.033629   1.840540
2        -4.937924 -34.183774 27.004663
0.006090                                      3.986095   0.033721   2.554880
3        -4.938669 -35.954281 21.672449      3.601573   0.033777   1.410494
0.006097
4        -4.939414 -37.724789 21.907251              ...          ...          ...
0.006105               6.944644 -37.795661 -0.860218   0.010220
...                 ...
...                    0.507755 -39.357199 -0.915698   0.010620
18393     2.682413
                       2.809146 -39.357199 -1.409596   0.013323 0.895685  -
0.011242               2.164859 -39.357199 -0.860218   0.012888 0.175348  -
18394   2.683338
0.011235               1.416690 -39.357199 -0.732044   0.012453 0.621020  -
18395   2.684263
0.011228                                                        1.390902  -
18396   2.685189                                                0.418993 -
0.011221
18397   2.686114
0.011214
```

```
              y.1
0 1 2 3        0
4      ...     0
18393          0
18394          0
18395          0
18396         ...
18397          0
               0
               0
               0
              0

[18398 rows x 62 columns]
```

```python
#Counting Unique value in each column
print(df.nunique())
```

```
time       18398
y              2
x1         14091
x2         15768
x3         16615
              ...
x57         1112
x58        13025
x59        12225
x60        10800
y.1            2
Length: 62, dtype: int64
```

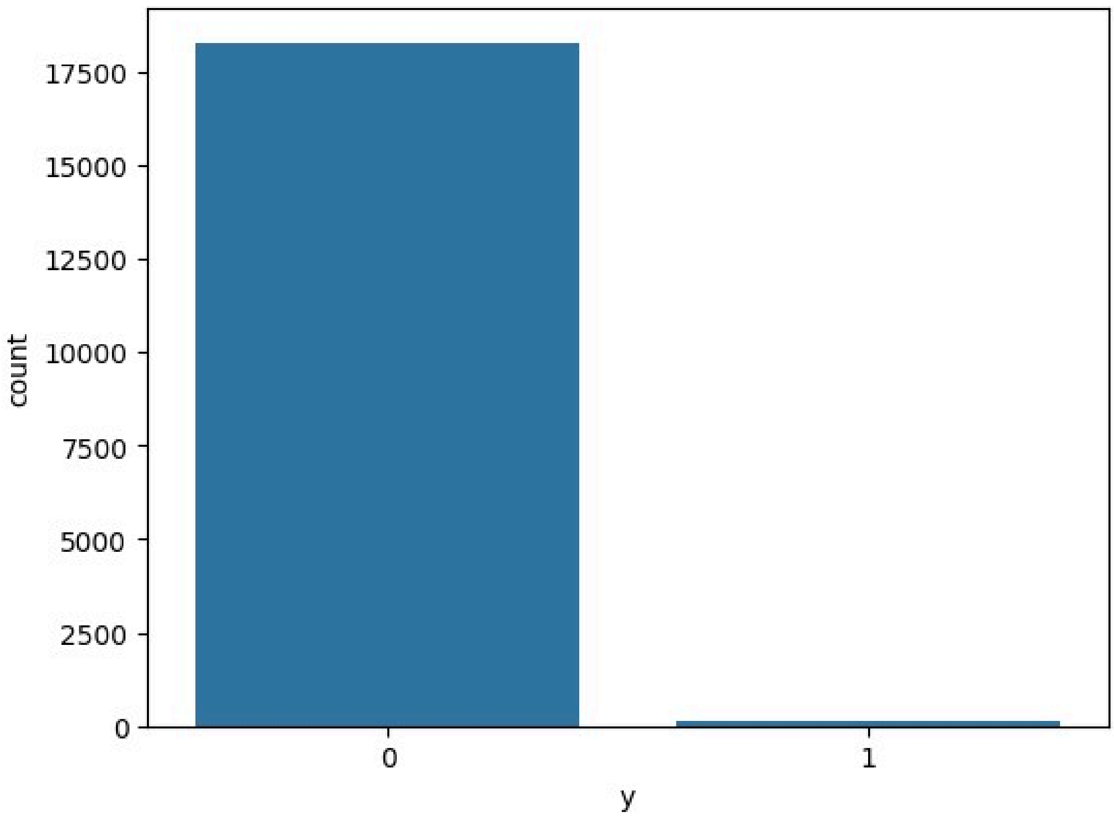
```python
### Seperating Input and Output columns
X = df.drop(['y','time'],axis = 1)
Y = df['y']
```

```python
##Zeroes and ones count in column 'y'
df['y'].value_counts()
```

```
y
0       18274
1         124
Name: count, dtype: int64
```

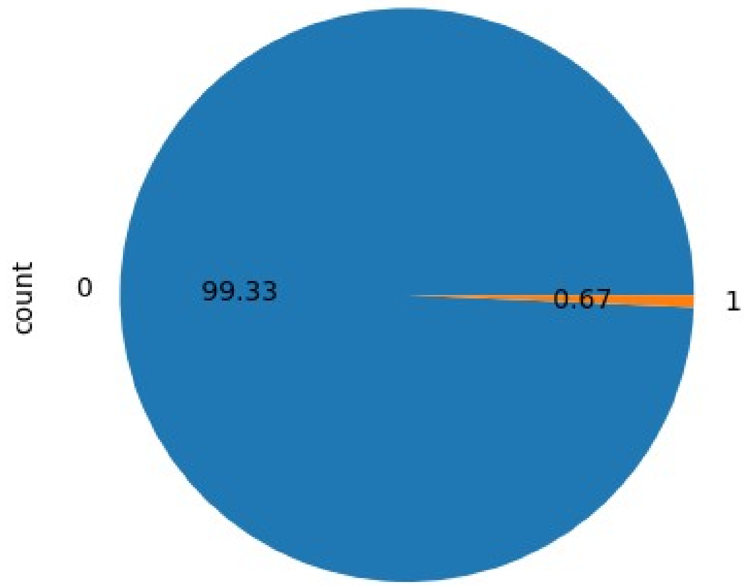
```python
# Representing Zeroes and ones count in bar chart
sns.countplot(x ='y',data = df)
```

```
<Axes: xlabel='y', ylabel='count'>
```




```
#Representing Zeroes and ones count in pie plot
df['y'].value_counts().plot.pie(autopct = '% .2f')
```

```
<Axes: ylabel='count'>
```




```python
# % of ones' count in the dataset
print(f"{124/18274*100 :.3f} %")
```

```
0.679 %
```

Data is extremely imbalanced

Percentage of data belonging to minority class	Degree of imbalance
20-40% of the dataset	Mild
1-20% of the dataset	Moderate
<1% of the dataset	Extreme

```
# Now Install library which will help to balance the dataset !pip install -U imbalanced-learn
```

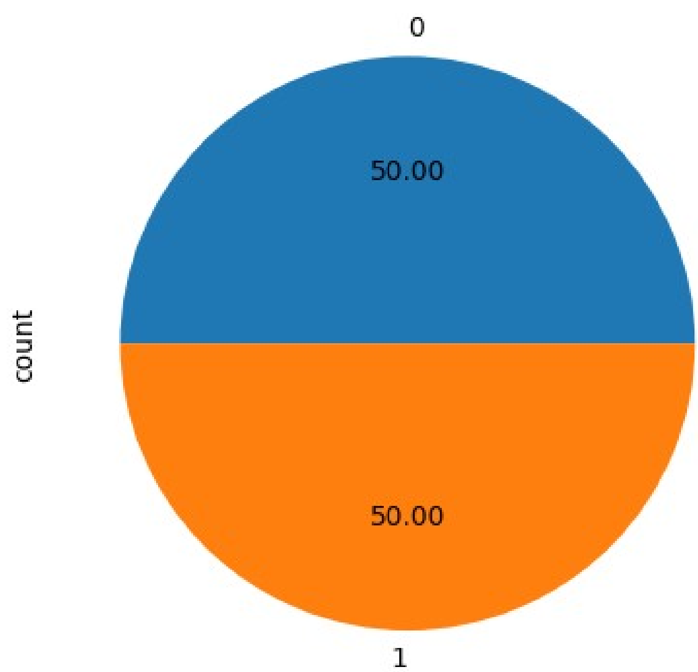
```
Requirement already satisfied: imbalanced-learn in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (0.12.4)
Requirement already satisfied: numpy>=1.17.3 in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (from imbalanced-learn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (from imbalanced-learn) (1.14.1)
```

```
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (from imbalanced-learn) (1.5.2) Requirement already satisfied: joblib>=1.1.1 in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (from imbalanced-learn) (1.4.2) Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\Eshteyaque.Ahmad\appdata\local\anaconda3\envs\eshteyaque\lib\site-packages (from imbalanced-learn) (3.5.0)
```

```python
""" We will use Oversampling technique - SMOTE, to balance the dataset
which will scale up the minority classes to match up with the majority
class """
```

```
' We will use Oversampling technique - SMOTE, to balance the dataset
which will scale up the minority classes to match up with the majority
class '
```

```python
from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_res, Y_res = sm.fit_resample(X, Y)
ax = Y_res.value_counts().plot.pie(autopct='%.2f')
```




