In [ ]:
```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.10/dist-packages (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from imbala
nced-learn) (1.25.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from imbalan
ced-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in /usr/local/lib/python3.10/dist-packages (from
imbalanced-learn) (1.2.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from imbala
nced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from
imbalanced-learn) (3.5.0)
```

In [1]:
```
#Importing the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import datetime as dt
# pd.set_option('display.max_columns', None)
# pd.set_option('display.max_rows', None)
```

In [2]:
```
#Reading the dataset into a dataframe from a CSV file
df=pd.read_csv("predictive_maintainece_dataset.csv")
df.head(20)
```

Out[2]:

	date	device	failure	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9
0	1/1/2015	S1F01085	0	215630672	55	0	52	6	407438	0	0	7
1	1/1/2015	S1F0166B	0	61370680	0	3	0	6	403174	0	0	0
2	1/1/2015	S1F01E6Y	0	173295968	0	0	0	12	237394	0	0	0
3	1/1/2015	S1F01JE0	0	79694024	0	0	0	6	410186	0	0	0
4	1/1/2015	S1F01R2B	0	135970480	0	0	0	15	313173	0	0	3
5	1/1/2015	S1F01TD5	0	68837488	0	0	41	6	413535	0	0	1
6	1/1/2015	S1F01XDJ	0	227721632	0	0	0	8	402525	0	0	0
7	1/1/2015	S1F023H2	0	141503600	0	0	1	19	494462	16	16	3
8	1/1/2015	S1F02A0J	0	8217840	0	1	0	14	311869	0	0	0
9	1/1/2015	S1F02DZ2	0	116440096	0	378	9	9	407905	0	0	170
10	1/1/2015	S1F02EVN	0	112348104	0	0	0	7	388146	0	0	1
11	1/1/2015	S1F02L38	0	223938928	0	0	0	2	215169	0	0	8
12	1/1/2015	S1F02MGA	0	44399688	0	266	1	6	399286	0	0	2269
13	1/1/2015	S1F02P76	0	104131304	1536	0	175	11	301679	0	0	0
14	1/1/2015	S1F02VAX	0	61019512	168	2	521	3	380496	0	0	3
15	1/1/2015	S1F02WFT	0	44348552	6150	14	1074	11	249515	0	0	21
16	1/1/2015	S1F0318A	0	35018688	0	0	0	9	394890	0	0	5
17	1/1/2015	S1F0322R	0	34540712	0	0	0	9	411399	0	0	0
18	1/1/2015	S1F0330P	0	125539768	0	0	12	14	297284	0	0	5
19	1/1/2015	S1F035SJ	0	220392160	0	0	0	9	389730	0	0	0

In [ ]:
```
df.tail()
```

Out[4]:

	date	device	failure	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9
124489	11/2/2015	Z1F0MA1S	0	18310224	0	0	0	10	353705	8	8	0
124490	11/2/2015	Z1F0Q8RT	0	172556680	96	107	4	11	332792	0	0	13
124491	11/2/2015	Z1F0QK05	0	19029120	4832	0	0	11	350410	0	0	0
124492	11/2/2015	Z1F0QL3N	0	226953408	0	0	0	12	358980	0	0	0
124493	11/2/2015	Z1F0QLC1	0	17572840	0	0	0	10	351431	0	0	70000

In [ ]:
```
#checking for any missing values in the dataframe
df.isnull().sum()
```

Out[5]:
```
date        0
device      0
failure     0
metric1     0
metric2     0
metric3     0
metric4     0
metric5     0
metric6     0
metric7     0
metric8     0
metric9     0
dtype: int64
```

In [ ]:
```
df['device'].value_counts()
```

Out[6]:
```
device
Z1F0QL3N    304
W1F0SJJ2    304
S1F0EGMT    304
S1F0FGBQ    304
S1F0FP0C    304
           ...
S1F0CSRZ      5
S1F0CT09      5
S1F04KSC      4
W1F0WJFT      3
W1F1DA5ÿ      1
Name: count, Length: 1169, dtype: int64
```

In [ ]:
```
#cheking for the number of unique devices in the dataset.
df['device'].nunique()
```

Out[7]:
```
1169
```

In [ ]:
```
#Checking if there are any instances of failure i.e. 1 in the dataset.
df[df['failure']==1]
```

