To predict the Rain Fall Based on Various Features of the Dataset

In [2]:
```
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 [3]:
```
df=pd.read_csv(r"C:\Users\sudheer\Downloads\Rainfall in India.csv")
df
```

Out[3]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NO
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.
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.
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.
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.
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.
...	...	...	...	...	...	...	...	...	...	...	...	...	.
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	184.
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	12.
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	78.
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	59.
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	231.

4116 rows × 19 columns

Data Preprocessing

```
In [4]: df.head()
```

Out[4]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	D
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	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	16
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	22
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	4
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	34

```
In [5]: df.tail()
```

Out[5]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV
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
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
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
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
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

```
In [6]: df.isnull().any()
```

```
Out[6]: 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 [7]: df.fillna(method='ffill',inplace=True)
```

```
In [8]: df.isnull().sum()
```

```
Out[8]: 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 [9]:

```
df.describe()
```

Out[9]:

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	
count	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4
mean	1958.218659	18.957240	21.823251	27.415379	43.160641	85.788994	230.567979	
std	33.140898	33.576192	35.922602	47.045473	67.816588	123.220150	234.896056	
min	1901.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.400000	
25%	1930.000000	0.600000	0.600000	1.000000	3.000000	8.600000	70.475000	
50%	1958.000000	6.000000	6.700000	7.900000	15.700000	36.700000	138.900000	
75%	1987.000000	22.200000	26.800000	31.400000	50.125000	97.400000	306.150000	
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.900000	2

In [10]:

```
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 [11]:

```
df.columns
```

Out[11]:

```
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 [12]:
```
df.shape
```

Out[12]:
```
(4116, 19)
```

In [13]:
```
df['ANNUAL'].value_counts()
```

Out[13]:
```
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 [14]:
```
df['Jan-Feb'].value_counts()
```

Out[14]:
```
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 [15]:
```
df['Mar-May'].value_counts()
```

Out[15]:
```
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 [16]:
```
df['Jun-Sep'].value_counts()
```

Out[16]:
```
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
```

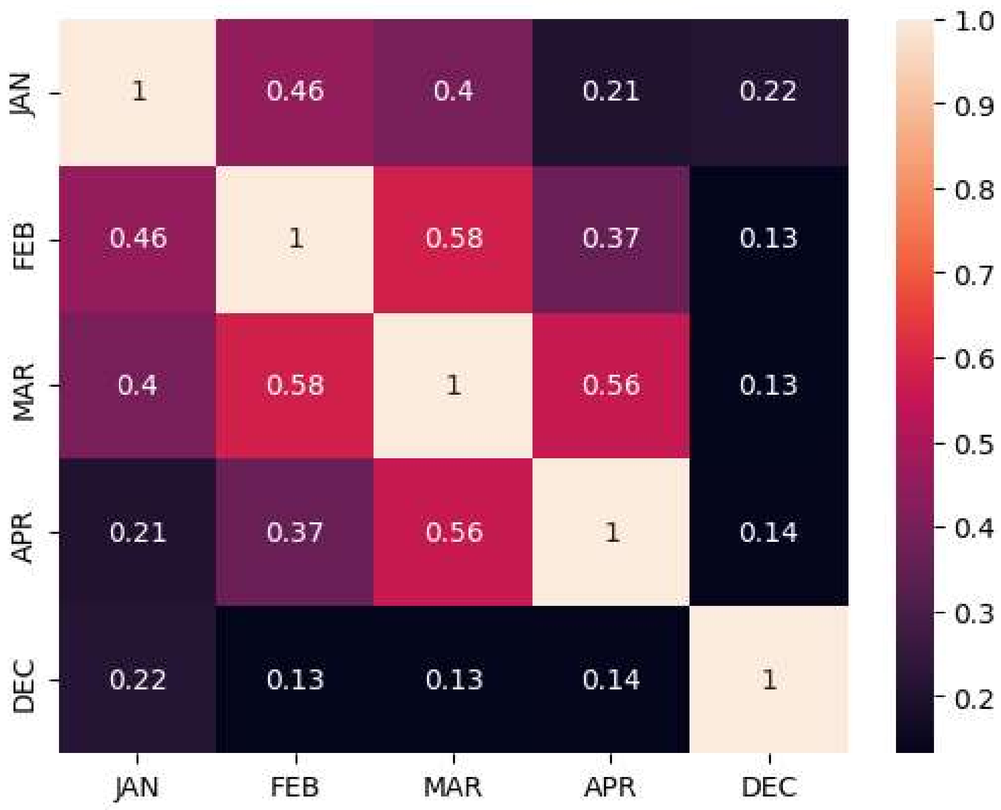
In [17]:
```
df['Oct-Dec'].value_counts()
```

Out[17]:
```
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 Data analysis

