In [1]: import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
 import seaborn as sns
 from sklearn.linear_model import LogisticRegression
 from sklearn.preprocessing import StandardScaler
 import re
 from sklearn.datasets import load_digits

In [2]: a=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\ma

Out[2]:

	date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
0	2001-08-01 01:00:00	NaN	0.37	NaN	NaN	NaN	58.400002	87.150002	NaN	34.529999	10:
1	2001-08-01 01:00:00	1.50	0.34	1.49	4.10	0.07	56.250000	75.169998	2.11	42.160000	100
2	2001-08-01 01:00:00	NaN	0.28	NaN	NaN	NaN	50.660000	61.380001	NaN	46.310001	100
3	2001-08-01 01:00:00	NaN	0.47	NaN	NaN	NaN	69.790001	73.449997	NaN	40.650002	6!
4	2001-08-01 01:00:00	NaN	0.39	NaN	NaN	NaN	22.830000	24.799999	NaN	66.309998	7:
217867	2001-04-01 00:00:00	10.45	1.81	NaN	NaN	NaN	73.000000	264.399994	NaN	5.200000	4
217868	2001-04-01 00:00:00	5.20	0.69	4.56	NaN	0.13	71.080002	129.300003	NaN	13.460000	21
217869	2001-04-01 00:00:00	0.49	1.09	NaN	1.00	0.19	76.279999	128.399994	0.35	5.020000	41
217870	2001-04-01 00:00:00	5.62	1.01	5.04	11.38	NaN	80.019997	197.000000	2.58	5.840000	3.
217871	2001-04-01 00:00:00	8.09	1.62	6.66	13.04	0.18	76.809998	206.300003	5.20	8.340000	3!

217872 rows × 16 columns

In [3]:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217872 entries, 0 to 217871
Data columns (total 16 columns):

#	Column	Non-Null Count	Dtype
0	date	217872 non-null	object
1	BEN	70389 non-null	float64
2	CO	216341 non-null	float64
3	EBE	57752 non-null	float64
4	MXY	42753 non-null	float64
5	NMHC	85719 non-null	float64
6	NO_2	216331 non-null	float64
7	NOx	216318 non-null	float64
8	OXY	42856 non-null	float64
9	0_3	216514 non-null	float64
10	PM10	207776 non-null	float64
11	PXY	42845 non-null	float64
12	S0_2	216403 non-null	float64
13	TCH	85797 non-null	float64
14	TOL	70196 non-null	float64
15	station	217872 non-null	int64
dtyp	es: float	64(14), int64(1),	object(1)

memory usage: 26.6+ MB

In [4]: b=a.fillna(value=333)

Out[4]:

	date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_
0	2001-08-01 01:00:00	333.00	0.37	333.00	333.00	333.00	58.400002	87.150002	333.00	34.5299
1	2001-08-01 01:00:00	1.50	0.34	1.49	4.10	0.07	56.250000	75.169998	2.11	42.16000
2	2001-08-01 01:00:00	333.00	0.28	333.00	333.00	333.00	50.660000	61.380001	333.00	46.31000
3	2001-08-01 01:00:00	333.00	0.47	333.00	333.00	333.00	69.790001	73.449997	333.00	40.65000
4	2001-08-01 01:00:00	333.00	0.39	333.00	333.00	333.00	22.830000	24.799999	333.00	66.3099§
217867	2001-04-01 00:00:00	10.45	1.81	333.00	333.00	333.00	73.000000	264.399994	333.00	5.20000
217868	2001-04-01 00:00:00	5.20	0.69	4.56	333.00	0.13	71.080002	129.300003	333.00	13.46000
217869	2001-04-01 00:00:00	0.49	1.09	333.00	1.00	0.19	76.279999	128.399994	0.35	5.02000
217870	2001-04-01 00:00:00	5.62	1.01	5.04	11.38	333.00	80.019997	197.000000	2.58	5.84000
217871	2001-04-01 00:00:00	8.09	1.62	6.66	13.04	0.18	76.809998	206.300003	5.20	8.34000

217872 rows × 16 columns

In [6]: c=b.head(11)