Out[8]:

	date	device	failure	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9
4885	1/5/2015	S1F0RRB1	1	48467332	64776	0	841	8	39267	56	56	1
6879	1/7/2015	S1F0CTDN	1	184069720	528	0	4	9	387871	32	32	3
8823	1/9/2015	W1F0PNA5	1	136429411	64784	0	406	30	224801	8	8	0
11957	1/13/2015	W1F13SRV	1	188251248	2040	0	0	6	39345	32	32	1
12668	1/14/2015	W1F1230J	1	220461296	0	0	0	14	325125	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
109927	8/4/2015	W1F1CB5E	1	16043296	88	0	0	9	30	0	0	0
114251	8/18/2015	Z1F0MRPJ	1	65654088	0	0	0	9	298592	0	0	11
122118	10/5/2015	S1F0JGJV	1	13739704	0	0	18	8	343760	0	0	0
122808	10/9/2015	Z1F14BGY	1	85259320	0	0	164	8	262932	0	0	0
124329	10/26/2015	W1F0T0B1	1	95073232	0	0	7	9	354861	22	22	0

106 rows × 12 columns

In [ ]:
```
aggregated = df.groupby('device')['failure'].agg(['min', 'max'])
aggregated
```

Out[9]:

	min	max
device		
S1F01085	0	0
S1F013BB	0	0
S1F0166B	0	0
S1F01E6Y	0	0
S1F01JE0	0	0
...	...	...
Z1F1VMZB	0	0
Z1F1VQFY	0	1
Z1F26YZB	0	0
Z1F282ZV	0	0
Z1F2PBHX	0	0

1169 rows × 2 columns

In [ ]:
```
#checking for devices which has both failure and non-failure instances
devices_with_both = aggregated[(aggregated['min'] == 0) & (aggregated['max'] == 1)].index
pd.Series(devices_with_both)
```

Out[10]:
```
0      S1F023H2
1      S1F03YZM
2      S1F09DZQ
3      S1F0CTDN
4      S1F0DSTY
         ...
101    Z1F1901P
102    Z1F1AG5N
103    Z1F1FCH5
104    Z1F1RJFA
105    Z1F1VQFY
Name: device, Length: 106, dtype: object
```

In [ ]:
```
# Filter the DataFrame for devices with both failure and non-failure instances
filtered_df = df[df['device'].isin(devices_with_both)]

# Grouping by device and failure columns , then counting the frequency of failure and non-failure of
frequency = filtered_df.groupby(['device', 'failure']).size().reset_index(name='frequency')
pd.crosstab(index=frequency['device'],columns=frequency['failure'],values=frequency['frequency'],aggf
```

Out[11]:

failure	0	1
device		
S1F023H2	18	1
S1F03YZM	214	1
S1F09DZQ	198	1
S1F0CTDN	6	1
S1F0DSTY	44	1
...	...	...
Z1F1901P	131	1
Z1F1AG5N	8	1
Z1F1FCH5	18	1
Z1F1RJFA	123	1
Z1F1VQFY	124	1