```python
X_res
```

	x1	x2	x3	x4	x5	x6 \
0	0.376665	-4.596435	-4.095756	13.497687	-0.118830	-20.669883
1	0.475720	-4.542502	-4.018359	16.230659	-0.128733	-18.758079
2	0.363848	-4.681394	-4.353147	14.127997	-0.138636	-17.836632
3	0.301590	-4.758934	-4.023612	13.161566	-0.148142	-18.517601
4	0.265578	-4.749928	-4.333150	15.267340	-0.155314	-17.505913
...	...	...	...	...	...	...
36543	0.123190	-5.907143	-5.243223	...	0.050505	-20.217502
36544	1.713375	-0.701378	-9.644510	-70.876037 35.501460	-0.492367	-80.683381
36545	-0.613582	-1.478861	-1.963563			9.743904
36546	-0.325275	-9.779309	-11.727837	145.395851	-0.103702	36.268184
36547	-0.301383	0.568078	-9.652514	89.769610 -88.446607	0.062049 -0.123511	-64.649525

	x7	x8	x9	x10	...	x51	x52 \
0	0.000732	-0.061114	-0.059966	-0.038189	...	29.984624	10.091721
1	0.000732	-0.061114	-0.059966	-0.038189	...	29.984624	10.095871
2	0.010803	-0.061114	-0.030057	-0.018352	...	29.984624	10.100265
3	0.002075	-0.061114	-0.019986	-0.008280	...	29.984624	10.104660
4	0.000732	-0.061114	-0.030057	-0.008280	...	29.984624	10.109054
...	...	...	...	...	...	...	...
36543	0.208618	0.089437	-0.058252	-0.009017	...	31.469783	0.886796
36544	0.095394	0.018844	0.072664	0.034269	...	29.984624	-4.665145
36545	0.005235	0.023728	-0.110563	-0.078383	...	29.984624	-1.272212
36546	-0.059389	-0.037282	-0.001641	-0.031279	...	31.309173	0.481610
36547	-0.001525	-0.085744	-0.049731	-0.035550	...	29.554408	-1.780379

	x54	x55	x56	x57	x58	x59

```
\
0           -4.936434 -24.590146   18.515436  3.473400  0.033444  0.953219
1           -4.937179 -32.413266   22.760065  2.682933  0.033536  1.090502
2           -4.937924 -34.183774   27.004663  3.537487  0.033629  1.840540
3           -4.938669 -35.954281   21.672449  3.986095  0.033721  2.554880
4           -4.939414 -37.724789   21.907251  3.601573  0.033777  1.410494
...               ...        ...         ...       ...       ...       ...
36543        1.348418 147.223957  -46.214293  1.460570 -0.100675  0.989833
36544 -5.850424 -87.113012 -117.867780 -2.174484      0.030733  0.512385
-40.410241 -0.712796                                  0.021017  3.595538
36545        1.887315 -34.705985
61.291453 -0.140618                                   0.015123  3.079882
36546 -4.983965 -39.008923
-71.361523 -1.177984                                  0.016106  2.684745
36547 -3.012029 -28.471037

                 x60 y.1
0         0.006076    0
1         0.006083    0
2         0.006090    0
3         0.006097    0
4         0.006105    0
...            ...  ...
36543     0.000255    0
36544     0.000855    0
36545     0.006391    0
36546     0.010029    0
36547     0.007003    0

[36548 rows x 60 columns]
```

Y_res

```
0        0
1        0
2        0
3        0
4        0
        ..
36543    1
36544    1
36545    1
36546    1
```

```
36547    1
Name: y, Length: 36548, dtype: int64
```

```
Y_res.value_counts()
```

```
y
0    18274
1    18274
Name: count, dtype: int64
```

Data Splitting

```
# Splitting the data into training and testing dataset
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X_res, Y_res,
test_size = 0.2, random_state=123)
X_train
```

```
\
          x1         x2                    x4        x53        x6
15236
                          0.340190.5954281 17.375912 -9.557884
3467
       0.112985 -1.955501 -3.326003 -112.113960 -0.016917   6.881905
8732
                                  193.899542 -0.272105  -16.111809
15750   0.299043 -2.908362 -6.682374
                                  189.186743 -0.243647  22.860329
24044 -0.090887614.5572300-49.885.0134918
                                             0.097490   32.608301
...                              218.398094
                                               ...         ...
-0.509073 1.612657 -4.989895                ...
                                  244.561713 -0.687235  26.937905
7763 0.421222 -1.813448 -6.310049
                                  187.502356 -0.000941  -13.812401
15897 0.069523 2.977344 3.374720
                                             0.078710   36.687660
17780 1.484900 -3.953427 -9.692695       56.548499
                                  -23.532758 -0.203797 -128.292789
28030 0.708519 2.901412 -6.339217
                                                        24.198830
15725                            193.932379   0.194051
```

```
          x7         x8         x9        x10 ...        x51
x52
15236   0.020874 -0.005866 -0.049021 -0.048260 ... ...  29.984624 -
3.128250                                                 29.984624
3467   -0.069155 -0.031206 -0.070037 -0.068402
```

```
4.131131
8732     0.130741 -0.081257 -0.070037 -0.078168        ...  ...  28.660161
0.294846                                               ...  ...  29.984624   -
15750 -0.019409 0.008773 -0.000149         0.001791    ...  ...  29.984624 ...
10.099442                                              ...  ...  29.984624
24044 -0.016794 0.027563 -0.018847 -0.052779           ...       29.984624   -
6.906621                                                         29.931645
...                 ...              ...             ...         ...  29.984624   .
..                 0.090558 0.202372 -0.095656 -0.075637         29.984624
7763
4.262131
15377 -0.049319 -0.061114 -0.040129 -0.058331                                -
3.753738                                                                     -
17730 -0.039246 0.008773 -0.040129 -0.002573                                 -
1.689041                                                                     -
28030   0.075331 0.001054 0.245567         0.003837
7.755202                                   0.171779
15725 -0.019409 -0.011064 0.049901
9.184891

                 x54           x55            x56           x57          x58
x59   \
   15236 -4.951394 -67.547421    15.551843 -2.047413     0.009474    0.150034
3467        0.626401 30.327945   94.529779    2.972911     0.029428    0.338144
8732       -4.904975 -57.939633   32.866907    1.642284     0.011228    1.421931
         15750 -4.972492 -96.391781 -51.338217 -3.149097 -0.005344    0.021227
         24044 -4.841939 -87.818713 -39.707157 -3.459498 -0.006421    0.479616
...                 ...               ...           ...         ...       ...       ...
7763       -4.982663 -20.718075     68.139123   2.222118     0.014912    1.160845
15377 -4.941107 -66.666318 -51.538504 -1.775807              0.016013    1.632204
17730   1.343881 75.917057                                   0.013303    0.180338
28030 -4.918541 -75.584446 -150.120545 -1.862119             0.015198    0.878159
          15725 -4.935096 -94.496762 -50.603201 -3.622180 -0.010034 -0.047285


                   x60 y.1
15236     0.003592     0
3467      0.006674     0
8732     -0.001253     0
  15750 -0.000550      0
```

```
24044 -0.000550        0
...                  ... ...
7763     -0.001995     0
15377     0.008914     0
17730 -0.006130        0
28030  0.003315        0
15725 -0.000550        0

[29238 rows x 60 columns]
```

Y_train

```
18609    1
21881    1
6061     0
17156    0
13041    0
         ..
7763     0
15377    0
17730    0
28030    1
15725    0
Name: y, Length: 25583, dtype: int64
```

Feature Engineering

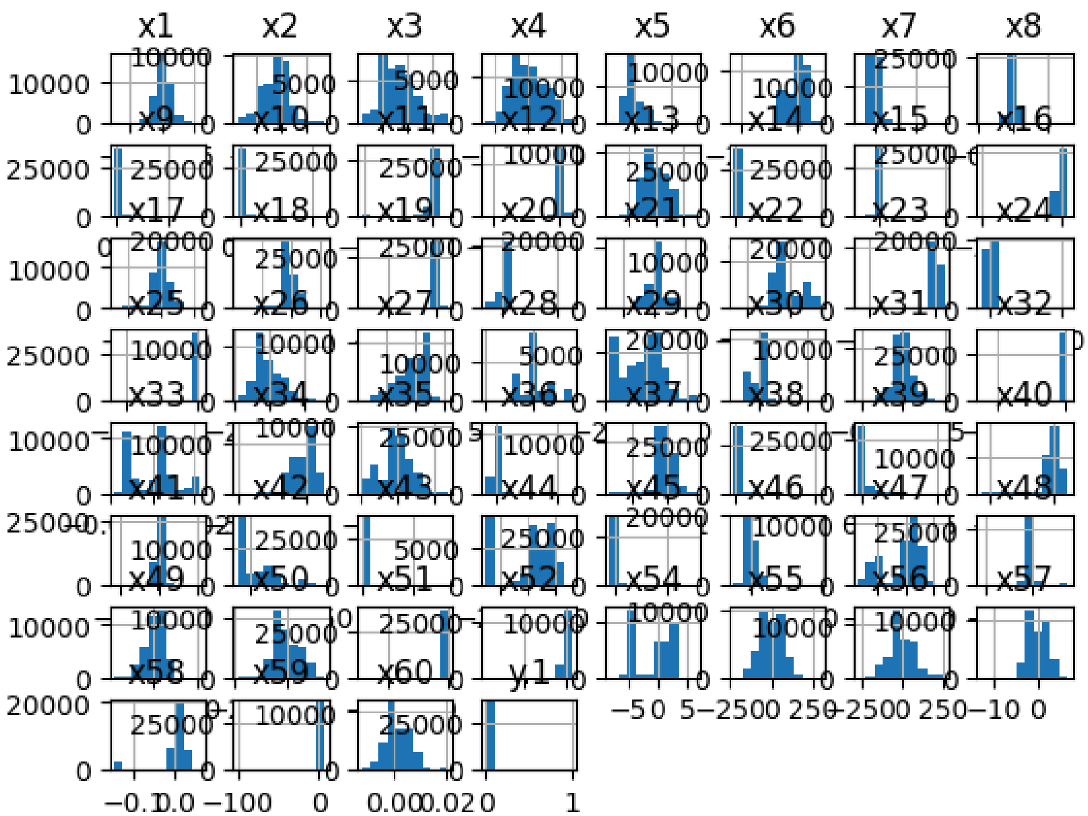
```
#Will convert raw data to useful features for ML model #success of a ML model largely depends on the quality of the features used in the model.