In [18]:

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



In [19]:

```
df.columns
```

Out[19]:

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

In [20]:

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

Linear Regression

In [21]:

```
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 [23]:

```
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_
```

```
9.948218787909045
```

Out[23]:

	coefficient
FEB	0.434775

In [24]:

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

```
0.20074709521051304
```

In [25]:

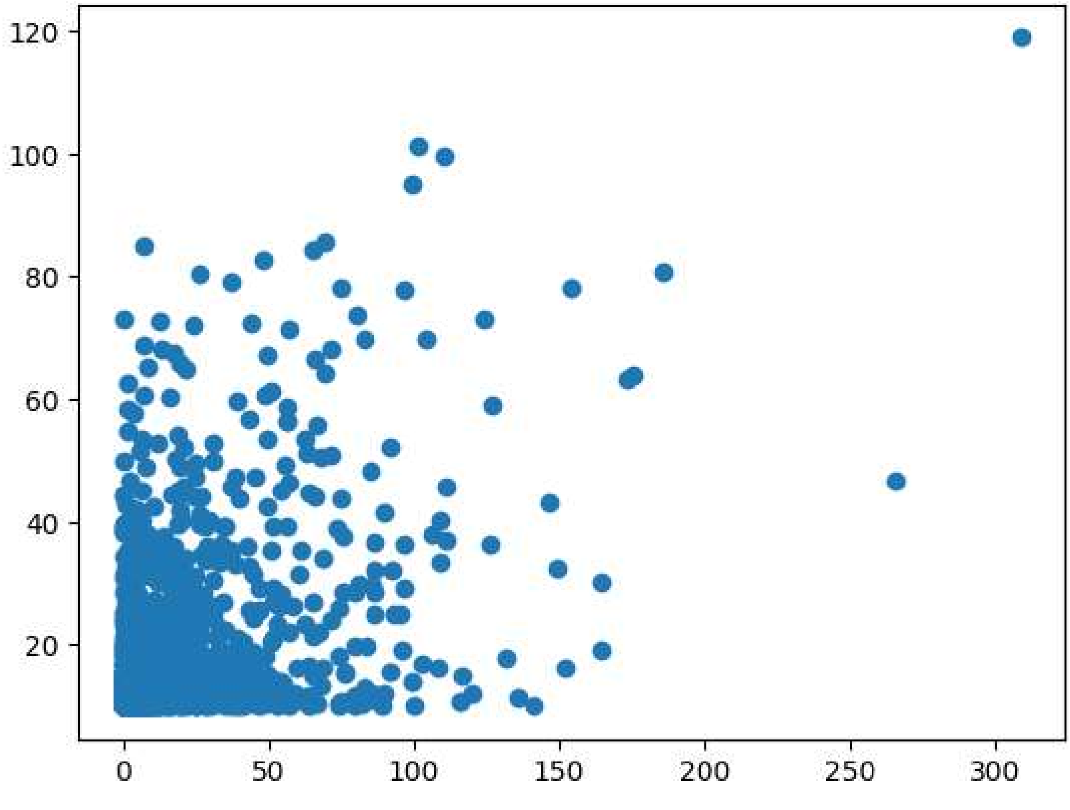
```
predictions=reg.predict(X_test)
```

In [26]:

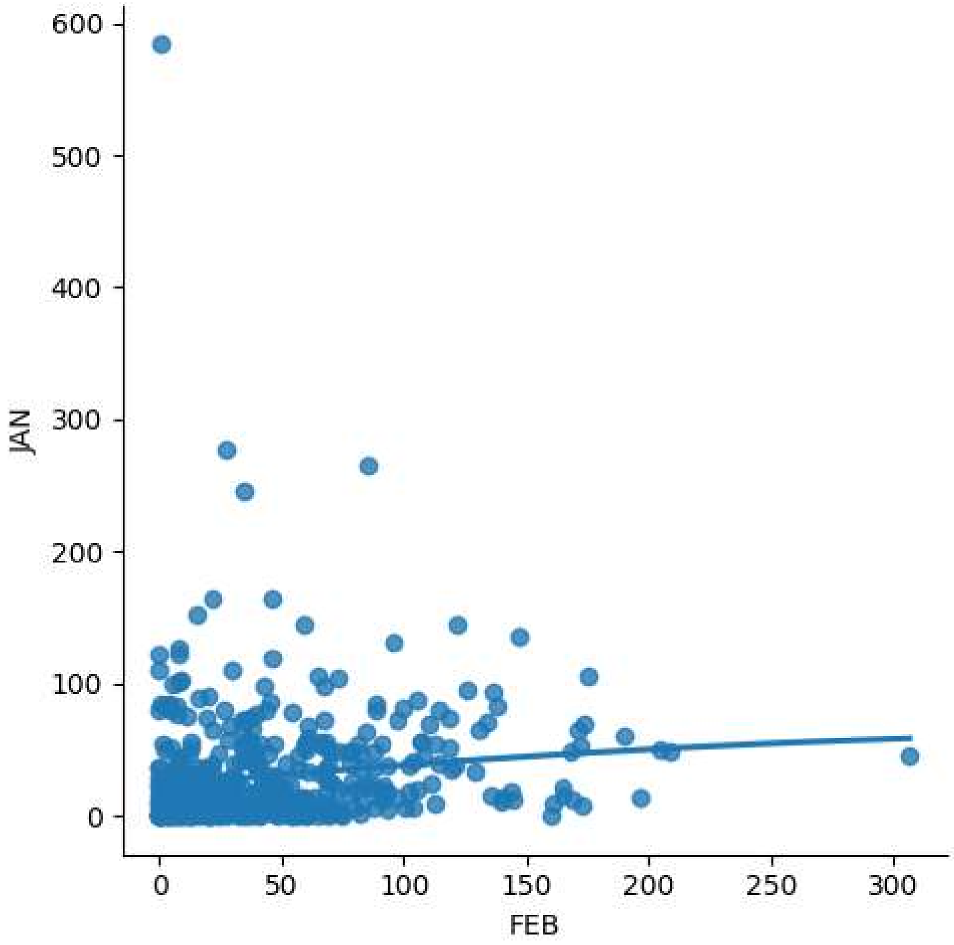
```
plt.scatter(y_test,predictions)
```

Out[26]:

```
<matplotlib.collections.PathCollection at 0x276a4380520>
```



In [27]:
```
df500=df[:][:500]
sns.lmplot(x="FEB",y="JAN",order=2,ci=None,data=df500)
plt.show()
```

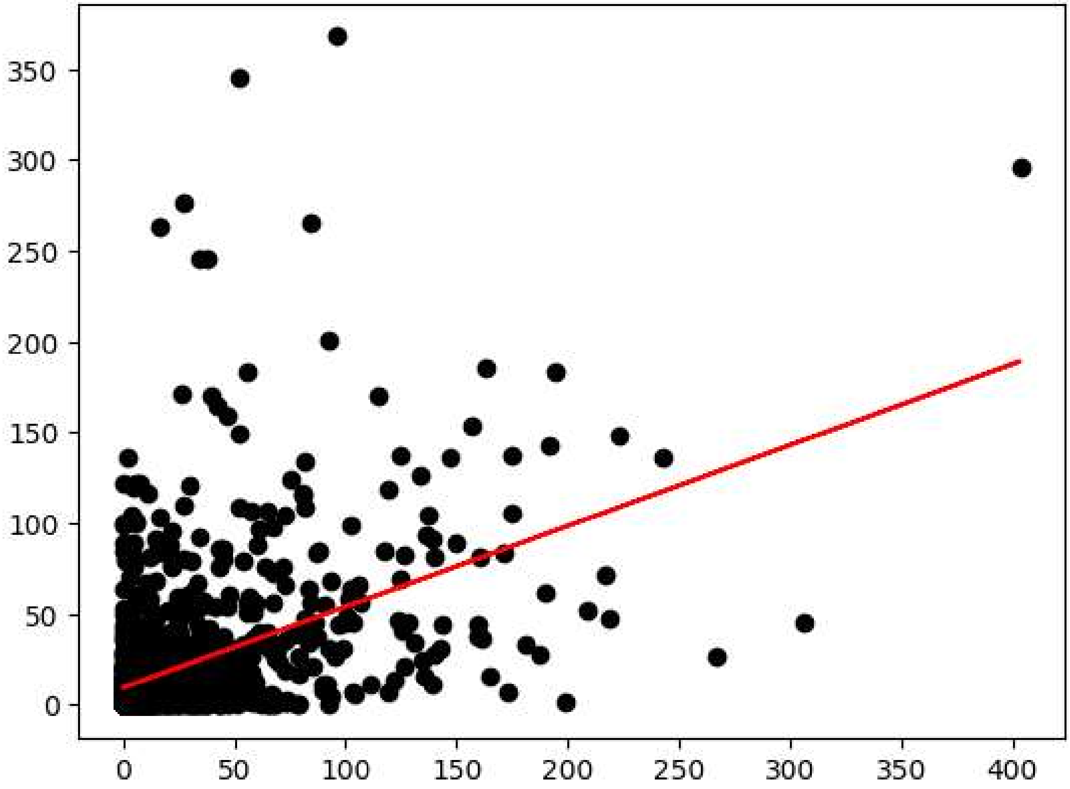


In [28]:
```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)
reg.fit(X_train,y_train)
reg.fit(X_test,y_test)
```

Out[28]:
```
▾ LinearRegression