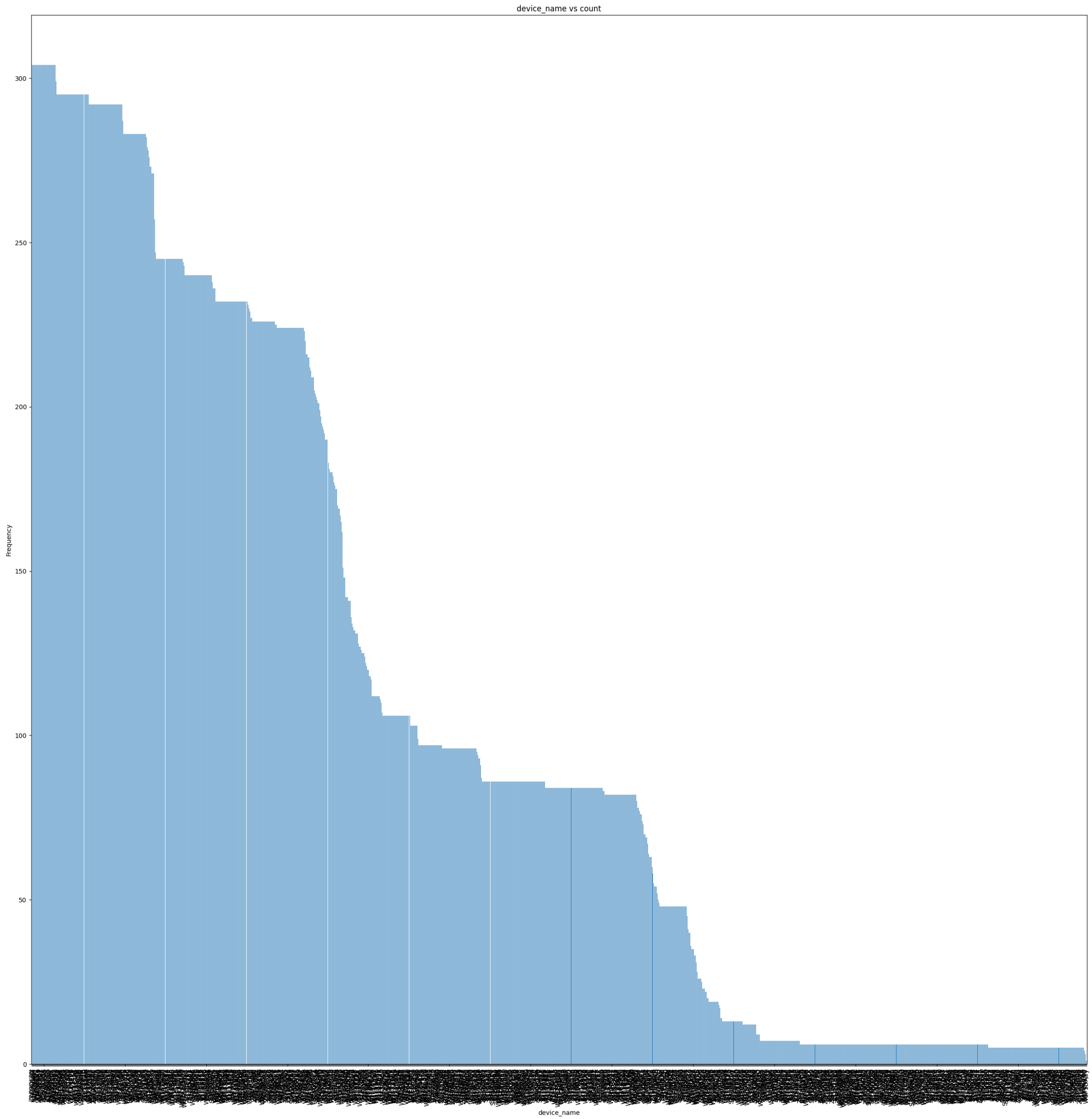
106 rows × 2 columns

In [ ]:
```
#checking for the total number of instances of failure and non-failure in the dataset.
df['failure'].value_counts()
```

Out[12]:
```
failure
0    124388
1       106
Name: count, dtype: int64
```

Seeing the above results we can conclude that there is a problem of class imbalance in this dataset , which might create a problem as the model may become biased towards the majority class during training.

In [ ]:
```
#Creating a bar-plot of the count of each device present in the dataset.
plt.figure(figsize=(30,30))
df['device'].value_counts().plot(kind='bar')
plt.xticks(rotation=90)
plt.xlabel('device_name')
plt.ylabel('Frequency')
plt.title('device_name vs count')
plt.show()
```



In [ ]:
```
#total length of the dataset.
len(df)
```

Out[14]: 124494

In [ ]:
```
#converting the date column from type object to type datetime.
df.date=pd.to_datetime(df['date'])
```

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

Out[16]:
```
date       datetime64[ns]
device             object
failure             int64
metric1             int64
metric2             int64
metric3             int64
metric4             int64
metric5             int64
metric6             int64
metric7             int64
metric8             int64
metric9             int64
dtype: object
```

In [ ]:
```
df.columns
```

Out[17]:
```
Index(['date', 'device', 'failure', 'metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9'],
      dtype='object')
```

In [ ]:
```
#Checking for the timeframe within which the data was captured.
print(df['date'].max())
print(df['date'].min())
```

```
2015-11-02 00:00:00
2015-01-01 00:00:00
```

In [3]:
```
#Creating a seperate dataframe with the independent features .
df_x=df[['device','metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9']]
```

In [ ]:
```
df_x.head(30)
```

Out[20]:

	device	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9
0	S1F01085	215630672	55	0	52	6	407438	0	0	7
1	S1F0166B	61370680	0	3	0	6	403174	0	0	0
2	S1F01E6Y	173295968	0	0	0	12	237394	0	0	0
3	S1F01JE0	79694024	0	0	0	6	410186	0	0	0
4	S1F01R2B	135970480	0	0	0	15	313173	0	0	3
5	S1F01TD5	68837488	0	0	41	6	413535	0	0	1
6	S1F01XDJ	227721632	0	0	0	8	402525	0	0	0
7	S1F023H2	141503600	0	0	1	19	494462	16	16	3
8	S1F02A0J	8217840	0	1	0	14	311869	0	0	0
9	S1F02DZ2	116440096	0	378	9	9	407905	0	0	170
10	S1F02EVN	112348104	0	0	0	7	388146	0	0	1
11	S1F02L38	223938928	0	0	0	2	215169	0	0	8
12	S1F02MGA	44399688	0	266	1	6	399286	0	0	2269
13	S1F02P76	104131304	1536	0	175	11	301679	0	0	0
14	S1F02VAX	61019512	168	2	521	3	380496	0	0	3
15	S1F02WFT	44348552	6150	14	1074	11	249515	0	0	21
16	S1F0318A	35018688	0	0	0	9	394890	0	0	5
17	S1F0322R	34540712	0	0	0	9	411399	0	0	0
18	S1F0330P	125539768	0	0	12	14	297284	0	0	5
19	S1F035SJ	220392160	0	0	0	9	389730	0	0	0
20	S1F0377V	166567552	0	0	23	14	321308	0	0	8
21	S1F039FE	218786520	0	0	6	4	394782	0	0	2
22	S1F03RV3	176851840	0	0	0	8	258058	0	0	0
23	S1F03YZM	55587136	0	0	0	7	199132	0	0	0
24	S1F044ET	161730848	0	0	0	5	226578	0	0	0
25	S1F049RX	181980928	0	0	4	7	395719	0	0	0
26	S1F04DH8	134506192	0	9	0	16	324354	0	0	145
27	S1F04KSC	105234552	392	24929	529	3	339205	0	0	10137
28	S1F04MVQ	41356960	1984	0	46	4	367145	0	0	65
29	S1F04R7Y	126680112	0	0	0	7	398672	0	0	51