# Extracting all numeric features in one variable
num_cols = X_res._get_numeric_data().columns
num_cols
```

```
Index(['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9', 'x10',
'x11',
'x21',   'x12', 'x13', 'x14', 'x15', 'x16', 'x17', 'x18', 'x19', 'x20', 'x22', 'x23', 'x24', 'x25',
         'x26', 'x27', 'x28', 'x29', 'x30', 'x32', 'x33', 'x34', 'x35', 'x36', 'x37', 'x38', 'x39',
'x31',
         'x40', 'x42', 'x43', 'x44', 'x45', 'x46', 'x47', 'x48', 'x49', 'x50', 'x52', 'x54', 'x55',
'x41',   'x56', 'x57', 'x58', 'x59', 'x60', 'y.1'],
'x51',

      dtype='object')
```

```python
# Plot the histograms
X_res[num_cols].hist(bins=10)
```

```
array([[<Axes: title={'center': 'x1'}>, <Axes: title={'center':
'x2'}>,
        <Axes: title={'center': 'x3'}>, <Axes: title={'center': <Axes: title=
'x4'}>, {'center': 'x5'}>, <Axes: title={'center': <Axes: title={'center': 'x7'}>,
'x6'}>, <Axes: title={'center':

'x8'}>],
       [<Axes: title={'center': 'x9'}>, <Axes: title={'center':
'x10'}>,
        <Axes: title={'center': 'x11'}>, <Axes: title={'center': <Axes: title=
'x12'}>, {'center': 'x13'}>, <Axes: title={'center': <Axes: title={'center': 'x15'}>,
'x14'}>, <Axes: title={'center':

'x16'}>],
       [<Axes: title={'center': 'x17'}>, <Axes: title={'center':
'x18'}>,
        <Axes: title={'center': 'x19'}>, <Axes: title={'center': <Axes: title=
'x20'}>, {'center': 'x21'}>, <Axes: title={'center': <Axes: title={'center': 'x23'}>,
'x22'}>, <Axes: title={'center':

'x24'}>],
       [<Axes: title={'center': 'x25'}>, <Axes: title={'center':
'x26'}>,
        <Axes: title={'center': 'x27'}>, <Axes: title={'center': <Axes: title=
'x28'}>, {'center': 'x29'}>, <Axes: title={'center': <Axes: title={'center': 'x31'}>,
'x30'}>, <Axes: title={'center':

'x32'}>],
       [<Axes: title={'center': 'x33'}>, <Axes: title={'center':
'x34'}>,
        <Axes: title={'center': 'x35'}>, <Axes: title={'center': <Axes: title=
'x36'}>, {'center': 'x37'}>, <Axes: title={'center': <Axes: title={'center': 'x39'}>,
'x38'}>, <Axes: title={'center':

'x40'}>],
       [<Axes: title={'center': 'x41'}>, <Axes: title={'center':
'x42'}>,
        <Axes: title={'center': 'x43'}>, <Axes: title={'center': <Axes: title=
'x44'}>, {'center': 'x45'}>, <Axes: title={'center': <Axes: title={'center': 'x47'}>,
'x46'}>, <Axes: title={'center':
```

```
'x48'}>],
          [<Axes: title={'center': 'x49'}>, <Axes: title={'center':
'x50'}>,
           <Axes:  title={'center':  'x51'}>,  <Axes:  title={'center':  <Axes:  title=
'x52'}>,   {'center': 'x54'}>, <Axes: title={'center': <Axes: title={'center': 'x56'}>,
           <Axes: title={'center':
'x55'}>,

'x57'}>],
          [<Axes: title={'center': 'x58'}>, <Axes: title={'center':
'x59'}>,
           <Axes: title={'center': 'x60'}>, <Axes: title={'center':
'y.1'}>,   <Axes: >, <Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



Dimensionality reduction - Principal Componenet analysis

Basically Reducing the number of features by transforming the data into a lower-dimensional space while retaining important information.

```
#Observing correlation b/w all features
X_train[num_cols].corr()
```

x1 x2 x3 x4 x5 x6
x7 \ x1 1.000000 0.084069 -0.105779 0.163079 -0.025989 -0.174184
0.206807

x2 0.084069 1.000000 0.521845 -0.060098 0.053239 - 0.111763
0.105085 0.309316 - 1.000000
x3 -0.105779 0.521845 1.000000 -0.200288 -0.028036 -0.068325 - 1.000000 -
0.053907
x4 0.163079 -0.060098 -0.200288 1.000000 0.087118
0.007755 0.309316 -0.068325
x5 -0.025989 0.053239 -0.028036
0.041858
x6 -0.174184 0.003550 0.111763
0.185740
x7 0.206807 -0.105085 0.053907 -0.007755 -0.041858 -0.185740
1.000000
x8 0.164196 0.170058 0.088091 0.063350 0.224671 0.064808
0.417490 0.088119 -0.112473
x9 0.007810 -0.087101 -0.058924 -0.008695 0.104906 -0.082165
0.305754 0.071768
x10 0.000231 -0.013258 0.026922 -0.062910 0.090622
0.129676 0.667859 -
x11 0.320249 0.266533 0.207619 0.004112 -0.059185
0.210842 0.059572
x12 0.428606 0.245025 0.189053 -0.026607 0.177492 -0.080192
0.309224
x13 0.014091 -0.063304 -0.011347
0.022321
x14 0.145603 0.049442 0.013414 -0.130440 -0.173737 -0.000178
0.012144
x15 -0.036054 -0.083182 -0.023861 -0.153299 0.064212 -0.237913 -
0.093415 0.020649 -0.047121
x16 0.339653 0.250920 0.255780 -0.081105
0.251208
x17 0.050072 0.323387 0.107934 0.116949 0.146184 - 0.152054 -
0.192899 0.148363 0.324581 0.017039
x18 0.081340 0.327707 0.113617 0.194335 -0.113567
0.239691
x19 -0.103546 0.073601 0.121728 -0.005982 -0.193920
0.034020
x20 0.014971 -0.073041 -0.034480 -0.065070 -0.151415
0.159769
x21 0.250143 0.057564 -0.181906 0.214502
0.042947 0.181531
x22 0.100446 0.222220 -0.014500 0.098037 0.566459 0.040472 -
0.138232 0.306208 0.140359
x23 -0.075332 0.004249 0.010131
0.068384
x24 -0.117655 -0.048825 0.021131 0.010696 -0.190925 -0.143766 -
0.099946

x25 0.354985 0.169349 0.165143 -0.041633 -0.019531 -0.109918
0.315253
x26 -0.126878 0.014028 0.237707 -0.275519 -0.034688 0.092735
0.096636 0.191164
x27 -0.033811 0.072479 0.187933 -0.097783 0.002436 0.023218 -
0.055576 0.072629 0.371444 -
x28 -0.225437 -0.098550 0.268833 -0.033342 0.045342
0.016594
x29 -0.355779 0.054562 0.356976 -0.603911
0.136738
x30 -0.145379 -0.188276 0.103788 -0.217991 -0.604530 -0.027546
0.140615
x31 0.010293 0.105333 0.086008 0.071137 -0.034827 0.099671 -
0.032405
x32 0.388889 0.204339 0.166043 0.007985 -0.023205 -0.058750
0.293818
x33 -0.291524 -0.208444 0.135354 -0.321745 -0.432638 -0.087390
0.067388
x34 -0.250226 -0.018225 0.137856 0.264800 -0.086218 0.967869 -
0.223604
x35 -0.038592 -0.088866 0.149440 -0.323515 -0.263395 -0.164077
0.098228
x36 0.029763 -0.010939 0.401174 -0.168193 0.106319 0.092242
0.518706 0.397789 0.169903
x37 0.184506 0.224059 0.241953 -0.010991 0.055504 -0.097919
0.139277 0.049226 -0.051425
x38 0.006614 -0.092014 -0.028417 -0.007408 0.059833
0.291839 0.029249 -0.063147
x39 0.031982 -0.055870 -0.026558 -0.021551 0.089733 -0.248708
0.116548 0.205902 -0.033896 -
x40 0.123050 0.204192 0.266117 -0.184548 0.118877
0.162333
x41 0.049128 -0.013641 -0.039084 0.026326
0.021674 0.011934
x42 0.170231 0.072263 -0.140190 0.041439
0.136795
x43 -0.048023 0.056959 0.067263
0.010286
x44 -0.213603 -0.143747 0.086158 -0.483883 -0.236929 -0.162198
0.153753
x45 -0.348889 -0.221391 -0.142414 0.027515 -0.011268 0.029843 -
0.207878
x46 0.042921 -0.206694 -0.020279 0.124609 -0.094658 -0.086779
0.244275 0.292972
x47 0.160704 0.119619 0.017012 0.138110 [illegible] -0.016863
0.072692 0.059263 -0.437601 0.022677
x48 0.244082 -0.123402 -0.057050
0.196465
x49 0.019593 -0.170183 -0.039402
0.192068

```
x50   0.134269 0.061094 0.019675 -0.275122 -0.358936        0.008763 -
0.043239
x51   0.372485 0.189591 0.153676            0.002815 -0.000060 -0.061855
0.286642                                    0.067635
x52   0.063473 0.076846 0.064336 -0.103462 -0.285335
                                    0.250196 -
0.018765                                    0.210419 -
x54 -0.365939 0.127888 0.429812 -0.467034
                                    0.572087 -  0.159760
0.158177                                    0.043529    0.195624
x55 -0.182015 0.118343 0.071921 -0.283370
0.003098
x56 -0.034292 0.045621 0.050182 -0.047020 -0.337245
0.154005
x57   0.186036 -0.018981 0.000267 -0.106942 -0.416979
0.067389
x58   0.062366 0.161531 -0.241157        0.014033 -0.042278 -0.146758 -
0.342651
x59   0.351140 0.182400 0.166398 -0.009013 -0.011512 -0.083605
0.289545
x60 -0.175277 -0.145551 -0.060453 -0.324576        0.023247     -0.398500
0.120603                                            0.119758 -0.125980
y.1 -0.051528 -0.158613 -0.147230 -0.084354
0.160705

              x8          x9         x10   ...          x51        x52
x54   \
x1    0.164196 0.007810 0.000231    ...     0.372485     0.063473 -0.365939
x2    0.170058 -0.087101 -0.013258  ...     0.189591  0.076846     0.127888
x3    0.088091 -0.058924 0.026922   ...     0.153676  0.064336     0.429812
x4    0.063350 -0.008695 -0.062910  ...       0.002815 -0.103462 -0.467034
x5    0.224671 0.088119 0.104906    ... -0.000060 -0.285335        0.159760
x6    0.064808 -0.112473 -0.082165  ... -0.061855                  0.250196
                                    0.067635
x7    0.417490 0.305754 0.129676    ...                   0.018765 -0.158177
                                    0.286642
x8    1.000000 0.054682 0.084748    ...                            0.183303
                                    0.381006 -0.104123
x9    0.054682 1.000000 0.623213    ...     0.053660 -0.046796 -0.055306
x10   0.084748 0.623213 1.000000    ...     0.067390 -0.039241     0.071604
x11   0.290835 0.050497 0.054981    ...     0.491499    0.050085   0.015080
x12   0.525598 0.054003 0.103940    ...     0.786865    0.064981   0.097660
x13 -0.010814 -0.082140 -0.072492   ... -0.059703       0.234750 -0.004515
```