Out[6]:

	date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
0	2001-08-01 01:00:00	333.00	0.37	333.00	333.00	333.00	58.400002	87.150002	333.00	34.529999	1
1	2001-08-01 01:00:00	1.50	0.34	1.49	4.10	0.07	56.250000	75.169998	2.11	42.160000	1
2	2001-08-01 01:00:00	333.00	0.28	333.00	333.00	333.00	50.660000	61.380001	333.00	46.310001	1
3	2001-08-01 01:00:00	333.00	0.47	333.00	333.00	333.00	69.790001	73.449997	333.00	40.650002	
4	2001-08-01 01:00:00	333.00	0.39	333.00	333.00	333.00	22.830000	24.799999	333.00	66.309998	
5	2001-08-01 01:00:00	2.11	0.63	2.48	5.94	0.05	66.260002	118.099998	3.15	33.500000	1
6	2001-08-01 01:00:00	333.00	0.28	333.00	333.00	333.00	35.799999	39.590000	333.00	68.250000	1
7	2001-08-01 01:00:00	333.00	0.67	333.00	333.00	333.00	74.830002	112.000000	333.00	26.410000	1
8	2001-08-01 01:00:00	333.00	0.41	333.00	333.00	333.00	33.209999	37.299999	333.00	62.299999	1
9	2001-08-01 01:00:00	333.00	0.17	333.00	333.00	0.13	24.129999	36.970001	333.00	46.200001	
10	2001-08-01 01:00:00	333.00	0.38	333.00	333.00	0.02	40.900002	46.610001	333.00	51.450001	1

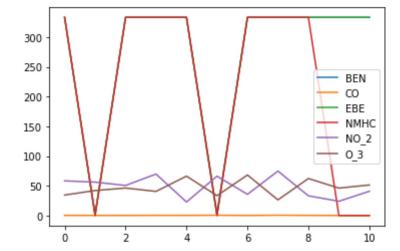
In [7]: d=c[['BEN','CO','EBE','NMHC','NO_2','O_3']]

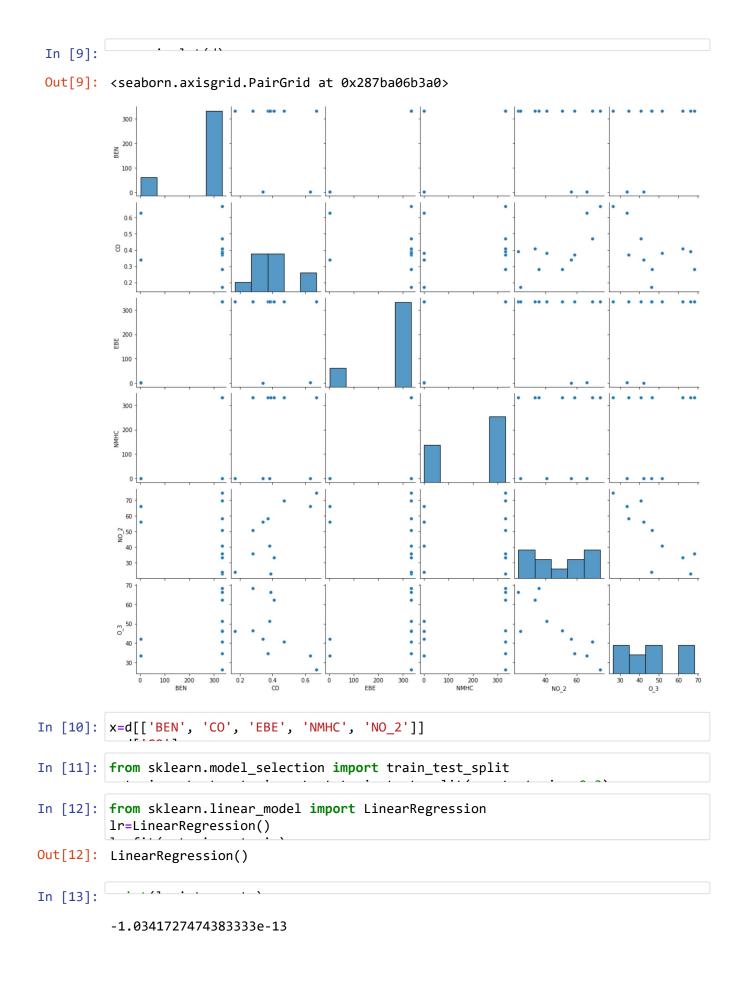
Out[7]:

	BEN	СО	EBE	NMHC	NO_2	O_3
0	333.00	0.37	333.00	333.00	58.400002	34.529999
1	1.50	0.34	1.49	0.07	56.250000	42.160000
2	333.00	0.28	333.00	333.00	50.660000	46.310001
3	333.00	0.47	333.00	333.00	69.790001	40.650002
4	333.00	0.39	333.00	333.00	22.830000	66.309998
5	2.11	0.63	2.48	0.05	66.260002	33.500000
6	333.00	0.28	333.00	333.00	35.799999	68.250000
7	333.00	0.67	333.00	333.00	74.830002	26.410000
8	333.00	0.41	333.00	333.00	33.209999	62.299999
9	333.00	0.17	333.00	0.13	24.129999	46.200001
10	333.00	0.38	333.00	0.02	40.900002	51.450001

In [8]:

Out[8]: <AxesSubplot:>





```
In [14]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[14]:
                   Co-efficient
            BEN 2.563701e-14
             CO 1.000000e+00
            EBE -2.540517e-14
           NMHC 7.820330e-17
           NO_2 -3.837914e-16
In [15]: prediction=lr.predict(x_test)
Out[15]: <matplotlib.collections.PathCollection at 0x287bb1fd040>
           0.60
           0.55
           0.50
           0.45
           0.40
           0.35
           0.30
                        0.35
                              0.40
                                    0.45
                                          0.50
                                                0.55
                  0.30
                                                      0.60
In [16]:
          1.0
In [17]: -
In [18]: rr=Ridge(alpha=10)
Out[18]: Ridge(alpha=10)
In [19]:
Out[19]: -1.271256674204904
In [20]: la=Lasso(alpha=10)
Out[20]: Lasso(alpha=10)
In [21]: -
Out[21]: -0.3006861214158223
```

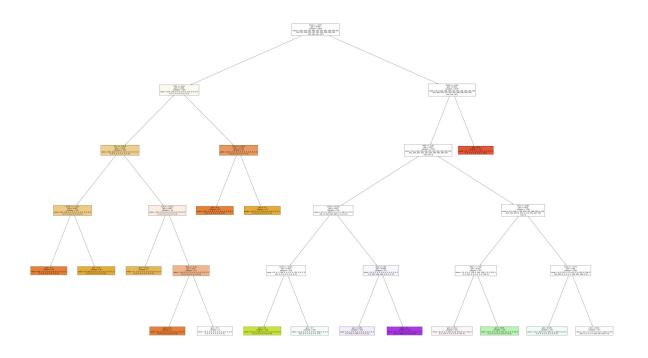
In [22]:	a1=b.head(6500)											
Out[22]:		date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	0_3	
	0	2001-08-01 01:00:00						58.400002				 1
	1	2001-08-01 01:00:00	1.50	0.34	1.49	4.1	0.07	56.250000	75.169998	2.11	42.160000	1
	2	2001-08-01 01:00:00	333.00	0.28	333.00	333.0	333.00	50.660000	61.380001	333.00	46.310001	1
	3	2001-08-01 01:00:00	333.00	0.47	333.00	333.0	333.00	69.790001	73.449997	333.00	40.650002	
	4	2001-08-01 01:00:00	333.00	0.39	333.00	333.0	333.00	22.830000	24.799999	333.00	66.309998	
	6495	2001-08-12 07:00:00	333.00	0.02	333.00	333.0	0.04	24.030001	25.850000	333.00	23.820000	
	6496	2001-08-12 07:00:00	333.00	0.19	333.00	333.0	333.00	36.919998	41.060001	333.00	38.169998	
	6497	2001-08-12 07:00:00	333.00	0.22	333.00	333.0	333.00	29.080000	35.060001	333.00	35.570000	
	6498	2001-08-12 07:00:00	333.00	0.16	333.00	333.0	333.00	21.020000	23.549999	333.00	45.139999	
	6499	2001-08-12 07:00:00	0.71	0.61	333.00	333.0	333.00	41.200001	51.410000	333.00	30.809999	
	6500 r	rows × 16 co	olumns									
In [23]:	e=a1[['BEN', '(0', 'E	BE',	'NMHC',	'NO	2','0_3	3',				
In [24]:	f=e.i	loc[:,0:14	1]									
In [25]:			/\ c·		-	(6)						
In [26]:	logr=	LogisticRe	egressi	on(ma	ax_iter	=1000	ð)					
Out[26]:	Logis	ticRegress	sion(ma	x_it	er=1000	00)						
In [27]:	from	sklearn.mo	odel_se	lect	ion imp	ort t	rain_te	est_split		~ ~ `		
In [28]:		^ ^^ ^^			22.22.4	4	1					
In [29]:	predi	ction=logr	r.predi	ct(i)							
	[2807	9039]	•									

