PROBLEM STATEMENT:- TO PREDICT THE RAIN FALL BASED ON VARIOUS FEATURES OF THE DATASET

In [1]:

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing,svm
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
df=pd.read_csv(r"C:\Users\samit\OneDrive\Desktop\jupyter\rainfall in india 1901-2015 csv.csv")
df
```

Out[2]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	J
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	13
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	15
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	15
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	2
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	184.3	14.9	1533.7	
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	12.4	8.8	1405.5	1
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	78.1	26.7	1426.3	6
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	59.0	62.3	1395.0	6
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	231.0	159.0	1642.9	

4116 rows × 19 columns

In [3]:

```
df.head()
```

Out[3]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	Jan-Feb
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	136.3
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	159.8
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	156.7
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	24.1
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	1.3

In [4]:

```
df.tail()
```

Out[4]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	Jan-Feb
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	184.3	14.9	1533.7	7.9
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	12.4	8.8	1405.5	19.3
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	78.1	26.7	1426.3	60.6
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	59.0	62.3	1395.0	69.3
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	231.0	159.0	1642.9	2.7

In [5]:

```
df.isnull().any()
```

Out[5]:

```
SUBDIVISION    False
YEAR           False
JAN             True
FEB             True
MAR             True
APR             True
MAY             True
JUN             True
JUL             True
AUG             True
SEP             True
OCT             True
NOV             True
DEC             True
ANNUAL          True
Jan-Feb         True
Mar-May         True
Jun-Sep         True
Oct-Dec         True
dtype: bool
```

In [6]:

```
df.fillna(method='ffill',inplace=True)
```

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
SUBDIVISION    0
YEAR           0
JAN            0
FEB            0
MAR            0
APR            0
MAY            0
JUN            0
JUL            0
AUG            0
SEP            0
OCT            0
NOV            0
DEC            0
ANNUAL         0
Jan-Feb        0
Mar-May        0
Jun-Sep        0
Oct-Dec        0
dtype: int64
```

In [8]:

```
df.describe()
```

Out[8]:

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AU
count	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.0000(
mean	1958.218659	18.957240	21.823251	27.415379	43.160641	85.788994	230.567979	347.177235	290.2397(
std	33.140898	33.576192	35.922602	47.045473	67.816588	123.220150	234.896056	269.321089	188.7856(
min	1901.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.400000	0.000000	0.0000(
25%	1930.000000	0.600000	0.600000	1.000000	3.000000	8.600000	70.475000	175.900000	155.8500(
50%	1958.000000	6.000000	6.700000	7.900000	15.700000	36.700000	138.900000	284.800000	259.4000(
75%	1987.000000	22.200000	26.800000	31.400000	50.125000	97.400000	306.150000	418.325000	377.8000(
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.900000	2362.800000	1664.6000(

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4116 entries, 0 to 4115
Data columns (total 19 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   SUBDIVISION  4116 non-null   object 
 1   YEAR         4116 non-null   int64  
 2   JAN          4116 non-null   float64
 3   FEB          4116 non-null   float64
 4   MAR          4116 non-null   float64
 5   APR          4116 non-null   float64
 6   MAY          4116 non-null   float64
 7   JUN          4116 non-null   float64
 8   JUL          4116 non-null   float64
 9   AUG          4116 non-null   float64
 10  SEP          4116 non-null   float64
 11  OCT          4116 non-null   float64
 12  NOV          4116 non-null   float64
 13  DEC          4116 non-null   float64
 14  ANNUAL       4116 non-null   float64
 15  Jan-Feb      4116 non-null   float64
 16  Mar-May      4116 non-null   float64
 17  Jun-Sep      4116 non-null   float64
 18  Oct-Dec      4116 non-null   float64
dtypes: float64(17), int64(1), object(1)
memory usage: 611.1+ KB
```

In [10]:

```
df.columns
```

Out[10]:

```
Index(['SUBDIVISION', 'YEAR', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
       'AUG', 'SEP', 'OCT', 'NOV', 'DEC', 'ANNUAL', 'Jan-Feb', 'Mar-May',
       'Jun-Sep', 'Oct-Dec'],
      dtype='object')
```

In [11]:

```
df.shape
```

Out[11]:

```
(4116, 19)
```

In [12]:

```
df['ANNUAL'].value_counts()
```

Out[12]:

```
ANNUAL
790.5     4
770.3     4
1836.2    4
1024.6    4
1926.5    3
         ..
443.9     1
689.0     1
605.2     1
509.7     1
1642.9    1
Name: count, Length: 3712, dtype: int64
```

In [13]:

```
df['Jan-Feb'].value_counts()
```

Out[13]:

```
Jan-Feb
0.0     238
0.1      80
0.2      52
0.3      38
0.4      32
       ...
23.3      1
95.2      1
76.9      1
66.5      1
69.3      1
Name: count, Length: 1220, dtype: int64
```

In [14]:

```
df['Mar-May'].value_counts()
```

Out[14]:

```
Mar-May
0.0      29
0.1      13
0.3      11
8.3      11
11.5     10
         ..
246.3     1
248.1     1
151.3     1
249.5     1
223.9     1
Name: count, Length: 2262, dtype: int64
```

In [15]:

```
df['Jun-Sep'].value_counts()
```

Out[15]:

```
Jun-Sep
434.3     4
334.8     4
573.8     4
613.3     4
1082.3    3
         ..
301.6     1
380.9     1
409.3     1
229.4     1
958.5     1
Name: count, Length: 3683, dtype: int64
```

In [16]:

```
df['Oct-Dec'].value_counts()
```

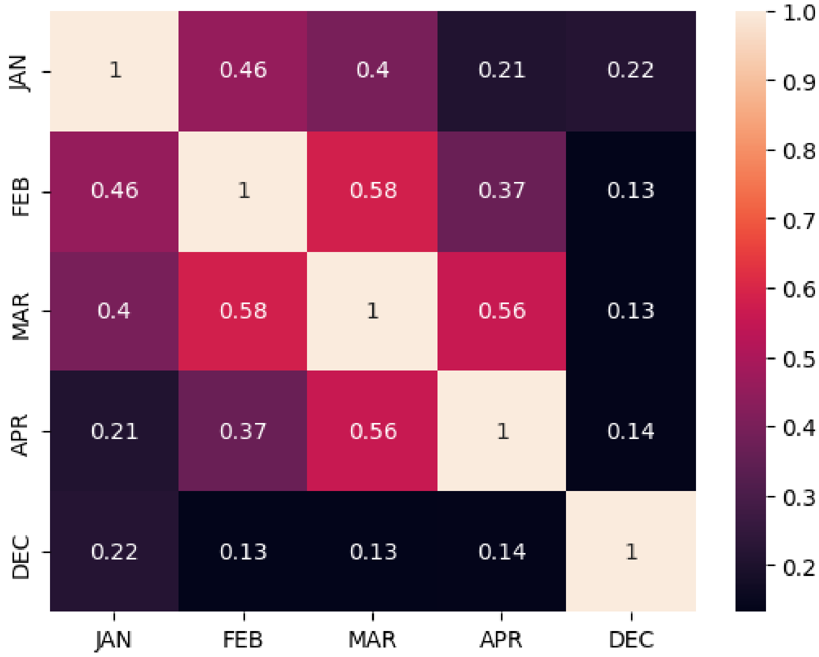
Out[16]:

```
Oct-Dec
0.0      16
0.1      15
0.5      13
0.6      12
0.7      11
         ..
191.5     1
124.5     1
139.1     1
41.5      1
555.4     1
Name: count, Length: 2389, dtype: int64
```

EXPLORATORY DATAanalysis:-

In [17]:

```
df=df[['JAN','FEB','MAR','APR','DEC']]
sns.heatmap(df.corr(),annot=True)
plt.show()
```



In [18]:

```
df.columns
```

Out[18]:

```
Index(['JAN', 'FEB', 'MAR', 'APR', 'DEC'], dtype='object')
```

In [19]:

```
x=df[["FEB"]]
y=df["JAN"]
```

LINEARREGRESSION:-

In [20]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=42)
```

In [21]:

```
from sklearn.linear_model import LinearRegression
reg=LinearRegression()
reg.fit(X_train,y_train)
print(reg.intercept_)
coeff_=pd.DataFrame(reg.coef_,x.columns,columns=['coefficient'])
coeff_
```

9.650666612303553

Out[21]:

	coefficient
FEB	0.442278

In [22]:

```
score=reg.score(X_test,y_test)
print(score)
```

0.1793580786264921

In [23]:

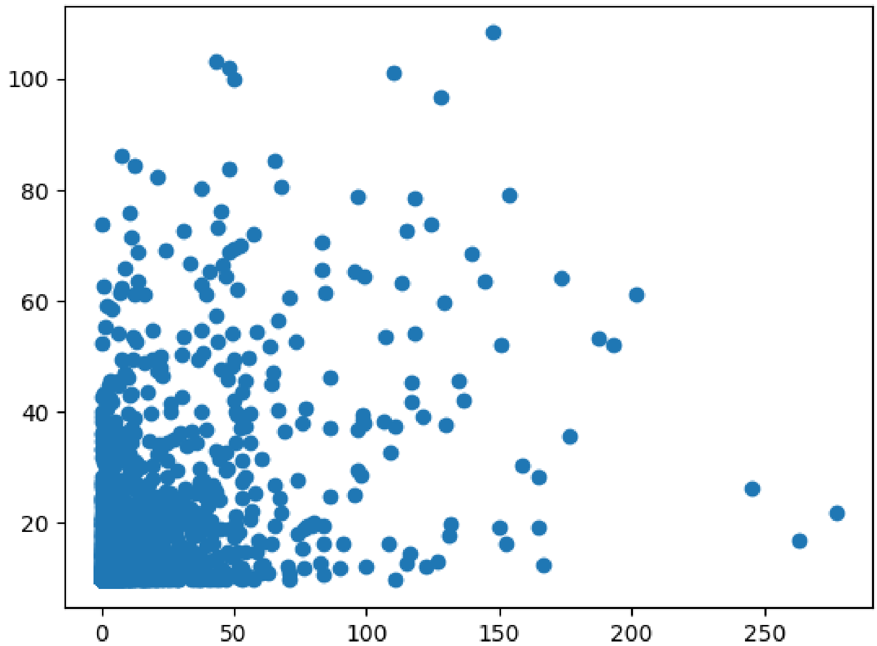
```
predictions=reg.predict(X_test)
```

In [24]:

```
plt.scatter(y_test,predictions)
```

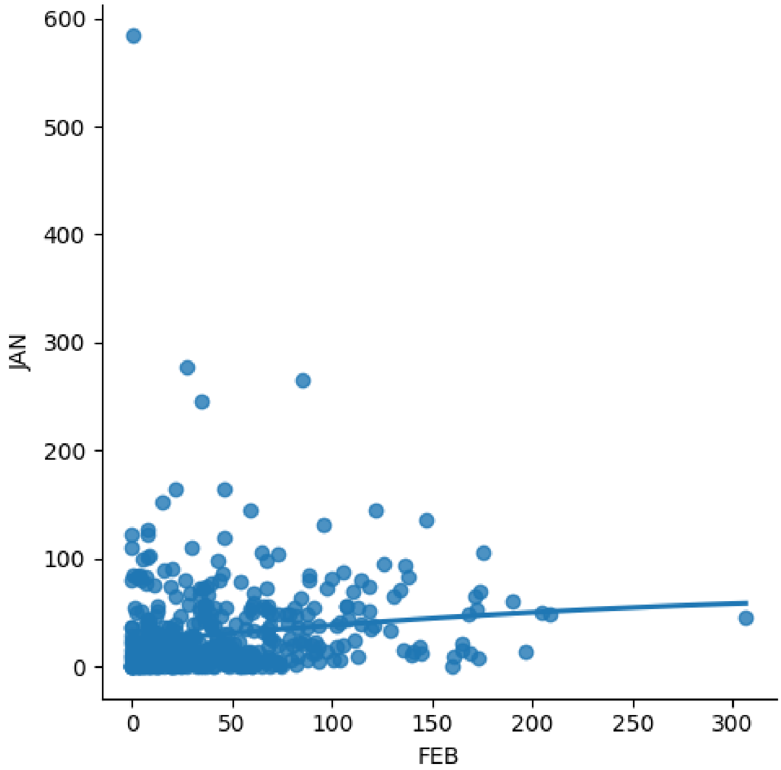
Out[24]:

<matplotlib.collections.PathCollection at 0x23740ebd3d0>



In [25]:

```
df500=df[:][:500]
sns.lmplot(x="FEB",y="JAN",order=2,ci=None,data=df500)
plt.show()
```



In [26]:

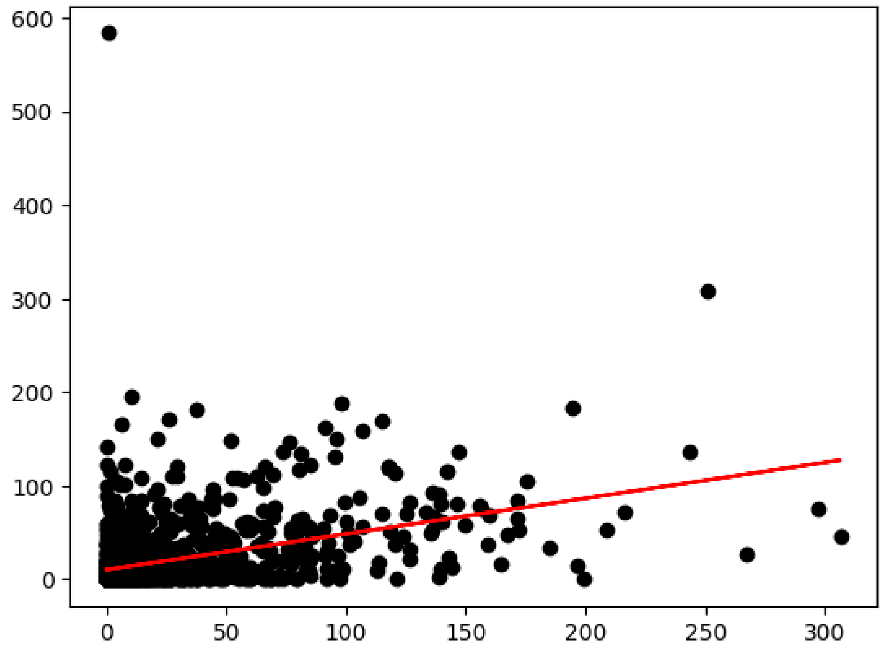
```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)
reg.fit(X_train,y_train)
reg.fit(X_test,y_test)
```

Out[26]:

```
▾ LinearRegression
LinearRegression()
```

In [27]:

```
y_pred=reg.predict(X_test)
plt.scatter(X_test,y_test,color='black')
plt.plot(X_test,y_pred,color='red')
plt.show()
```



In [28]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
model=LinearRegression()
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
r2=r2_score(y_test,y_pred)
print("R2 Score:",r2)
```

```
R2 Score: 0.1661333137628389
```

RIDGE MODEL:-

In [29]:

```
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

In [46]:

```
features= df.columns[0:1]
target= df.columns[-5]
```

In [47]:

```
x=np.array(df['JAN']).reshape(-1,1)
y=np.array(df['FEB']).reshape(-1,2)
```

In [48]:

```
x= df[features].values
y= df[target].values
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=17)
```

In [49]:

```
ridgeReg=Ridge(alpha=10)
ridgeReg.fit(x_train,y_train)
train_score_ridge=ridgeReg.score(x_train,y_train)
test_score_ridge=ridgeReg.score(x_test,y_test)
```

In [50]:

```
print("\n Ridge Model:\n")
print("the train score for ridge model is{}".format(train_score_ridge))
print("the test score for ridge model is{}".format(test_score_ridge))
```