x14 -0.011147 -0.026306 -0.025038 ... 0.013041 0.127976 -0.031930 x15 -0.134794 0.038151 0.006471 ... -0.001058 -0.048362 0.046950 x16 0.443987 0.012746 0.085831 ... 0.803574 0.007357 0.198592 x17 0.094280 -0.094052 0.024152 ... -0.016968 0.014475 0.142548 x18 0.075986 -0.115021 -0.016863 ... -0.039415 0.117424 0.144883 x19 -0.060798 -0.171601 -0.011407 ... 0.003066 0.110315 -0.012959 x20 -0.091784 0.252598 0.214279 ... 0.012938 0.078401 0.030746 x21 0.198948 -0.043518 -0.035521 ... 0.034520 -0.244845 -0.184157 x22 0.330107 -0.020311 0.062431 ... -0.007581 -0.291862 0.211410 x23 0.164155 -0.002448 0.093070 ... 0.000498 -0.267033 0.177342 x24 -0.123213 0.076803 -0.079980 ... -0.030638 -0.291327 -0.072906 x25 0.358927 0.055546 0.075390 ... 0.922441 0.061714 -0.065007 x26 0.126905 -0.040943 0.068967 ... 0.011307 0.051549 0.513467 x27 0.156947 -0.067218 0.070485 ... -0.004076 -0.046091 0.544594 x28 0.029582 -0.030765 0.023507 ... 0.004319 -0.169310 0.383947 x29 0.090017 -0.075062 0.019028 ... -0.055557 -0.015076 0.801815 x30 -0.335454 -0.030024 -0.085533 ... 0.019464 0.330261 -0.165822 x31 -0.031196 -0.022835 -0.053922 ... 0.006695 0.016740 0.019551 x32 0.383546 0.048066 0.066471 ... 0.930353 0.049949 -0.062486 x33 -0.303485 -0.048883 -0.065796 ... 0.024437 0.259457 -0.059335 x34 0.009224 -0.113706 -0.087405 ... -0.060816 0.105932 0.274402 x35 -0.064917 -0.113463 -0.017757 ... 0.077740 0.184269 0.121565 x36 0.358481 0.133217 0.130591 ... 0.269864 -0.087199 0.473111 x37 0.693164 -0.015669 0.081525 ... 0.455623 -0.142176 0.467503 x38 0.083042 0.765825 0.401966 ... 0.054277 -0.029996 -0.063736 x39 0.116466 0.356443 0.673197 ... 0.068700 -0.006022 0.022128

x40	0.335660	0.014510	0.0871[illegible]	...	...	0.452826	-0.004302	0.365446
x41	0.042574	-0.024395	0.0464[illegible]	...	...	0.004772	-0.064031	-0.085608
x42	0.161205	0.090080	0.0687[illegible]	...		0.034360	-0.220459	-0.123855
x43	0.039901	-0.016504	-0.0071[illegible]			0.008495	-0.004159	0.117603
x44	-0.223854	-0.004185	0.003153			0.079299	0.254257	0.001486
x45	-0.390553	-0.027371	-0.059030		...	-0.890010	-0.027871	-0.013835
x46	-0.029629	0.029632	-0.039068	...		0.022119	0.010894	-0.189148
x47	0.342790	0.042664	0.113220	...		-0.020322	-0.089631	0.334569
x48	-0.017780	0.076556	-0.025999	...	...	0.004677 ...	0.115783 -0.046100	-0.287198
x49	-0.192752	-0.046775	-0.136604	-0.115684		[illegible]	0.283265	-0.313285
x50	-0.181244	-0.171232	-0.048931			0.039721	0.560490	-0.104824
x51	0.381006	0.053660	0.067390			1.000000	0.018709	-0.046100
x52	-0.104123	-0.046796	-0.039241			0.018709	1.000000	-0.115684
x54	0.183303	-0.055306	0.071604					1.000000
x55	0.291674	0.031043	0.127447		...	-0.029572		0.548485
x56	-0.175460	-0.085944	-0.087521		...	-0.025544	0.319665	-0.001489
x57	-0.173570	-0.168036	-0.083554	...		0.046344	0.537975	-0.243889
x58	-0.142560	-0.164641	-0.169038		...	-0.017314	0.074990	-0.291449
x59	0.379018	0.058884	0.066013	...	...	0.924150	0.027308	-0.062852
x60	-0.131704	0.041663	0.044417	...		0.063602	0.061383	-0.123407
y.1	0.069936	0.222279	0.085825			0.009521	-0.187576	-0.014380

	x55	x56	x57	x58	x59	x60	
y.1							
x1	-0.182015	-0.034292	0.186036	0.062366	0.351140	-0.175277	-0.051528
x2	0.118343	0.045621	-0.018981	0.161531	0.182400	-0.145551	-0.158613
x3	0.071921	0.050182	0.000267	-0.241157	0.166398	-0.060453	-0.147230

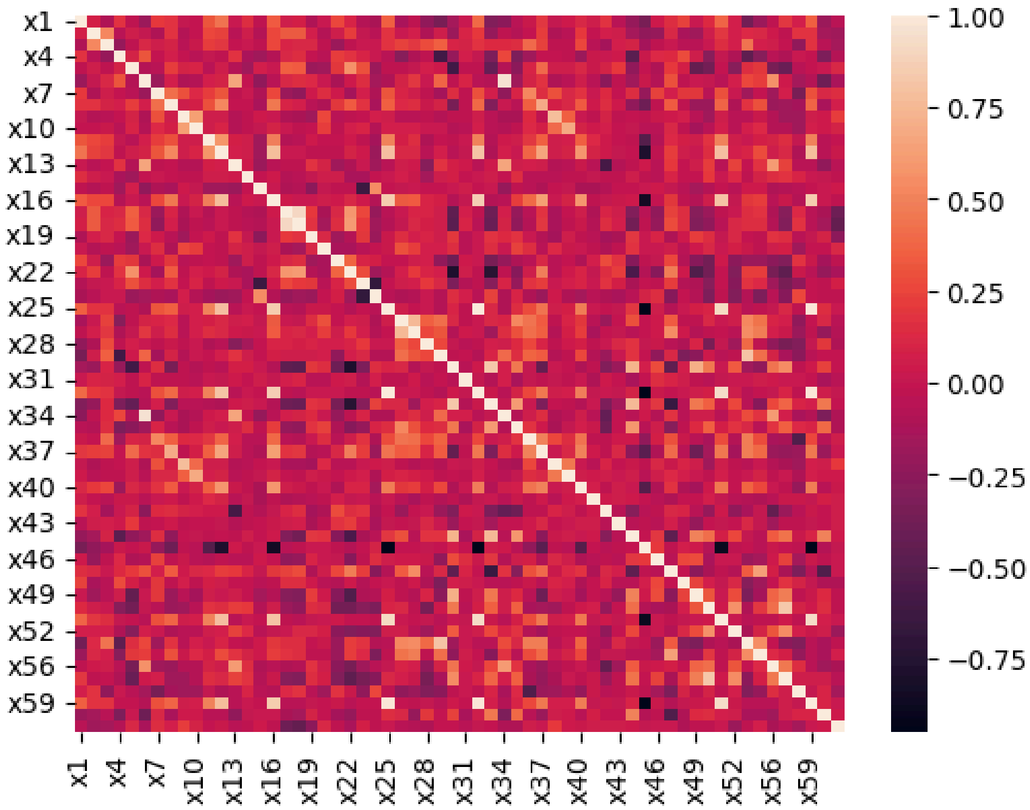
x4 -0.283370 -0.047020 -0.106942 0.014033 -0.009013 -0.324576 -
0.084354
x5 0.195624 -0.337245 -0.416979 -0.042278 -0.011512 0.023247
0.119758
x6 0.210419 0.572087 0.043529 -0.146758 -0.083605 -0.398500 -
0.125980
x7 -0.003098 -0.154005 0.067389 -0.342651 0.289545 0.120603
0.160705 0.379018 -0.131704
x8 0.291674 -0.175460 -0.173570 -0.142560 0.041663
0.069936 0.044417
x9 0.031043 -0.085944 -0.168036 -0.164641 0.058884
0.222279 0.066013
x10 0.127447 -0.087521 -0.083554 -0.169038
0.085825
x11 0.082135 0.085998 0.156182 0.007240 0.490636 -0.052056 -
0.001547 0.786132 -0.052224
x12 0.269005 0.057399 0.110558 -0.103582
0.029879
x13 0.178890 0.605483 0.238720 -0.058988 -0.065637 -0.239735 -
0.064467
x14 0.090877 0.140848 0.183529 [illegible] - 0.010752
0.021963 0.017537
x15 0.045139 -0.090591 -0.090070 [illegible] 0.002769
0.045821 0.129937 -0.044476 -0.117180 -
x16 0.217869 -0.039012 0.030577 [illegible] -0.146219 -
0.019926 0.091063 -
x17 0.171025 -0.101337 -0.279541 0.000261
0.399310
x18 0.144260 -0.081619 -0.305192
0.436355
x19 -0.028375 0.165336 0.151449 -0.047569 0.007148
0.256022
x20 -0.014645 0.058310 0.081878 -0.172903 -0.003189
0.120473
x21 -0.181867 -0.255696 -0.297027 0.180442 0.028349 -0.141292 -
0.027083 0.025962 -0.044263 -0.215280 -
x22 0.223985 -0.341842 -0.466326
0.134504
x23 0.129072 -0.160297 -0.334252 -0.233377 -0.012237 -0.024053
0.083527
x24 -0.333829 -0.042308 -0.268046 0.259437 -0.012956 -0.036271 -
0.036701
x25 -0.020787 0.001700 0.119576 -0.016771 0.988968 0.148081
0.018361 0.000762 0.110648 -
x26 0.421020 0.097478 0.072004 -0.221604
0.053731
x27 0.477857 0.071358 0.029206 -0.195111 -0.032318 -0.210280 -
0.085124
x28 -0.013892 -0.226716 -0.335661 -0.289299 0.008185 0.194042 -
0.102578