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```
In [30]: L
Out[30]: array([28079001, 28079003, 28079004, 28079006, 28079007, 28079009,
              28079011, 28079012, 28079014, 28079015, 28079016, 28079018,
              28079019, 28079021, 28079022, 28079023, 28079024, 28079025,
              28079035, 28079036, 28079038, 28079039, 28079040, 28079099],
             dtype=int64)
In [31]:
Out[31]: 0.0
In [32]:
Out[32]: 0.0
In [33]:
Out[33]: 0.8682051282051282
In [34]: | from sklearn.linear_model import ElasticNet
        en=ElasticNet()
Out[34]: ElasticNet()
In [35]:
        [1.02462182e-04 0.000000000e+00 3.82222044e-08 3.53327940e-04
         4.61591830e-03]
In [36]:
        0.09074088811121622
In [37]: | prediction=en.predict(x_test)
        -0.8094046147861065
In [38]: from sklearn.ensemble import RandomForestClassifier
        rfc=RandomForestClassifier()
Out[38]: RandomForestClassifier()
        parameters={'max_depth':[1,2,3,4,5],
        'min_samples_leaf':[5,10,15,20,25],
         'n_estimators':[10,20,30,40,50]
```

```
In [43]: from sklearn.tree import plot tree
                            plt.figure(figsize=(80,50))
Out[43]: [Text(2187.36, 2491.5, 'X[10] <= -0.957\ngini = 0.958\nsamples = 2879\nvalue
                             = [191, 204, 182, 188, 168, 185, 180, 198, 209, 190 \ 194, 201, 184, 200, 187,
                            181, 204, 188, 188, 189\n200, 148, 194, 197]'),
                               Text(1160.64, 2038.5, X[1] <= -0.01 \text{ ngini} = 0.499 \text{ nsamples} = 240 \text{ nvalue} = 0.499 \text{ nsamples} = 240 \text{ nvalue} = 0.499 \text{ nsamples} = 0.499 \text{ nsamples} = 0.499 \text{ nvalue} = 0.499 \text{ nvalue}
                             0]'),
                               Text(714.24, 1585.5, 'X[1] <= -0.016 \setminus gini = 0.424 \setminus gini = 158 \setminus g
                             0]'),
                               Text(357.12, 1132.5, 'X[10] <= -1.033\ngini = 0.401\nsamples = 139\nvalue =
                             Text(178.56, 679.5, 'gini = 0.0\nsamples = 41\nvalue = [65, 0, 0, 0, 0, 0, 0]
                             0, 0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(535.6800000000001, 679.5, 'gini = 0.0\nsamples = 98\nvalue = [0, 169,
                             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(1071.3600000000001, 1132.5, 'X[6] \leftarrow -0.319 \mid = 0.497 \mid = 1
                             0, 0, 0]'),
                                Text(892.8, 679.5, 'gini = 0.219\nsamples = 5\nvalue = [1, 7, 0, 0, 0, 0, 0, 0, 0]
                             0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(1249.92, 679.5, X[6] < -0.15 \le 0.42 \le 14 \le 14
                             Text(1071.360000000001, 226.5, 'gini = 0.0\nsamples = 5\nvalue = [8, 0, 0,
                             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(1428.48, 226.5, 'gini = 0.5\nsamples = 9\nvalue = [6, 6, 0, 0, 0, 0, 0, 0, 0]
                             0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                               Text(1607.04, 1585.5, X[10] \leftarrow -1.033  ngini = 0.276 \ nsamples = 82 \ nvalue =
                             Text(1428.48, 1132.5, 'gini = 0.0\nsamples = 67\nvalue = [111, 0, 0, 0, 0,
                             0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(1785.6, 1132.5, 'gini = 0.0\nsamples = 15\nvalue = [0, 22, 0, 0, 0, 0,
                             Text(3214.08, 2038.5, 'X[10] \le 2.391 = 0.954 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 2639 = 26
                              [0, 0, 182, 188, 168, 185, 180, 198, 209, 190, 194\n201, 184, 200, 187, 181,
                             204, 188, 188, 189, 200\n148, 194, 197]'),
                               Text(3035.52, 1585.5, X[0] <= -0.41  = 0.952\nsamples = 2519\nvalue =
                             [0, 0, 182, 188, 168, 185, 180, 198, 209, 190, 194\n201, 184, 200, 187, 181,
                             204, 188, 188, 189, 200\n148, 194, 0]'),
                                Text(2321.28, 1132.5, 'X[10] <= 0.032\ngini = 0.833\nsamples = 729\nvalue =
                             0, 0, 0]'),
                               Text(1964.16, 679.5, 'X[10] <= -0.602\ngini = 0.667\nsamples = 358\nvalue =
                             0]'),
                                Text(1785.6, 226.5, 'gini = 0.0\nsamples = 118\nvalue = [0, 0, 0, 188, 0, 0,
                             0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(2142.7200000000003, 226.5, 'gini = 0.5\nsamples = 240\nvalue = [0, 0,
                             0, 0, 0, 0, 0, 0, 190, 0, 0, 0, 0\n181, 0, 0, 0, 0, 0, 0, 0, 0]'),
                                Text(2678.4, 679.5, X[6] <= 2.68 \text{ ngini} = 0.666 \text{ nsamples} = 371 \text{ nvalue} = [0, 0.666]
                             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 204, 188, 188, 0, 0, 0, 0, 0]'),
                                Text(2499.84, 226.5, 'gini = 0.499\nsamples = 250\nvalue = [0, 0, 0, 0, 0, 0, 0]
```

