	Credential's
	Name : Mayank Anand Registration Number : 2141001045
In [47]:	<pre># importing libraries import pandas as pd</pre>
	<pre>import numpy as np from matplotlib import pyplot as plt</pre>
In [48]:	Exploratory data analysis (EDA)  # to load the dataset
In [49]:	<pre>df = pd.read_csv("Training Dataset.csv") # to view the first few data's of the dataframe</pre>
Out[49]:	df.head()  timestamp value is_anomaly predicted  1 1425008573 42 False 44.072500
	1       1425008873       41       False       50.709390         2       1425009173       41       False       81.405120
	3 1425009473 61 False 39.950367 4 1425009773 44 False 35.350160
	# to view the last few data's of the dataframe  df.tail()
Out[50]:	timestamp         value         is_anomaly         predicted           15825         1429756073         44         False         53.624115           15826         1429756373         45         False         59.752296
	15827       1429756673       48       False       52.147630         15828       1429756973       26       False       58.007545         15829       1429757273       38       False       59.144700
In [51]:	# to display about the total number of rows and columns in the dataset  df.shape
ouc[Ji].	(15830, 4)  # to get info of dataframe
111 [32].	<pre>df.info() <class 'pandas.core.frame.dataframe'=""></class></pre>
	RangeIndex: 15830 entries, 0 to 15829  Data columns (total 4 columns):  # Column Non-Null Count Dtype  0 timestamp 15830 non-null int64
	1 value 15830 non-null int64 2 is_anomaly 15830 non-null bool 3 predicted 15830 non-null float64 dtypes: bool(1), float64(1), int64(2)
In [53]:	memory usage: 386.6 KB  # to get statistical information about the dataset  df.describe()
Out[53]:	timestamp         value         predicted           count         1.583000e+04         15830.000000         15830.000000
	mean         1.427383e+09         85.572205         71.870715           std         1.370962e+06         321.760918         92.450520           min         1.425009e+09         0.000000         -281.389070
	25%       1.426196e+09       29.000000       32.919171         50%       1.427383e+09       47.000000       49.771124         75%       1.428570e+09       76.000000       75.948052
Tn [54].	max 1.429757e+09 13479.000000 2716.127200  # to get to know the columns name
Out[54]:	<pre>df.columns Index(['timestamp', 'value', 'is_anomaly', 'predicted'], dtype='object')</pre>
In [55]:	<pre># to count how many value are anamoly and not count=df['is_anomaly'].value_counts()</pre>
Out[55]:	False 15054 True 776 Name: is_anomaly, dtype: int64
In [56]:	# to know the datatypes of the columns  df.dtypes
Out[56]:	timestamp int64 value int64 is_anomaly bool predicted float64
	Data Visualization
In [57]:	<pre># Plotting the bar chart  plt.figure(figsize=(12, 6)) count.plot(kind='bar', color='skyblue')</pre>
	<pre>plt.title('Distribution of Anomaly') plt.xlabel('Vlid or Invalid') plt.ylabel('Count') plt.xticks(rotation=0)</pre>
	<pre>plt.grid(axis='y', linestyle='') plt.show()</pre> <pre>Distribution of Anomaly</pre>
	14000
	12000
	10000
	8000
	4000
	2000
	False True  Vlid or Invalid
To [50].	False  Vlid or Invalid  Handling Missing Values and Data Cleaning
In [58]: Out[58]:	Handling Missing Values and Data Cleaning   df.isnull().sum()  timestamp 0 value 0 is_anomaly 0
Out[58]:	Handling Missing Values and Data Cleaning  df.isnull().sum()  timestamp 0 value 0 is_anomaly 0 predicted 0 dtype: int64  # Importing label encoder
Out[58]:	Handling Missing Values and Data Cleaning  df.isnull().sum()  timestamp 0 value 0 is_anomaly 0 predicted 0 dtype: int64
Out[58]: In [59]:	Handling Missing Values and Data Cleaning  df.isnull().sum()  timestamp 0 value 0 is.anomaly 0 predicted 0 dtype: int64  # Importing label encoder from sklearn import preprocessing  # Creating label encoder object
Out[58]:  In [59]:	False Vild or Invalid  Handling Missing Values and Data Cleaning  df.isnull().sum()  timestamp 0 value 1 value
Out[58]:  In [59]:  In [60]:	False Vild or Invalid  Handling Missing Values and Data Cleaning  df.isnull().sum()  timestamp 0 value 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Out[58]:  In [59]:  In [60]:  Out[61]:	Handling Missing Values and Data Cleaning  df.isnull() sum()  timestamp   0   value   value   0   value   value   value   value   value   value   valu
Out[58]:  In [59]:  In [60]:  Out[61]:	Handling Missing Values and Data Cleaning  df.isnull().sum()  ttimestamp
Out[58]:  In [59]:  In [60]:  Out[61]:  In [62]:	Handling Missing Values and Data Cleaning  df.ismult().sum()  Limestamp 0   Imparting label encoder from sklearn import preprocessing label encoder object   Imparting label encoder   Imparting lab
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Out[58]:  In [59]:  In [60]:  In [61]:  Out[61]:  In [62]:  In [63]:  Out[63]:  Out[64]:  Out[67]:  In [68]:  Out[67]:	Finding Missing Values and Data Cleaning
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