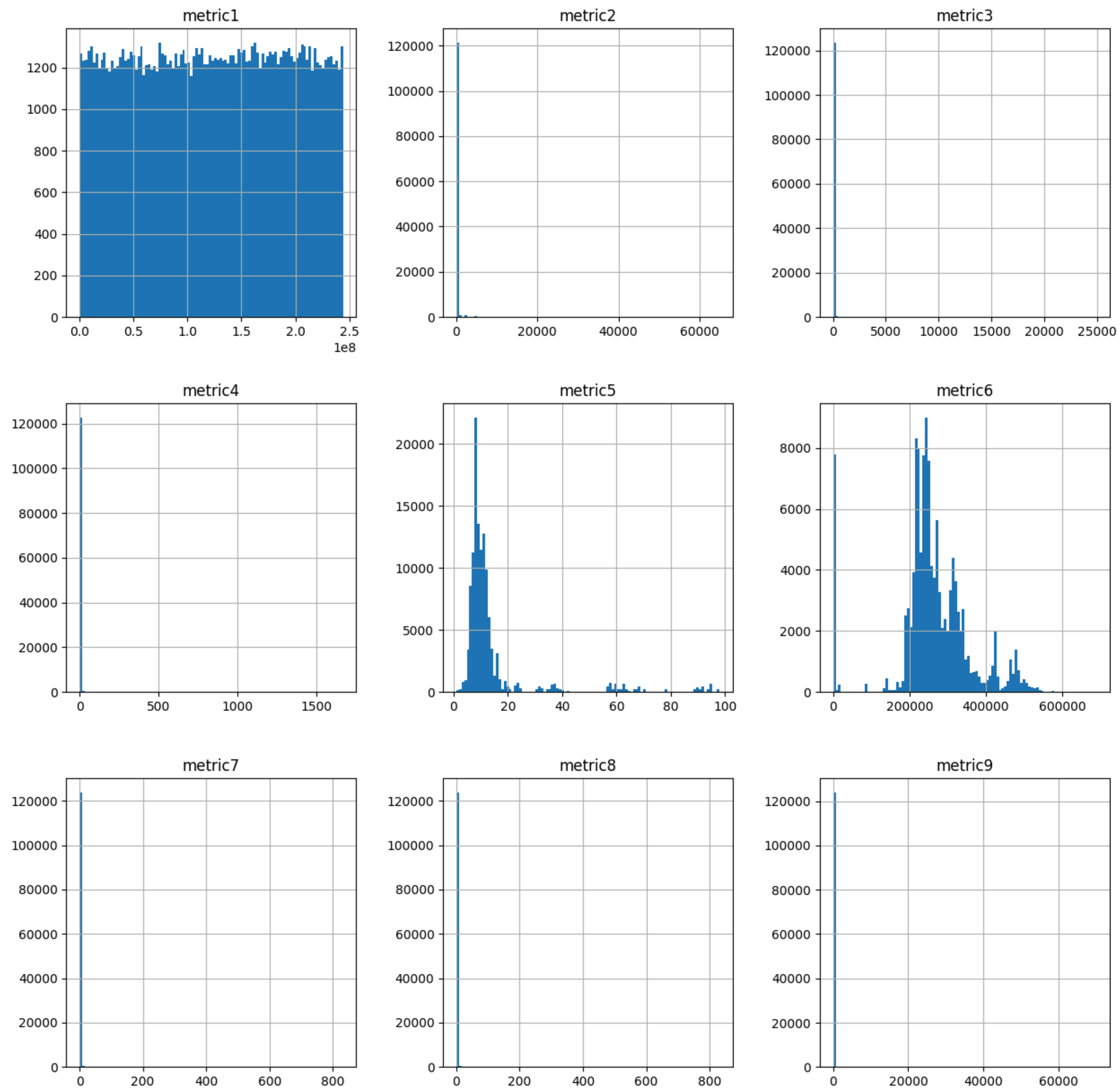
In [ ]:
```
df_x.columns
```

Out[21]:
```
Index(['device', 'metric1', 'metric2', 'metric3', 'metric4', 'metric5',
       'metric6', 'metric7', 'metric8', 'metric9'],
      dtype='object')
```