LinearRegression()
```

In [29]:
```
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 [30]:
```
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: 0.21616507872152835
```

Ridge Regression

In [31]:
```
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

In [32]:
```
features= df.columns[0:5]
target= df.columns[-5]
```

In [33]:

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

In [34]:

```
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 [35]:

```
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 [36]:

```
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 is0.9999999999874192
the test score for ridge model is0.99999999998833
```

In [37]:

```
lr=LinearRegression()
```

Lasso Model

In [38]:

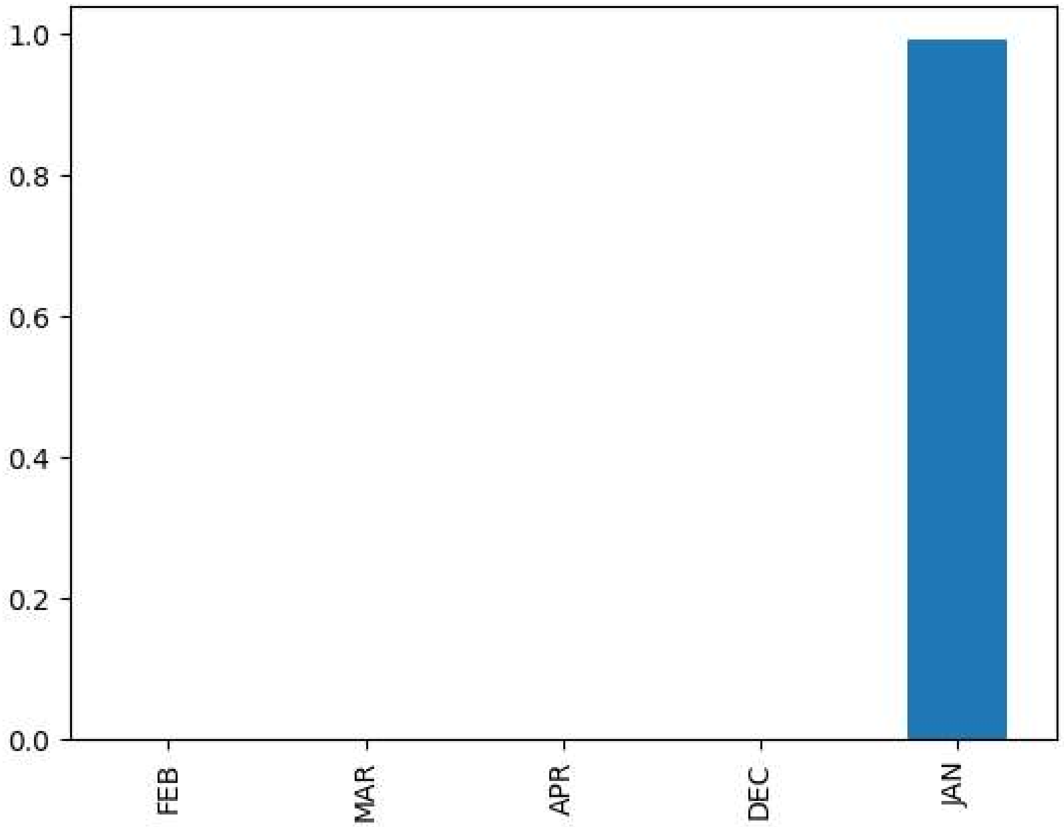
```
print("\n Lasso Model:\n")
lasso=Lasso(alpha=10)
lasso.fit(x_train,y_train)
train_score_ls=lasso.score(x_train,y_train)
test_score_ls=lasso.score(x_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is{}".format(test_score_ls))
```

```
 Lasso Model:

The train score for ls model is 0.9999207747038827
The test score for ls model is0.9999206791315255
```

In [39]:
```
pd.Series(lasso.coef_,features).sort_values(ascending=True).plot(kind="bar")
```

Out[39]:
```
<Axes: >
```



In [40]:
```
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_tr
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999921
0.9999999999999921
```

Elastic Net

In [41]:
```
from sklearn.linear_model import ElasticNet
eln=ElasticNet()
eln.fit(x,y)
print(eln.coef_)
print(eln.intercept_)
print(eln.score(x,y))
```

```
[9.99098574e-01 0.00000000e+00 3.02728910e-05 0.00000000e+00
 0.00000000e+00]
0.016258606966612632
0.9999992160905338
```

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 FO R THIS DATA SET*

```
In [ ]:
```