x29 0.419014 0.092074 -0.132074 -0.243121 -0.064137 -0.002107 -
0.001569
x30 -0.230699 0.434090 0.545362 -0.031721 0.045274 0.235431 -
0.001771 0.023608 -0.005124 -0.132893 -
x31 0.060473 0.046751 0.024088
0.053024
x32 -0.008163 0.005395 0.099245 -0.016853 0.991002 0.054479
0.008068 0.075821 0.447921 -
x33 -0.269966 0.265064 0.373454 0.103329
0.007298
x34 0.180294 0.605800 0.076459 -0.129058 -0.078073 -0.327000 -
0.111284
x35 -0.064795 0.171000 0.350463 0.125916 0.101222 0.384607 -
0.103372
x36 0.277621 -0.122127 -0.119594 -0.539611 0.262133 -0.061030
0.060406 0.455697 -0.176571
x37 0.384038 -0.182399 -0.215887 -0.177817 0.057358
0.024127 0.041439
x38 0.019173 -0.071275 -0.113096 -0.154447 [illegible] -0.051925
0.203679 0.066431 0.080686
x39 0.086571 -0.022208 0.016623 -0.111179 0.026783 -0.012778
0.041757 0.002485 -0.009164
x40 0.264165 0.012409 -0.036151 -0.201568 0.489931
0.028963
x41 -0.093318 -0.060674 0.028081 0.029110 0.004881
0.056631
x42 0.006569 -0.434727 -0.187898 -0.045558
0.062176
x43 0.004460 -0.162864 -0.033873 -0.027297
0.051532
x44 -0.055312 0.330996 0.425781 0.028908 0.104252
0.041074
x45 -0.057850 0.030890 -0.000098 -0.028042 -0.947100 -0.070187
0.005229
x46 -0.148149 0.039551 0.242155 -0.144471 0.026767 -0.033001
0.021510
x47 0.647607 0.081878 -0.114531 -0.315054 -0.076627 -0.533136
0.009289
x48 -0.152061 -0.011870 0.172929 0.092620 0.002689 -0.103130 -
0.090816 0.137015 -
x49 -0.136331 0.381148 0.469330 -0.032198 [illegible] -
0.024065 [illegible]
x50 0.189267 0.410046 0.828841 0.087008 [illegible] -
0.030883 0.027308
x51 -0.029572 -0.025544 0.046344 -0.017314
0.009521
x52 0.089787 0.319665 0.537975 0.074990
0.187576
x54 0.548485 -0.001489 -0.243889 -0.291449 -0.062852 -0.123407 -
0.014380

```
x55   1.000000 0.130555 0.081863 -0.218429 -0.043398 -0.134590
0.068141
x56   0.130555 1.000000 0.447214        0.140274  -0.037379  -0.161349  -
0.114680                                0.059524  -  0.096954  -  0.103409
x57   0.081863 0.447214 1.000000        0.061533 0.037684
0.054019                                1.000000   0.005363
x58 -0.218429 0.140274 0.061533         0.005363   1.000000
0.148272                                0.096954   0.103409
x59 -0.043398 -0.037379 0.050000                   0.016150
0.016150
x60 -0.134590 -0.161349 0.059524
0.037684
y.1    0.068141 -0.114680 -0.054019 -0.148272
1.000000

[60 rows x 60 columns]
```

```
#Observing Correlation via heat map
sns.heatmap(data= X_train[num_cols].corr())
```

```
<Axes: >
```




```
X_train.describe()
```

	x1	x2	x3	x4	x5 \
count	29238.000000	29238.000000	29238.000000	29238.000000	29238.000000
mean	0.074386	-2.388121	-3.479189	5.436828	-0.031725
std	0.731781	5.559442	6.767939	129.591824	0.584093
min	-3.787279	-17.316550	-18.198509	-322.781610	-1.623988
25%	-0.304898	-6.269648	-8.966241	-94.817109	-0.404666
50%	0.113318	-1.451957	-4.116914	-6.119270	-0.141337
75%	0.443885	0.784189	0.672001	102.899725	0.211119
max	3.053444	16.742105	15.900116	334.694098	4.239385

	x6	x7	x8	x9	x10 \
count	29238.000000	29238.000000	29238.000000	29238.000000	29238.000000
mean	-4.680699	0.011974	-0.004039	0.012431	-0.000600
std	40.940411	0.108611	0.082882	0.173839	0.102495
min	-279.408440	-0.429273	-0.451141	-0.120087	-0.098310
25%	-39.600153	-0.049319	-0.051043	-0.059966	-0.048260
50%	5.844685	0.000732	-0.011064	-0.029299	-0.018352
75%	26.849670	0.060853	0.038986	0.010131	0.012368
max	96.060768	1.705590	0.788826	3.206675	2.921802

	...	x51	x52	x54	x55 \
count	...	29238.000000	29238.000000	29238.000000	29238.000000
mean	...	11.638219	-0.812641	-0.665653	-3.857103
std	...	258.719785	10.461626	3.316290	65.721542
min	...	-3652.989000	-187.702316	-6.569237	-209.886410
25%	...	29.984624	-4.573589	-4.952808	-48.612269
50%	...	29.984624	-1.454222	0.604562	-1.943421
75%	...	29.984624	3.818460	2.394793	41.291979
max	...	40.152348	14.180588	6.475137	287.252017

	x56	x57	x58	x59	x60 \

```
count     29238.000000 29238.000000      29238.000000   29238.000000
29238.000000                                 -0.000157        0.475719
mean         -3.017051          0.037325      0.044493        7.737157
0.001734    75.588047           2.252481     -0.149790     -100.810500
std                           -12.640370     -0.000449        0.391867
0.004767                       -1.726978      0.013693        0.804750
min        -269.039500         -0.219349      0.020921        1.275744     -
0.012229                        1.874218      0.067249        6.985460     -
25%         -51.596782        6.922008
0.001514    -16.215734
50%          48.139368
0.000972   252.147455
75%
0.005536
max
0.020495

                   y.1
count     29238.000000
mean          0.018264
std           0.133906
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max           1.000000

[8 rows x 60 columns]
```