In [ ]:
```
#Taking all the columns except the device column from df_x dataframe and creating a seperate datafram
df_x_subset=df_x[['metric1', 'metric2', 'metric3', 'metric4', 'metric5',
                  'metric6', 'metric7', 'metric8', 'metric9']]
```

In [ ]:
```
#Checking the distribution of each of the numerical features in the dataset.
#fig, axis = plt.subplots(9, 9)
df_x_subset.hist(bins=100,figsize=(15,15))
```

Out[23]:
```
array([[<Axes: title={'center': 'metric1'}>,
        <Axes: title={'center': 'metric2'}>,
        <Axes: title={'center': 'metric3'}>],
       [<Axes: title={'center': 'metric4'}>,
        <Axes: title={'center': 'metric5'}>,
        <Axes: title={'center': 'metric6'}>],
       [<Axes: title={'center': 'metric7'}>,
        <Axes: title={'center': 'metric8'}>,
        <Axes: title={'center': 'metric9'}>]], dtype=object)
```



Upon checking the distribution of each numerical feature in the dataset we find that almost all are heavily skewed in nature.

In [ ]:
```
#Implementing the process of normalizing the numerical features in the dataset in order to bring them

from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
df_x_subset_scaled=scaler.fit_transform(df_x_subset)
print(type(df_x_subset_scaled))
df_x_subset_scaled=pd.DataFrame(df_x_subset_scaled)
df_x_subset_scaled.head(20)
```

```
<class 'numpy.ndarray'>
```

Out[24]:

	0	1	2	3	4	5	6	7	8
0	0.883224	0.000847	0.000000	0.031212	0.051546	0.591204	0.000000	0.000000	0.000100
1	0.251374	0.000000	0.000120	0.000000	0.051546	0.585017	0.000000	0.000000	0.000000
2	0.709821	0.000000	0.000000	0.000000	0.113402	0.344461	0.000000	0.000000	0.000000
3	0.326427	0.000000	0.000000	0.000000	0.051546	0.595191	0.000000	0.000000	0.000000
4	0.556935	0.000000	0.000000	0.000000	0.144330	0.454420	0.000000	0.000000	0.000043
5	0.281959	0.000000	0.000000	0.024610	0.051546	0.600051	0.000000	0.000000	0.000014
6	0.932748	0.000000	0.000000	0.000000	0.072165	0.584075	0.000000	0.000000	0.000000
7	0.579599	0.000000	0.000000	0.000600	0.185567	0.717481	0.019231	0.019231	0.000043
8	0.033660	0.000000	0.000040	0.000000	0.134021	0.452528	0.000000	0.000000	0.000000
9	0.476939	0.000000	0.015163	0.005402	0.082474	0.591882	0.000000	0.000000	0.002429
10	0.460178	0.000000	0.000000	0.000000	0.061856	0.563210	0.000000	0.000000	0.000014
11	0.917254	0.000000	0.000000	0.000000	0.010309	0.312211	0.000000	0.000000	0.000114
12	0.181861	0.000000	0.010670	0.000600	0.051546	0.579375	0.000000	0.000000	0.032414
13	0.426522	0.023642	0.000000	0.105042	0.103093	0.437742	0.000000	0.000000	0.000000
14	0.249936	0.002586	0.000080	0.312725	0.020619	0.552110	0.000000	0.000000	0.000043
15	0.181652	0.094662	0.000562	0.644658	0.103093	0.362049	0.000000	0.000000	0.000300
16	0.143437	0.000000	0.000000	0.000000	0.082474	0.572996	0.000000	0.000000	0.000071
17	0.141479	0.000000	0.000000	0.000000	0.082474	0.596952	0.000000	0.000000	0.000000
18	0.514211	0.000000	0.000000	0.007203	0.134021	0.431364	0.000000	0.000000	0.000071
19	0.902727	0.000000	0.000000	0.000000	0.082474	0.565509	0.000000	0.000000	0.000000

In [ ]:
```
#Reassigning the column names.
df_x_subset_scaled.columns=df_x_subset.columns
```

In [ ]:
```
df_x_subset_scaled.head(10)
```

Out[26]:

	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9
0	0.883224	0.000847	0.000000	0.031212	0.051546	0.591204	0.000000	0.000000	0.000100
1	0.251374	0.000000	0.000120	0.000000	0.051546	0.585017	0.000000	0.000000	0.000000
2	0.709821	0.000000	0.000000	0.000000	0.113402	0.344461	0.000000	0.000000	0.000000
3	0.326427	0.000000	0.000000	0.000000	0.051546	0.595191	0.000000	0.000000	0.000000
4	0.556935	0.000000	0.000000	0.000000	0.144330	0.454420	0.000000	0.000000	0.000043
5	0.281959	0.000000	0.000000	0.024610	0.051546	0.600051	0.000000	0.000000	0.000014
6	0.932748	0.000000	0.000000	0.000000	0.072165	0.584075	0.000000	0.000000	0.000000
7	0.579599	0.000000	0.000000	0.000600	0.185567	0.717481	0.019231	0.019231	0.000043
8	0.033660	0.000000	0.000040	0.000000	0.134021	0.452528	0.000000	0.000000	0.000000
9	0.476939	0.000000	0.015163	0.005402	0.082474	0.591882	0.000000	0.000000	0.002429

In [ ]:
```
#Encoding the device feature in the dataset using Label Encoding.

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
df_x['device'] = le.fit_transform(df_x['device'])
print(type(df_x['device']))
df_x['device'].head()
```

```
<class 'pandas.core.series.Series'>

<ipython-input-27-faf144be2b3e>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  df_x['device'] = le.fit_transform(df_x['device'])
```

Out[27]:
```
0    0
1    2
2    3
3    4
4    5
Name: device, dtype: int64
```

The reason I didn't use one-hot encoding to encode the device column in this case, is because here the number of samples in the dataset is huge and doing one-hot encoding would only increase the dimentionality of the dataset massively , creating a very sparse matrix .

In [ ]:
```
#Checking for Multi-collinearity in the dataset.
import seaborn as sns
plt.figure(figsize=(15,15))
sns.heatmap(df_x_subset_scaled.corr(),annot=True)
```

Out[28]: `<Axes: >`

In [ ]:
```
df_x_subset_scaled.columns
```

Out[29]:
```
Index(['metric1', 'metric2', 'metric3', 'metric4', 'metric5', 'metric6',
       'metric7', 'metric8', 'metric9'],
      dtype='object')
```

We need to eliminate one among the metric8 or metric7 as both are highly correlated with each other , so one needs to be dropped .Among the metric8 and metric7 , we drop metric8 because we see that it is showing less variance and would not affect the model as much as metric7.Hence I decide to drop metric8.

In [ ]:
```
#Dropping metric8 from the dataset.
df_x_subset_scaled=df_x_subset_scaled[['metric1', 'metric2', 'metric3', 'metric4', 'metric5', 'metric
                                       'metric7', 'metric9']]
```

In [ ]:
```
#Verifying the case of multi-collinearity again using a heatmap.
plt.figure(figsize=(15,15))
sns.heatmap(df_x_subset_scaled.corr(),annot=True)
```

Out[31]: <Axes: >

In [ ]:
```
len(df_x)
```

Out[32]: 124494

In [ ]:
```
df_x_deviceonly=df_x['device']
df_x_deviceonly
```

Out[33]:
```
0            0
1            2
2            3
3            4
4            5
          ...
124489    1045
124490    1068
124491    1075
124492    1081
124493    1082
Name: device, Length: 124494, dtype: int64
```

In [ ]:
```
len(df_x_subset_scaled)
```

Out[34]:
```
124494
```

In [ ]:
```
df_x_deviceonly = df_x_deviceonly.reset_index(drop=True)
df_x_subset_scaled = df_x_subset_scaled.reset_index(drop=True)
df_x_subset_scaled.head()
```

Out[35]:

	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric9
0	0.883224	0.000847	0.00000	0.031212	0.051546	0.591204	0.0	0.000100
1	0.251374	0.000000	0.00012	0.000000	0.051546	0.585017	0.0	0.000000
2	0.709821	0.000000	0.00000	0.000000	0.113402	0.344461	0.0	0.000000
3	0.326427	0.000000	0.00000	0.000000	0.051546	0.595191	0.0	0.000000
4	0.556935	0.000000	0.00000	0.000000	0.144330	0.454420	0.0	0.000043

In [ ]:
```
#Merging the two datasets - df_x_deviceonly and df_x_subset_scaled based on their indexes .
merged_df = pd.merge(df_x_deviceonly, df_x_subset_scaled, left_index=True, right_index=True)
print(len(merged_df))
merged_df.head(20)
```

```
124494
```