```
0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 204, 0, 188, 0, 0, 0, 0]'),
  Text(2856.96, 226.5, 'gini = 0.0\nsamples = 121\nvalue = [0, 0, 0, 0, 0, 0, 0, 0]
0, 0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 188, 0, 0, 0, 0, 0, 0]'),
 Text(3749.76, 1132.5, 'X[3] <= -0.085 / ngini = 0.933 / nsamples = 1790 / nvalue = 1790 / nv
[0, 0, 182, 0, 168, 185, 180, 198, 209, 0, 194\n201, 184, 200, 6, 181, 0, 0,
0, 189, 200, 148\n194, 0]'),
  Text(3392.64, 679.5, X[8] < -1.091 = 0.832 = 707 = 707
Text(3214.08, 226.5, 'gini = 0.811\nsamples = 515\nvalue = [0, 0, 0, 0, 140,
0, 28, 144, 0, 0, 0, 155, 0\n0, 0, 154, 0, 0, 0, 0, 0, 181, 0]'),
  Text(3571.2, 226.5, 'gini = 0.695\nsamples = 192\nvalue = [0, 0, 0, 0, 18,
0, 152, 54, 0, 0, 0, 46, 0 \setminus 0, 27, 0, 0, 0, 0, 0, 0, 13, 0]'),
  Text(4106.88, 679.5, 'X[10] <= -0.373\ngini = 0.89\nsamples = 1083\nvalue =
[0, 0, 182, 0, 10, 185, 0, 0, 209, 0, 194, 0\n184, 200, 6, 0, 0, 0, 0, 189, 2
00, 148, 0, 0]'),
  Text(3928.32, 226.5, 'gini = 0.676\nsamples = 370\nvalue = [0, 0, 182, 0, 1]
0, 185, 0, 0, 209, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
  Text(4285.4400000000005, 226.5, 'gini = 0.834\nsamples = 713\nvalue = [0, 0,
0, 0, 0, 0, 0, 0, 0, 194, 0, 184\n200, 6, 0, 0, 0, 189, 200, 148, 0,
0]'),
  Text(3392.64, 1585.5, 'gini = 0.0\nsamples = 120\nvalue = [0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 197]')]
```



From this observation I had observe that the GRIDSEARCH is a highest accuracy of 0.9621978021978022

In []:

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