Scaling down the features

```
#Scaling the columns in order to have more uniform distribution - We apply Yeo-Johnson Transform from sklearn.preprocessing import PowerTransformer boxcox = PowerTransformer() X_scaled = boxcox.fit_transform(X_res) X_scaled
```

```
array([[ 3.81889646e-01, -3.98515966e-01, -1.46922678e-03, ...,



          -1.64173622e-01, 9.37183457e-01, -1.35716344e-01],
         [ 5.26239506e-01, -3.88792501e-01,       1.11631202e-02, ...,
          -6.06407073e-02, 9.38506198e-01, -1.35716344e-01],
         [ 3.63340078e-01, -4.13832850e-01, -4.36263146e-02, ...,
           5.89206738e-01, 9.39828687e-01, -1.35716344e-01],
         ...,
         [-9.54098977e-01, 1.63743754e-01,        3.37751551e-01, ...,
           2.61684068e+00, 9.96536882e-01, -1.35716344e-01],
         [-5.84283564e-01, -1.33257519e+00, -1.32131555e+00, ...,
           1.95163403e+00, 1.64554634e+00, -1.35716344e-01],
```

```
       [-5.53047055e-01, 5.33311277e-01, -9.50691774e-01, ...,
         1.48013870e+00, 1.11025352e+00, -1.35716344e-01]])

## To display X_scaled as a DataFrame
X_scaled_df = pd.DataFrame(X_scaled, columns=X_res.columns)
print(X_scaled_df)

                 x1          x2          x3          x4        x5          x6
x7    \
0              0.381890 -0.398516 -0.001469  0.132479
0.018342 -0.568235 -
0.038212
1         0.526240 -0.388793 0.011163
0.152415 -0.001269 -0.532933 -
0.038212
0.137084 -0.021018 -0.515783
2         0.363340 -0.413833 -0.043626
0.130022 -0.040104 -0.528466 -
0.059892
3         0.273669 -0.427812 0.010306
0.145397 -0.054588 -0.509605 -
0.025045
4         0.222136 -0.426188 -0.040343
0.038212
...              ...         ...         ...         ...      ...          ...
...
36543          0.020918 -0.634793 -0.191039 -0.561167      0.332184 -0.559914
1.733541
0.291396 -0.814875 -1.576482
36544  2.449727 0.304055 -0.949277
0.830347
0.154323
36545 -0.954099 0.163744 0.337752         1.063217    0.048034      1.130400 -
0.005827
0.675342    0.352125
0.019089 -1.319566 -
36546 -0.584284 -1.332575 -1.321316
0.654801
36547 -0.553047 0.533311 -0.950692 -0.694546
0.060399

                 x8          x9         x10 ...           x51         x52        x54
\
0             -0.689910 -0.622008 -0.338508 ...       0.080069      1.833449 -1.209384

1             -0.689910 -0.622008 -0.338508 ...       0.080069      1.834403 -1.209509

2              -0.689910 -0.087960 0.067208 ...       0.080069      1.835412 -1.209634

3               -0.689910 0.068052 0.248779 ...       0.080069      1.836422 -1.209759

4              -0.689910 -0.087960 0.248779 ...       0.080069      1.837432 -1.209885

...                ...         ...        ... ...             ...          ...         ...

36543           1.141652 -0.588320 0.236020 ...                                  0.440542
                                                 1.521700 -0.005931
36544            0.309154 1.080125 0.865474 ...       0.080069 -0.617209 -1.358684

36545          0.368190 -1.814855 -1.393327 ...                                  0.709579
                                                 0.080069 -0.285506
```

```
36546    -0.385691    0.324870    -0.189516 ...         1.357514 -0.066459 -1.217363
36547 -1.010032 -0.426622 -0.280589              ... -0.306348 -0.340106 -0.861056

                x55          x56            x57        x58          x59         x60
y.1
0              -0.334412 0.392335 1.511999    1.575970 -0.164174 0.937183  -
0.135716
1         -0.449437 0.441441 1.169347         1.584385 -0.060641 0.938506  -
0.135716
2         -0.475430 0.490149 1.539732        1.592911  0.589207 0.939829  -
0.135716
3         -0.501410 0.428900 1.733683        1.601364  1.332612 0.941151  -
0.135716
4         -0.527378 0.431610 1.567458        1.606518  0.199535 0.942662 -
0.135716
...             ...          ...          ...          ...          ...          ...
...
36543   2.359045 -0.534413 0.636896 -2.093521 -0.137045 -0.254866 -
0.135716
36544 -1.248274 -1.697927 -0.982147          1.336030 -0.462287 -0.122919 -
0.135716
36545 -0.483094 -0.442690 -0.323708       0.592399    2.616841       0.996537 -
0.135716
36546 -0.546205 0.874209 -0.068251        0.218555    1.951634       1.645546 -
0.135716
36547 -0.391511 -0.937148 -0.532500       0.277252    1.480139       1.110254 -
0.135716
[36548 rows x 60 columns]

## Now, further splitting the data into training and testing based on
scaled values
X_train_sc, X_test_sc, Y_train_sc, Y_test_sc =
train_test_split(X_scaled_df, Y_res, test_size = 0.2,
random_state=123)

 X_train_sc

x7               x1           x2             x3           x4          x5             x6
     \
15236          0.330189 0.603209 -0.552396   1.375394     1.605863 -0.356665
0.156556
3467     0.006659 0.077748 0.123198 -0.915552         0.212106    0.059107 -
0.760029
8732     0.270016 -0.094126 -0.434108       1.398622 -0.300498 -0.483424
1.126667
15750   1.103654 0.846468 -0.169641       1.366123 -0.238843      0.621058 -
```

0.238843 24044 -0.273255 1.580371
-0.850291 0.212451 ... ... 7763 1.567282 0.412282 0.988937 -
... ...
... ... 1.746937 -1.323684 ...
-0.821480 0.722105 -0.148838 0.773220

0.788706
15377 0.446606 0.103376 -0.370712 1.354504 0.241137 -0.439705 -
0.547782 0.441239 1.146716 -
17730 -0.053813 0.968870 1.046099 0.380602
0.442265
28030 2.080371 -0.282583 -0.957799 -0.160547 -0.154380 -2.309889
0.655773
15725 0.864459 0.955137 -0.375666 1.398848 0.568669 0.670708 -
0.238843

x8 x9 x10 ... x51 x52 x54
\
15236 0.006987 -0.413570 -0.571424 ... 0.080069 -0.475127 -1.211898
3467 -0.309002 -0.828158 -1.098683 ... 0.080069 0.564684 0.117708
8732 -0.951280 -0.828158 -1.386757 ... -1.066749 -0.093162 -1.204088
15750 0.186706 0.344309 0.415446 ... 0.080069 -1.063350 -1.215439
24044 0.414388 0.084996 -0.682344 ... 0.080069 -0.809584 -1.193444
... ...
7763 2.389024 -1.420573 -1.309931 ... 0.080069 0.588845 -1.217145
15377 -0.689910 -0.255504 -0.824317 ... 0.080069 -0.534201 -1.210169
17730 0.186706 -0.255504 0.344981 ... 0.031746 -0.330472 0.438372
28030 0.092198 1.887042 0.447601 ... 0.080069 -0.879002 -1.206373
15725 -0.057326 0.888957 1.872794 ... 0.080069 -0.992603 -1.209159

x55 x56 x57 x58 x59 x60
y.1
15236 -0.963344 0.357764 -0.924658 -0.093350 -0.665835 0.451535 -
0.135716
3467 0.503471 1.236892 1.295178 1.225886 -0.565033 1.049281 -
0.135716 0.209313 -0.595793 -
8732 -0.823146 0.556877 0.716288 -0.001015
0.135716
15750 -1.383172 -0.615817 -1.424266 -0.734708 -0.728555 -0.435098 -

```
0.135716   24044   -1.258539   -0.431617   -1.565465   -0.772945   -0.482283
-0.435098 - 0.135716 ... ... 7763

          ...        ...          ...      ...        ...        ...
            -0.277358 0.949527 0.969035
                                          0.206117 -0.005688 -0.768783 -
0.135716                                                      1.453370 -
15377 -0.950495 -0.619007 -0.801917    0.271179386 0.394853324 -1.799586 -
0.135716                                  0.222943 -0.218674 -0.241566 -
17730   1.223906 0.923128 -0.801917
0.135716
28030 -1.080471 -2.234050 -0.840901
0.135716
15725 -1.355632 -0.604117 -1.639535 -0.894073 -0.759767 -0.435098 -
0.135716

[29238 rows x 60 columns]

X_scaled_df.describe()

                 x1            x2            x3            x4
x5   \
count       3.654800e+04 3.654800e+04  3.654800e+04  3.654800e+04
3.654800e+04
mean    6.221234e-18 -6.843358e-17 -1.244247e-17 -3.421679e-17 -
4.665926e-17
std     1.000014e+00 1.000014e+00    1.000014e+00   1.000014e+00
1.000014e+00
min    -4.543615e+00 -2.690137e+00 -2.515620e+00 -2.759972e+00 -
4.437926e+00
25%    -5.534697e-01 -7.032891e-01 -8.326755e-01 -7.616707e-01 -
6.044112e-01
50%     9.229517e-03 1.669920e-01 -5.721958e-03 -2.032956e-02 -
2.830933e-02
75%     4.816622e-01 5.692326e-01    7.143310e-01   7.655529e-01
5.908173e-01
max     4.716381e+00 3.460680e+00    2.388219e+00   2.362790e+00
3.794102e+00

                 x6            x7            x8            x9
x10  \
count       3.654800e+04 3.654800e+04  3.654800e+04  3.654800e+04
3.654800e+04
mean   -6.221234e-18 3.110617e-17    2.099667e-17 -1.088716e-17 -
2.391287e-17
std     1.000014e+00 1.000014e+00    1.000014e+00   1.000014e+00
1.000014e+00
min    -4.475132e+00 -5.692855e+00 -6.424467e+00 -2.087710e+00 -
2.056124e+00
25%    -9.049585e-01 -5.477824e-01 -5.606866e-01 -6.220080e-01 -
```

```
5.714242e-01
50%      2.542399e-02 -3.821154e-02 -5.732608e-02 -7.713820e-02
6.720843e-02
75%      7.707192e-01 5.267675e-01      5.489173e-01   4.815339e-01
5.775432e-01                            7.684405e+00   2.405039e+00
max      3.604507e+00 7.719614e+00
2.513861e+00

         ...               x51                x52            x54            x55 \
count        ... 3.654800e+04 3.654800e+04  3.654800e+04   3.654800e+04
mean          ... 1.050611e-15 2.799555e-17  2.799555e-17   3.110617e-17
std          ... 1.000014e+00 1.000014e+00  1.000014e+00   1.000014e+00
min          ... -7.961188e+00 -9.783648e+00 -1.711381e+00 -3.323567e+00
25%            ... 8.006864e-02 -6.086076e-01 -1.212105e+00 -6.910733e-01
50%      ... 8.006864e-02 -3.061275e-01       1.092092e-01   5.019114e-03
75%      ... 8.006864e-02 4.960211e-01        9.933361e-01   6.769392e-01
max      ... 1.388752e+01 2.809207e+00        3.812686e+00   4.602692e+00

                  x56             x57            x58            x59
x60
count     3.654800e+04 3.654800e+04  3.654800e+04  3.654800e+04
3.654800e+04                          3.897992e-17   6.843358e-17
mean   -2.488494e-17 6.221234e-18
2.021901e-17                          1.000014e+00   1.000014e+00
std      1.000014e+00 1.000014e+00
1.000014e+00
min    -4.250150e+00 -5.791120e+00 -2.212102e+00 -5.295292e+00 -
3.547702e+00
25%    -6.194874e-01 -7.784508e-01 -5.463565e-01 -5.354201e-01 -
6.589753e-01
50%    -6.979482e-02 -1.032931e-01      1.369049e-01 -2.708045e-01 -
1.034212e-01
75%      7.237340e-01 8.152391e-01      5.870559e-01   8.523002e-02
8.324430e-01
max      2.898191e+00 2.996698e+00      6.279333e+00   8.282744e+00
3.195467e+00

                  y.1
count    3.654800e+04
mean    -4.043802e-17
std      1.000014e+00
min     -1.357163e-01
25%     -1.357163e-01
50%     -1.357163e-01
75%     -1.357163e-01
max      7.368309e+00

[8 rows x 60 columns]
```

```
#Importing PCA library
#Telling PCA to retain 90% of useful features and then create new
dimensions
from sklearn.decomposition import PCA
pca = PCA(0.90)
X_pca = pca.fit_transform(X_scaled_df)
X_pca.shape
```

```
(36548, 26)
```

```
## Each value will tell how much % of usefulness it contributes to the
entire dataset
pca.explained_variance_ratio_
```

```
array([0.16405375, 0.1145583 , 0.08261669, 0.07065509, 0.05393095,
0.04271356, 0.03966432, 0.03552791, 0.0340095 , 0.02983506,
0.02528292, 0.02266675, 0.02099167, 0.01786314, 0.01699457,
0.0161314 , 0.01576427, 0.01515727, 0.01428581, 0.01337401,
0.01195731, 0.01145649, 0.00998132, 0.00936646, 0.00900109,
0.00774108])
```

```
#To display how many dimensions we will feed now in our model
pca.n_components_
```

```
26
```

```
# Will now again do train test split but now with the X_pca
X_train_sc_pca, X_test_sc_pca, Y_train_sc_pca, Y_test_sc_pca =
train_test_split(X_pca, Y_res, test_size = 0.2, random_state=123)
```

```
X_train_sc_pca
```

```
array([[-1.85904913, -3.43825123,          1.57555331,   ...,   -0.09662878,
-0.22846121, 0.61013392],
[ 3.3451392 , 1.9950538 ,                  1.76736295,   ...,   -0.11005107,
0.23110504, -0.12187116],
[ 2.52467669, -1.31695532,                 1.13665655, ..., -0.25767517,
0.50666258, -0.27040914],
        ...,
        [-2.90046972, 0.88216013,              3.47542271, ..., -1.00079079,
        -1.51671085, -0.5722476 ],             0.51266168, ..., -0.45545897,
                                                                0.31846568,
        [-0.16058809, -5.23636177, -1.71785398, ...,
                1.30601642, 2.4340082 ],
            [-3.42476415, -4.85333061,
          0.97360167, -0.06335646]])
```