Out[36]:

	device	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric9
0	0	0.883224	0.000847	0.000000	0.031212	0.051546	0.591204	0.000000	0.000100
1	2	0.251374	0.000000	0.000120	0.000000	0.051546	0.585017	0.000000	0.000000
2	3	0.709821	0.000000	0.000000	0.000000	0.113402	0.344461	0.000000	0.000000
3	4	0.326427	0.000000	0.000000	0.000000	0.051546	0.595191	0.000000	0.000000
4	5	0.556935	0.000000	0.000000	0.000000	0.144330	0.454420	0.000000	0.000043
5	6	0.281959	0.000000	0.000000	0.024610	0.051546	0.600051	0.000000	0.000014
6	7	0.932748	0.000000	0.000000	0.000000	0.072165	0.584075	0.000000	0.000000
7	8	0.579599	0.000000	0.000000	0.000600	0.185567	0.717481	0.019231	0.000043
8	9	0.033660	0.000000	0.000040	0.000000	0.134021	0.452528	0.000000	0.000000
9	10	0.476939	0.000000	0.015163	0.005402	0.082474	0.591882	0.000000	0.002429
10	11	0.460178	0.000000	0.000000	0.000000	0.061856	0.563210	0.000000	0.000014
11	12	0.917254	0.000000	0.000000	0.000000	0.010309	0.312211	0.000000	0.000114
12	13	0.181861	0.000000	0.010670	0.000600	0.051546	0.579375	0.000000	0.032414
13	14	0.426522	0.023642	0.000000	0.105042	0.103093	0.437742	0.000000	0.000000
14	15	0.249936	0.002586	0.000080	0.312725	0.020619	0.552110	0.000000	0.000043
15	17	0.181652	0.094662	0.000562	0.644658	0.103093	0.362049	0.000000	0.000300
16	19	0.143437	0.000000	0.000000	0.000000	0.082474	0.572996	0.000000	0.000071
17	20	0.141479	0.000000	0.000000	0.000000	0.082474	0.596952	0.000000	0.000000
18	21	0.514211	0.000000	0.000000	0.007203	0.134021	0.431364	0.000000	0.000071
19	23	0.902727	0.000000	0.000000	0.000000	0.082474	0.565509	0.000000	0.000000

In [ ]:
```
#Creating the dependent variable.
y = df['failure']
```

Implementing the process of splitting the dataset into train set and test set.

In [ ]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(merged_df, y, test_size=0.3, random_state=42, str

print("----------------Checking the shape of the datasets-------------------------------------")
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
----------------Checking the shape of the datasets-------------------------------------
(87145, 9)
(37349, 9)
(87145,)
(37349,)
```

As stated above , to handle the problem of class imbalance efficiently , implementing SMOTE here .

In [ ]:
```
from collections import Counter
from imblearn.over_sampling import SMOTE

counter=Counter(y_train)
print('Before',counter)
smote = SMOTE(random_state=42)
x_train_resampled, y_train_resampled = smote.fit_resample(x_train, y_train)
counter=Counter(y_train_resampled)
print('After',counter)
```

```
Before Counter({0: 87071, 1: 74})
After Counter({0: 87071, 1: 87071})
```

Implementing Random Forest algorithm here for classification.

The reason I chose Random forests model is because it deals with the problem of overfitting efficiently .

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

#Initializing the random forest model.
rf_model = RandomForestClassifier(random_state=42,n_estimators=100)

# Training the model on the resampled training data
rf_model.fit(x_train_resampled, y_train_resampled)
```

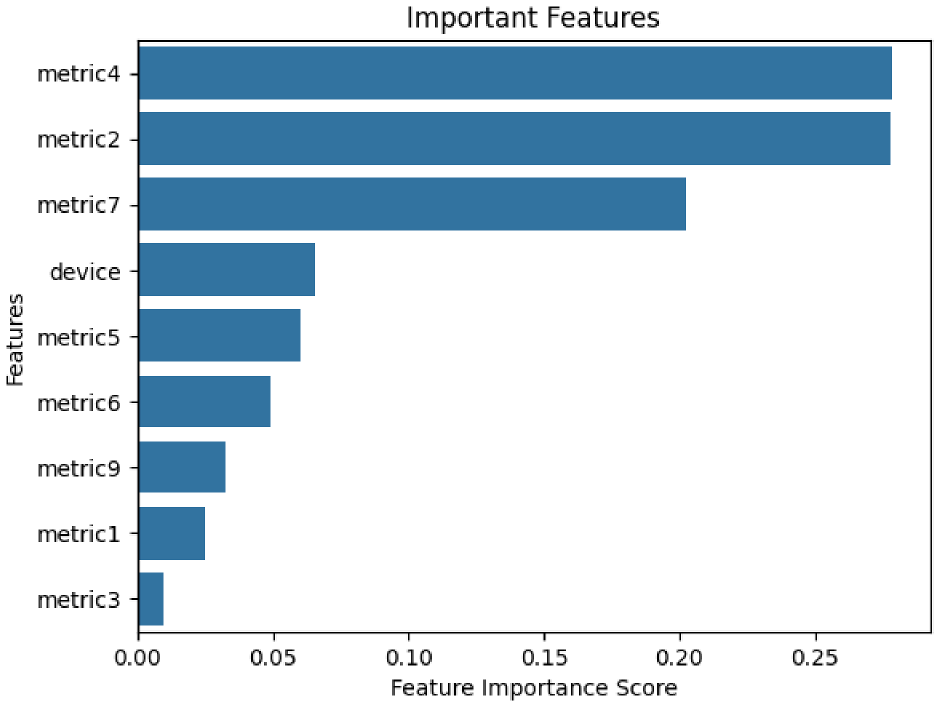
Out[40]:
```
RandomForestClassifier(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Assesing the importance of each feature in the training set.

In [ ]:
```
feature_imp = pd.Series(rf_model.feature_importances_,index=x_train_resampled.columns).sort_values(as
print(feature_imp)
sns.barplot(x=feature_imp, y=feature_imp.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Important Features")
plt.show()
```