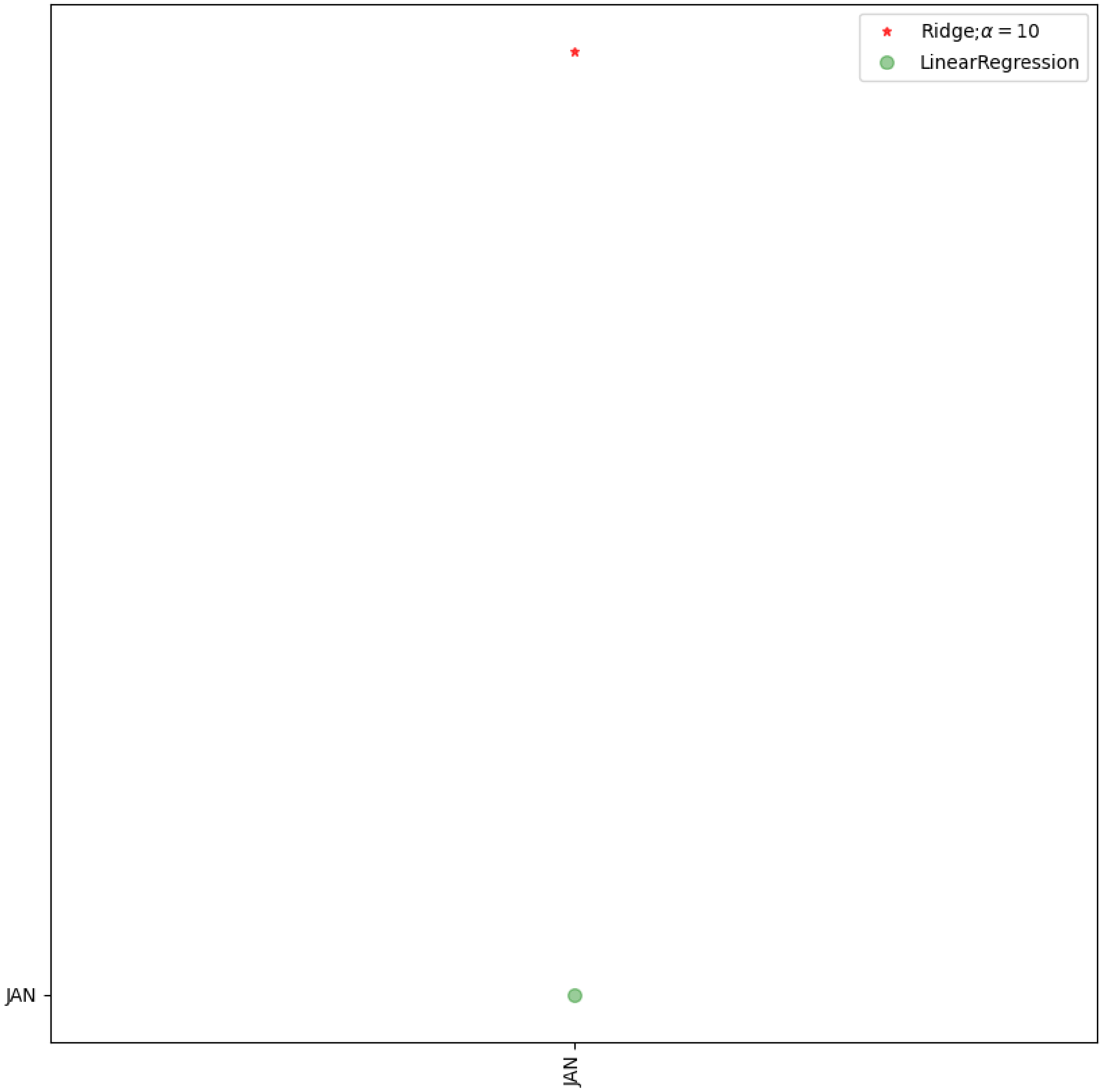
```
 Ridge Model:

the train score for ridge model is0.9999999999904551
the test score for ridge model is0.9999999999904435
```