Model Selection

```
#Since it is a classification problem, We will use the following
models for it and will compare their accuracy on test data against
each other.
```

```
#1. Logistic Regression from sklearn.linear_model import
LogisticRegression model1 = LogisticRegression()
model1.fit(X_train_sc_pca,Y_train_sc_pca)
model1.score(X_test_sc_pca,Y_test_sc_pca)
```

```
0.8383036935704514
```

```
#2. Decision Tree
from sklearn import tree
model2 = tree.DecisionTreeClassifier()
model2.fit(X_train_sc_pca,Y_train_sc_pca)
model2.score(X_test_sc_pca,Y_test_sc_pca)
```

```
0.9800273597811218
```

```
#3. KNN
from sklearn.neighbors import KNeighborsClassifier
model3 = KNeighborsClassifier(n_neighbors=3)
model3.fit(X_train_sc_pca,Y_train_sc_pca)
model3.score(X_test_sc_pca,Y_test_sc_pca)
```

```
0.9941176470588236
```

```
#4. Random Forest
from sklearn.ensemble import RandomForestClassifier
model4 = RandomForestClassifier(n_estimators=30)
model4.fit(X_train_sc_pca,Y_train_sc_pca)
model4.score(X_test_sc_pca,Y_test_sc_pca)
```

```
0.9991792065663475
```

Model Validation

To check where model performs good and where it performs bad

1. For Logistic Regression

```
Y_predicted_md1 = model1.predict(X_test_sc_pca)
Y_predicted_md1
```

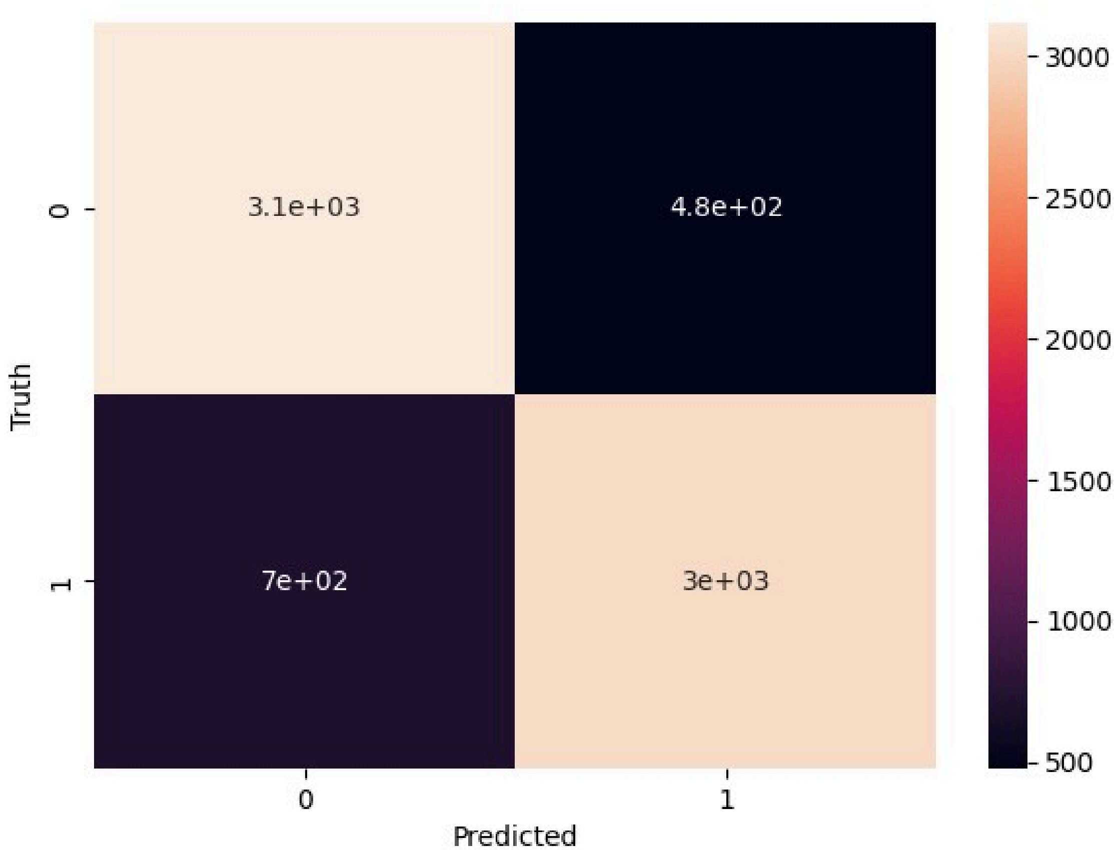
```
array([1, 0, 0, ..., 1, 0, 1], dtype=int64)
```

```
from sklearn.metrics import confusion_matrix
cm1 = confusion_matrix(Y_test_sc_pca,Y_predicted_md1)
cm1
```

```
array([[3118, 479],
       [ 703, 3010]], dtype=int64)
```

```
plt.figure(figsize = (7,5))
sns.heatmap(cm1,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Text(58.222222222222214, 0.5, 'Truth')




```
from sklearn.metrics import classification_report
print(classification_report(Y_test_sc_pca,Y_predicted_md1))
```

	precision	recall	f1-score	support
0	0.82	0.87	0.84	3597
1	0.86	0.81	0.84	3713
accuracy			0.84	7310
macro avg	0.84	0.84	0.84	7310
weighted avg	0.84	0.84	0.84	7310

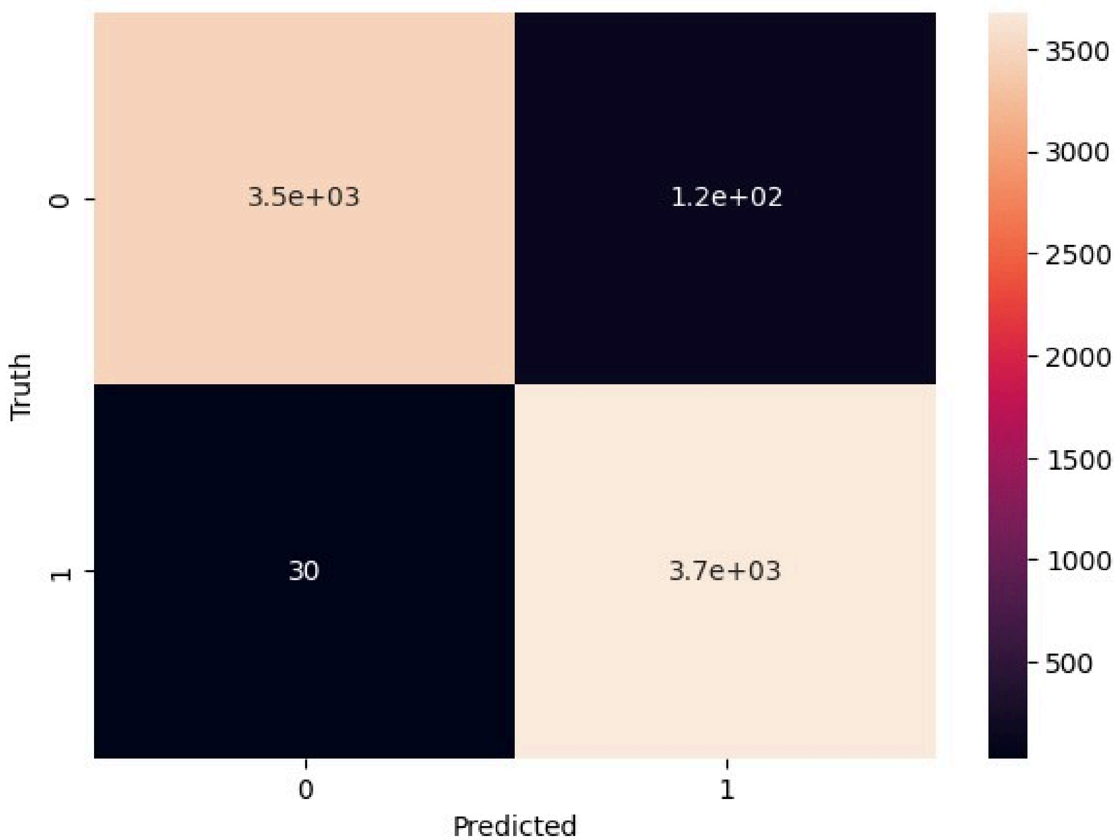
2. For Decision Tree