```
metric4    0.278787
metric2    0.277881
metric7    0.202706
device     0.065364
metric5    0.060247
metric6    0.048754
metric9    0.032293
metric1    0.024714
metric3    0.009254
dtype: float64
```



Making Predictions on the test set.

In [ ]:
```
# Making predictions on the test data
y_pred = rf_model.predict(x_test)
print(y_pred[:10])
y_prob = rf_model.predict_proba(x_test)
print(y_prob[:10])
```

```
[0 0 0 0 0 0 0 0 0 0]
[[1.00000000e+00 0.00000000e+00]
 [9.99737222e-01 2.62777559e-04]
 [9.99247487e-01 7.52513395e-04]
 [1.00000000e+00 0.00000000e+00]
 [9.98984709e-01 1.01529095e-03]
 [9.86592593e-01 1.34074074e-02]
 [9.99247487e-01 7.52513395e-04]
 [9.98984709e-01 1.01529095e-03]
 [9.99247487e-01 7.52513395e-04]
 [9.98984709e-01 1.01529095e-03]]
```

Evaluating the results

In [ ]:
```
from sklearn.metrics import classification_report,accuracy_score,confusion_matrix

# Classification report
print(classification_report(y_test, y_pred))

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     37317
           1       0.24      0.16      0.19        32

    accuracy                           1.00     37349
   macro avg       0.62      0.58      0.59     37349
weighted avg       1.00      1.00      1.00     37349

Accuracy: 0.9988486974216177
Confusion Matrix:
[[37301    16]
 [   27     5]]
```

Implementing hyper-parameter tuning using GridSearchCV

In [ ]:
```
from sklearn.model_selection import GridSearchCV
rfc = RandomForestClassifier()

forest_params = [{'max_depth': list(range(10, 20)), 'max_features': ['sqrt']}]
grid_search = GridSearchCV(rfc, forest_params, cv = 10, scoring='f1',return_train_score=True)
grid_search.fit(x_train_resampled, y_train_resampled)

print(grid_search.best_params_)
```

```
{'max_depth': 19, 'max_features': 'sqrt'}
```

In [ ]:
```
#Creating the best model object using the optimal hyperparameters
best_model = grid_search.best_estimator_
best_model
```

Out[45]:
```
RandomForestClassifier(max_depth=19)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:
```
#making predictions using the best_model
y_predictions = best_model.predict(x_test)
```

In [ ]:
```
#Evaluating the best model

from sklearn.metrics import classification_report, confusion_matrix

#Classification report
print("Classification Report:")
print(classification_report(y_test, y_predictions))

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

#Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_predictions))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     37317
           1       0.15      0.09      0.12        32

    accuracy                           1.00     37349
   macro avg       0.57      0.55      0.56     37349
weighted avg       1.00      1.00      1.00     37349

Accuracy: 0.9988486974216177
Confusion Matrix:
[[37300    17]
 [   29     3]]
```

```
# Format for sklearn.metrics.confusion_matrix
           prediction
            0        1
          -----    -----
      0 | TN     |  FP
actual    -----    -----
      1 | FN     |  TP
```

1. I tried to implementing Hyperparameter tuning using GridSearchCV to fine-tune the model in order to further reduce the Type I and Type II errors . But we observe that in this case it has not improved the performance of the model on key metrics like precision, recall, and F1-score but it gets slightly decreased .

2. The default model performed better in terms of precision, recall, and F1-score before hyper-parameter tuning was done.

3. Given these results, there is no need to implement hyperparameter tuning using GridSearchCV for this particular problem .