In [51]:

```
lr=LinearRegression()
```

In [52]:

```
ure(figsize= (10,10))
t(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color='red',label=r'Ridge;$\alpha=1(
t(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="green",label='LinearRegression')
cks(rotation = 90)
end()
w()
```



LASSO MODEL:-

In [53]:

```
print("\n Lasso Model:\n")
lasso=Lasso(alpha=10)
lasso.fit(x_train,y_train)
train_score_ls=lasso.score(x_train,y_train)
test_score_ls=lasso.score(x_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is{}".format(test_score_ls))
```

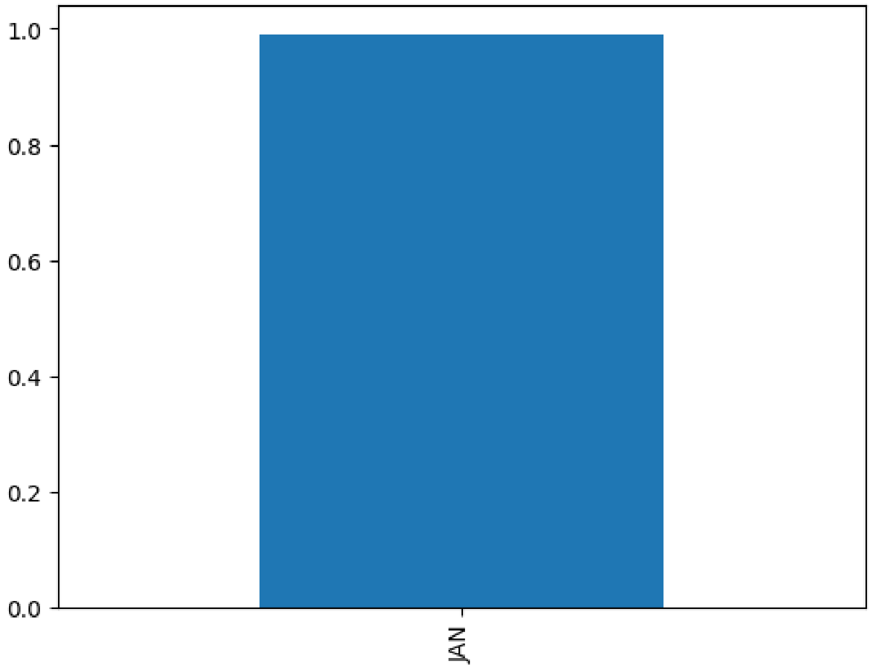
```
 Lasso Model:

The train score for ls model is 0.9999207747038827
The test score for ls model is0.9999206791315256
```

In [54]:

```
pd.Series(lasso.coef_,features).sort_values(ascending=True).plot(kind="bar")
```

Out[54]:

<Axes: >



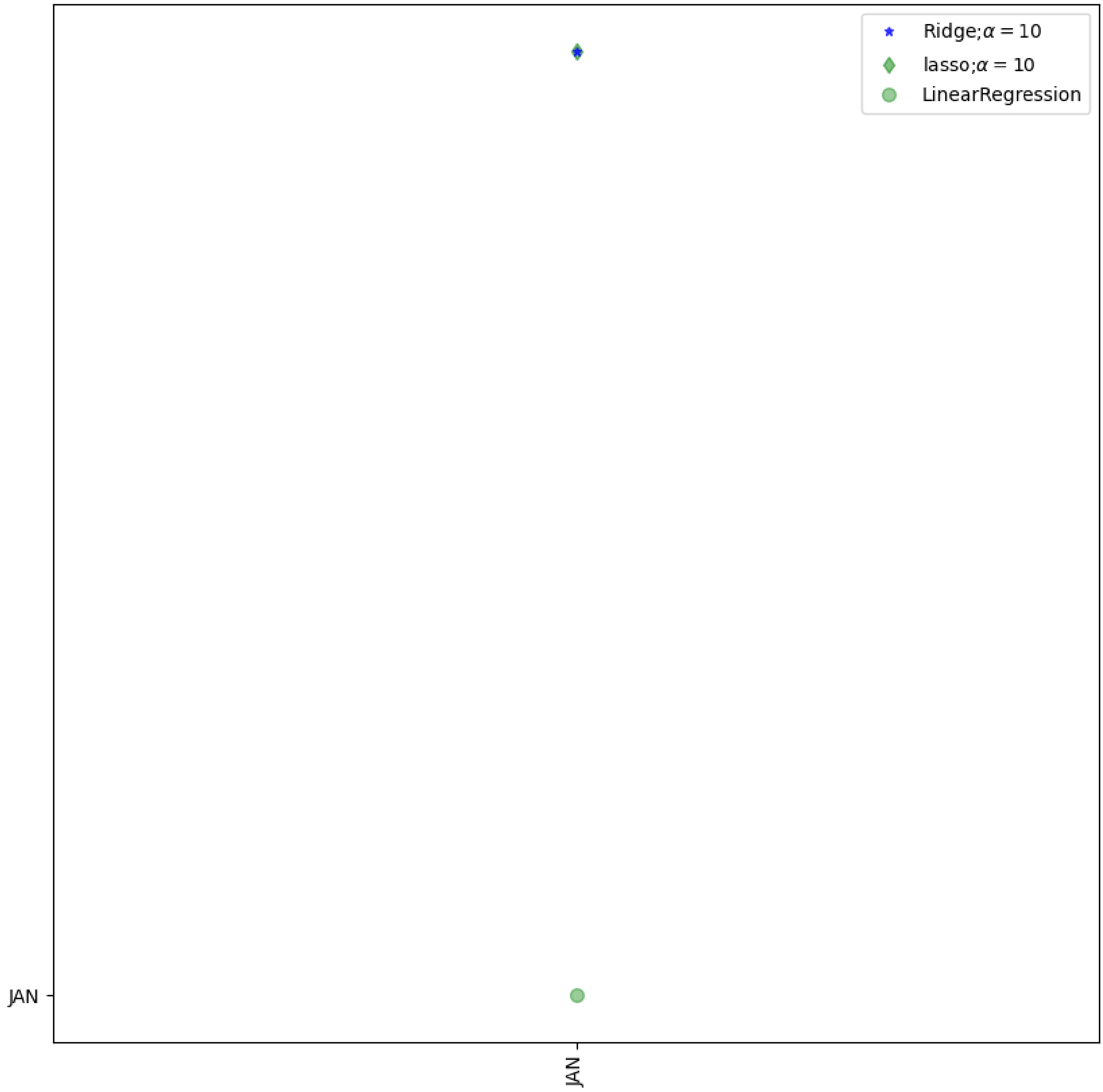
In [55]:

```
from sklearn.linear_model import LassoCV
lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,10],random_state=0).fit(x_train,y_train)
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999921
0.9999999999999921
```

In [56]:

```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color="blue",label=r'Ridge;$'
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='green',label=r'lasso;$\alpha=1(
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="green",label='LinearRegression')
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



ELASTIC NET

In [57]:

```
from sklearn.linear_model import ElasticNet
eln=ElasticNet()
eln.fit(x,y)
print(eln.coef_)
print(eln.intercept_)
print(eln.score(x,y))
```

```
[0.99911315]
0.01681222287140116
0.9999992134975881
```

In [58]:

```
y_pred_elastic = reg.predict(x_train)
mean_squared_error=np.mean((y_pred_elastic - y_train)**2)
print(mean_squared_error)
```

```
431.73307573428445

C:\Users\samit\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\base.py:439: User
Warning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

conclusion:-

```
THE SCORE OF LINEAR REGRESSION IS :- 0.1793580786264921
THE SCORE OF RIDGE MODEL IS :- 0.99999999998833
THE SCORE OF LASSO MODEL IS :- 0.999999999999992
THE SCORE OF ELASTIC NET IS :- 0.9999992160905338
AMONG ALL MODELS LASSO YEILD HIGHEST ACCURACY.SO,WE PREFER LASSO MODEL FOR THIS DATASET
```