```
Y_predicted_md2 = model2.predict(X_test_sc_pca)
Y_predicted_md2
cm2 = confusion_matrix(Y_test_sc_pca,Y_predicted_md2)
cm2
```

```
array([[3481, 116],
       [ 30, 3683]], dtype=int64)
```

```
plt.figure(figsize = (7,5))
sns.heatmap(cm2,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(58.222222222222214, 0.5, 'Truth')
```




```
from sklearn.metrics import classification_report
print(classification_report(Y_test_sc_pca,Y_predicted_md2))
```

	precision	recall	f1-score	support
0	0.99	0.97	0.98	3597
1	0.97	0.99	0.98	3713

```
accuracy 0.98 7310  macro avg 0.98 0.98 0.98 7310 weighted
avg 0.98 0.98 0.98 7310
```

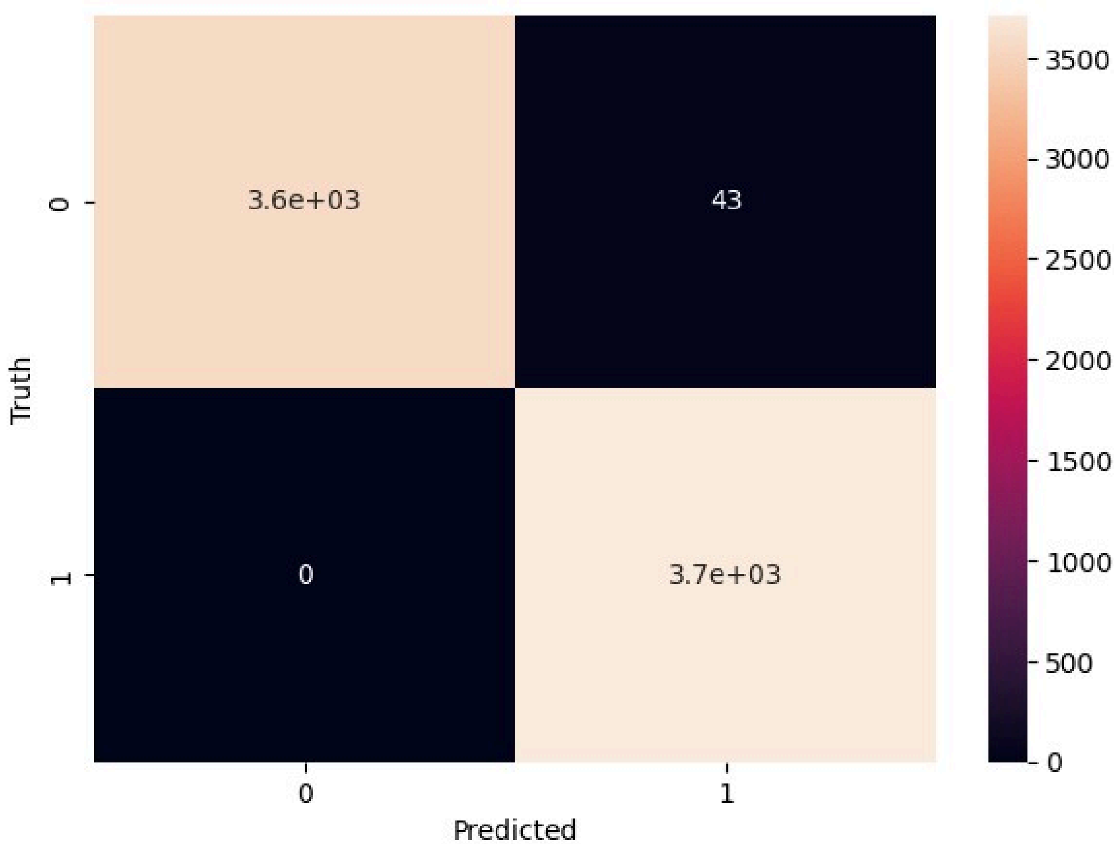
3. For KNN

```
Y_predicted_md3 = model3.predict(X_test_sc_pca)
Y_predicted_md3
cm3 = confusion_matrix(Y_test_sc_pca,Y_predicted_md3)
cm3
```

```
array([[3554,    43],
       [   0, 3713]], dtype=int64)
```

```
plt.figure(figsize = (7,5))
sns.heatmap(cm3,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(58.222222222222214, 0.5, 'Truth')
```



```
from sklearn.metrics import classification_report
print(classification_report(Y_test_sc_pca,Y_predicted_md3))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      3597
           1       0.99      1.00      0.99      3713

    accuracy                           0.99      7310
   macro avg       0.99      0.99      0.99      7310
weighted avg       0.99      0.99      0.99      7310
```

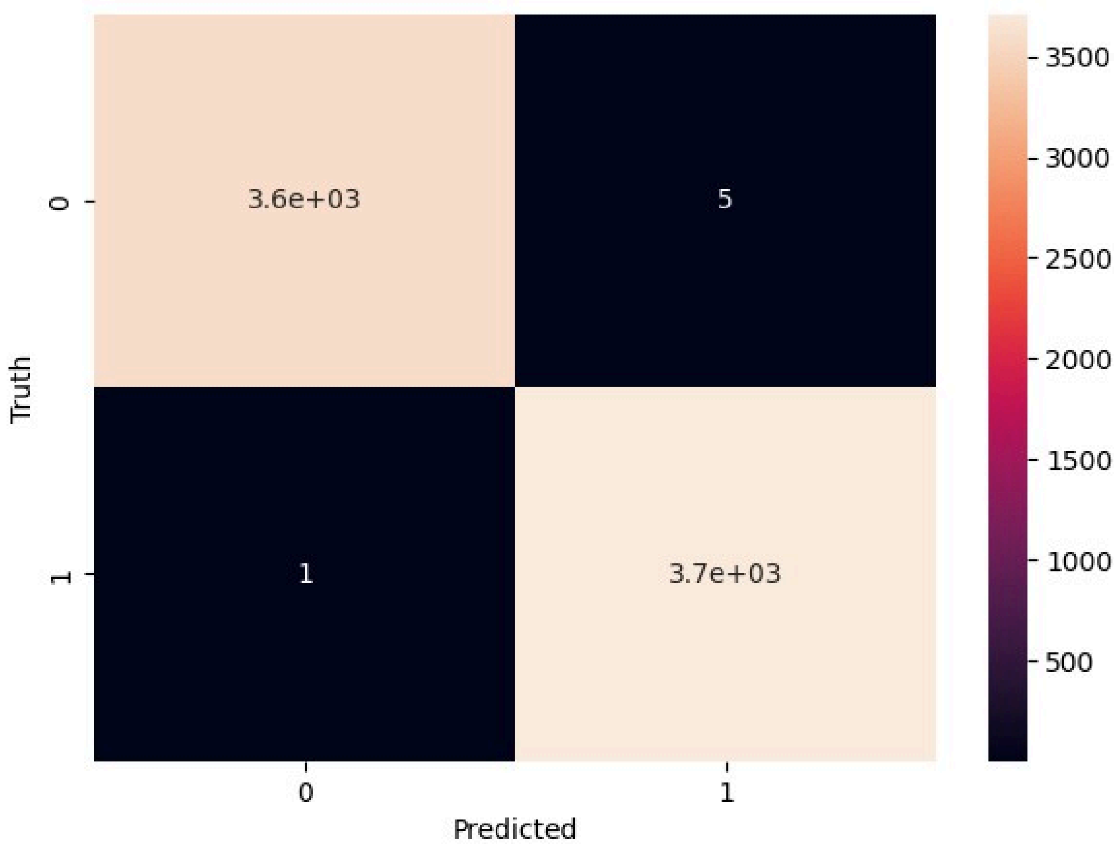
4. For Random Forest

```
Y_predicted_md4 = model4.predict(X_test_sc_pca)
Y_predicted_md4
cm4 = confusion_matrix(Y_test_sc_pca,Y_predicted_md4)
cm4
```

```
array([[3592,    5],
       [   1, 3712]], dtype=int64)
```

```
plt.figure(figsize = (7,5))
sns.heatmap(cm4,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(58.222222222222214, 0.5, 'Truth')
```




```
from sklearn.metrics import classification_report
print(classification_report(Y_test_sc_pca,Y_predicted_md4))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	3597
1	1.00	1.00	1.00	3713
accuracy			1.00	7310
macro avg	1.00	1.00	1.00	7310
weighted avg	1.00	1.00	1.00	7310

Conclusion

Considering the Classification report from the above four models, we found Random Forest Algorithm - accuracy, precision, f1-score is acheieving 99.99 % accuracy on test data set. With a dataset comprising over 18,000 rows and utilizing binary labels for anomaly identification, the model has demonstrated exceptional performance, achieving an outstanding accuracy of 99.99%. This high level of accuracy underscores the model's reliability in detecting anomalies and predicting machine breakdowns, which can significantly reduce downtime, minimize risks, and optimize maintenance schedules across industries.