

PROBLEM STATEMENT : TO PREDICT THE RAINFALL BASED ON VARIOUS FEATURES OF THE DATASET

In [48]:

```
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 [49]:

```
df=pd.read_csv(r"C:\Users\jas_m\Downloads\rainfall in india 1901-2015.csv")
df
```

Out[49]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	O
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	38
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	19
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	18
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	22
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	26
...
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	11
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	14
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	7
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	16
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	16

4116 rows × 19 columns

In [50]:

```
df.head()
```

Out[50]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	
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	5
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	3
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	2
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	3
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	

In [51]:

```
df.tail()
```

Out[51]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	

In [52]:

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

Out[52]:

```
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 [53]:

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

In [54]:

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

Out[54]:

```
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 [55]:

```
df.describe()
```

Out[55]:

	YEAR	JAN	FEB	MAR	APR	MAY	
count	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000
mean	1958.218659	18.957240	21.823251	27.415379	43.160641	85.788994	230.518659
std	33.140898	33.576192	35.922602	47.045473	67.816588	123.220150	234.816588
min	1901.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.415379
25%	1930.000000	0.600000	0.600000	1.000000	3.000000	8.600000	70.415379
50%	1958.000000	6.000000	6.700000	7.900000	15.700000	36.700000	138.957240
75%	1987.000000	22.200000	26.800000	31.400000	50.125000	97.400000	306.165894
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.922602

In [56]:

```
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 [57]:

```
df.columns
```

Out[57]:

```
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 [58]:

```
df.shape
```

Out[58]:

```
(4116, 19)
```

In [59]:

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

Out[59]:

```
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: ANNUAL, Length: 3712, dtype: int64
```

In [60]:

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

Out[60]:

```
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: Jan-Feb, Length: 1220, dtype: int64
```

In [61]:

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

Out[61]:

```
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: Mar-May, Length: 2262, dtype: int64

In [62]:

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

Out[62]:

```
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: Jun-Sep, Length: 3683, dtype: int64

In [63]:

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

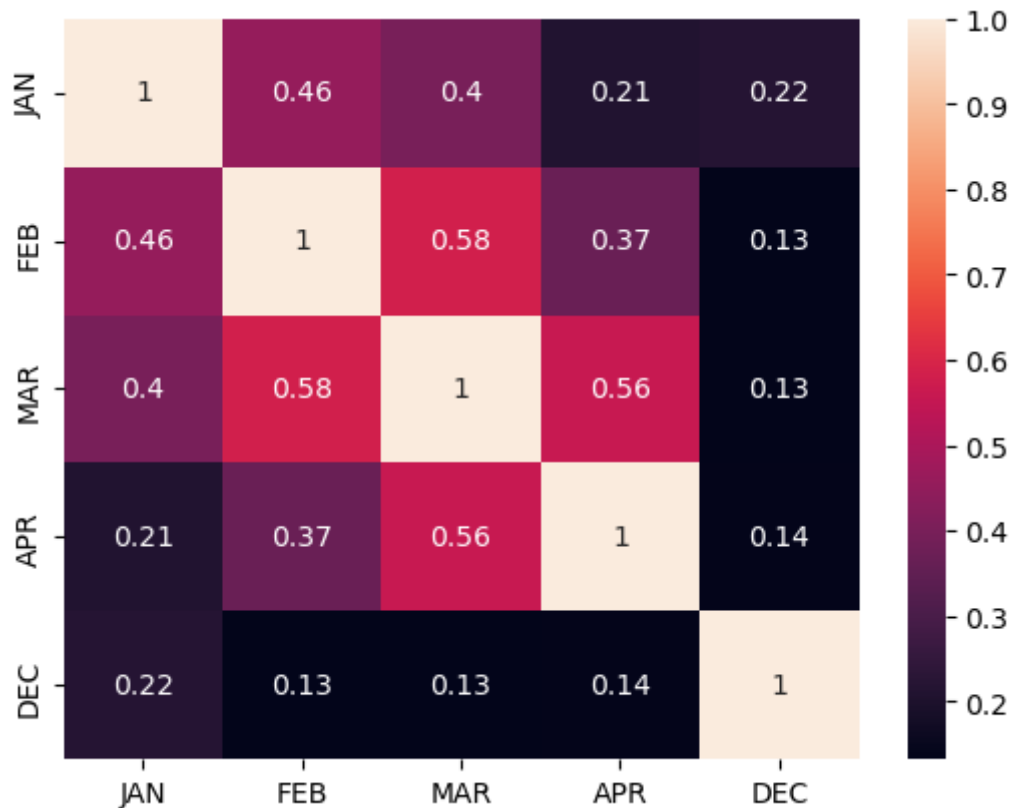
Out[63]:

```
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: Oct-Dec, Length: 2389, dtype: int64

In [64]:

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



In [65]:

```
df.columns
```

Out[65]:

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

In [66]:

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

In [67]:

```
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 [68]:

```
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[68]:

	coefficient
FEB	0.442278

In [69]:

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

0.1793580786264921

In [70]:

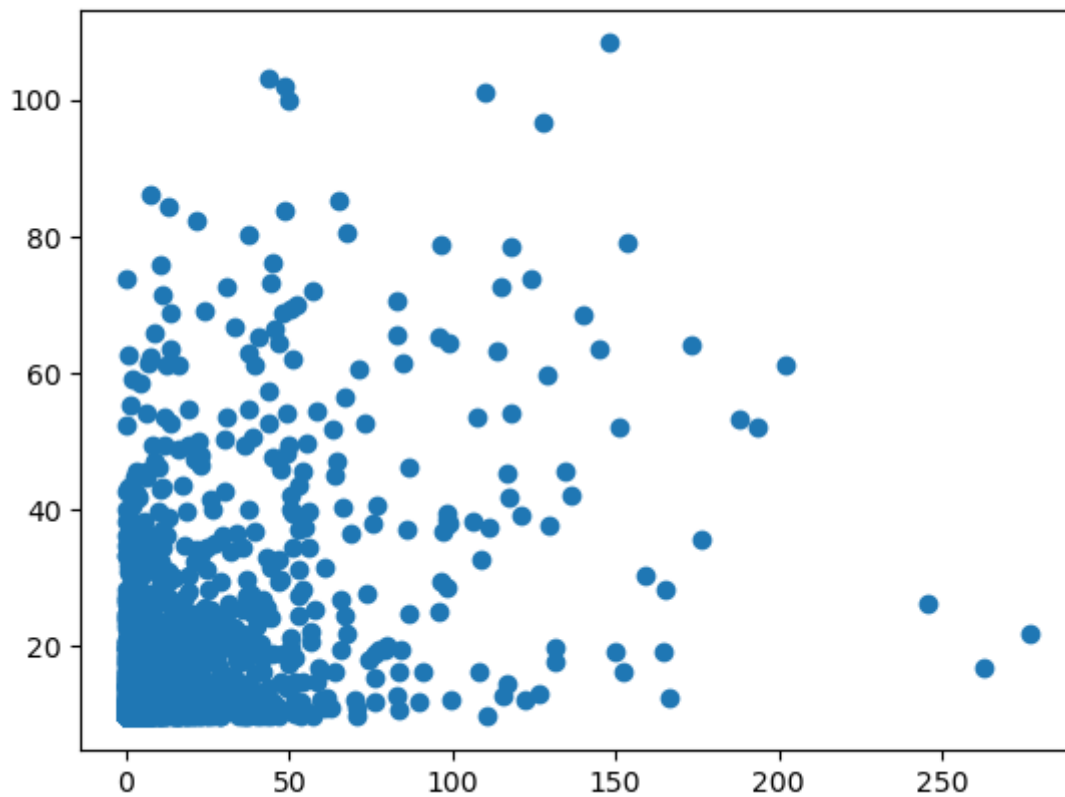
```
predictions=reg.predict(X_test)
```


In [71]:

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

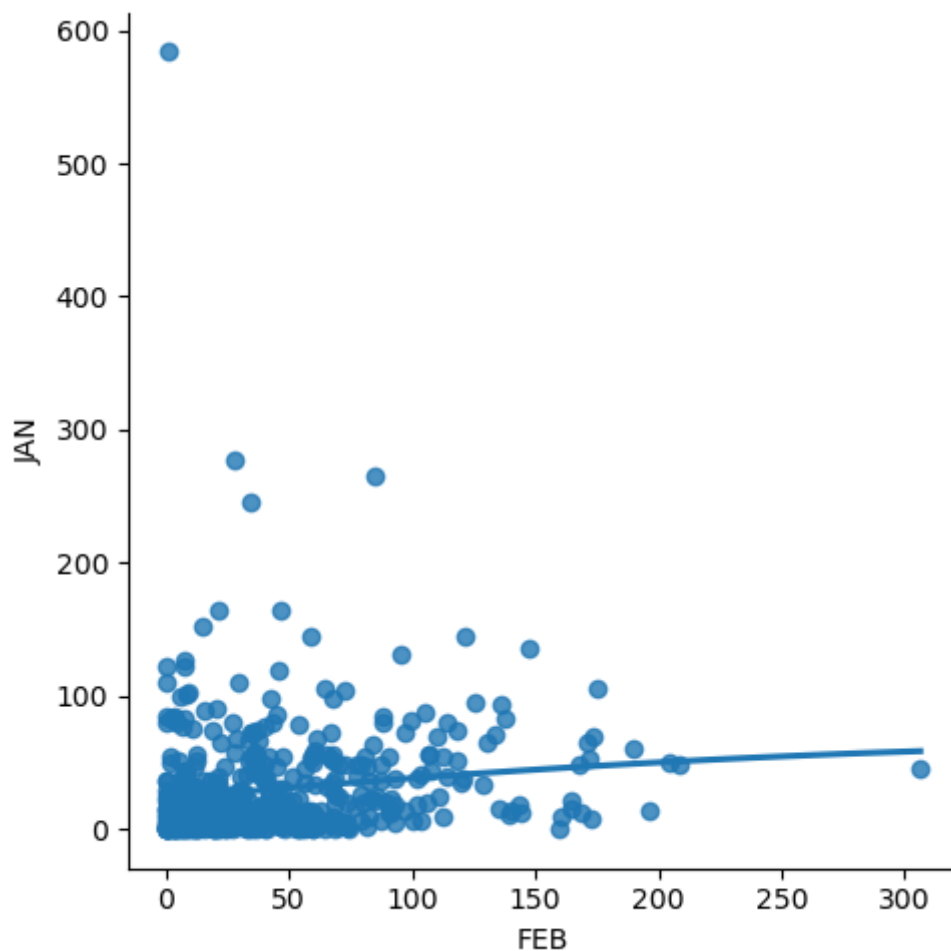
Out[71]:

<matplotlib.collections.PathCollection at 0x273b7ba2650>



In [72]:

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



In [73]:

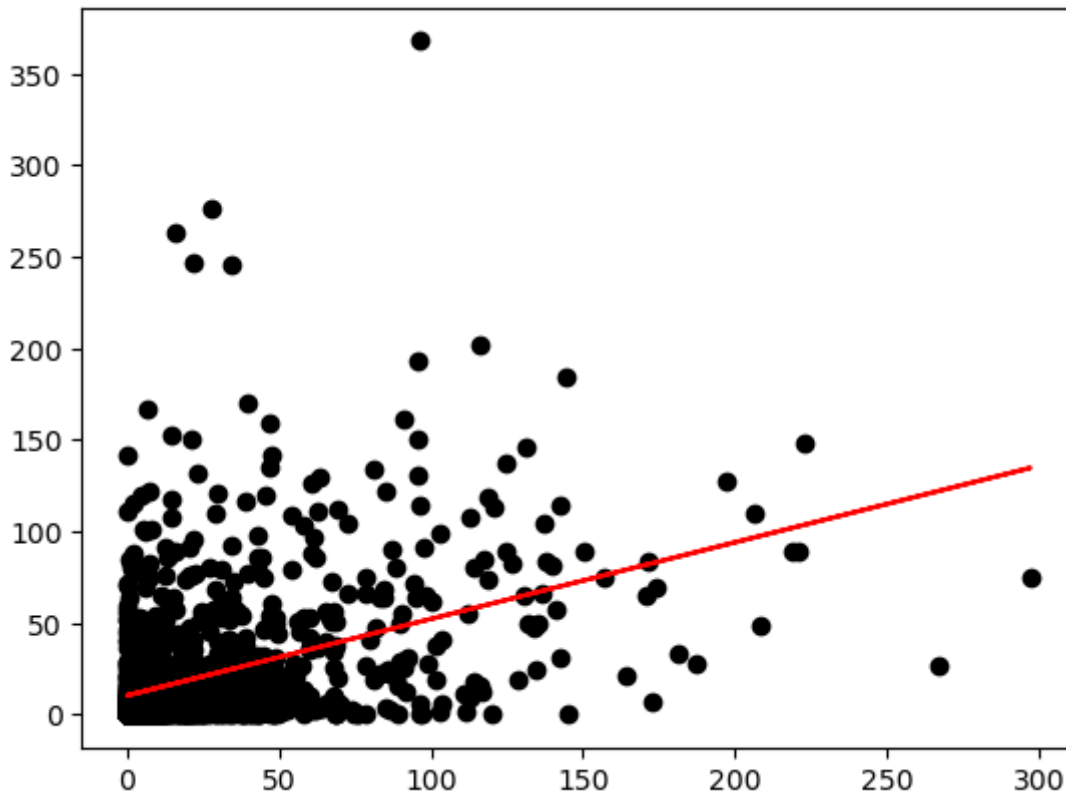
```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)  
reg.fit(X_train,y_train)  
reg.fit(X_test,y_test)
```

Out[73]:

```
LinearRegression  
LinearRegression()
```

In [74]:

```
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 [75]:

```
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: 0.184398519704562

In [76]:

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

In [77]:

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

In [78]:

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

In [79]:

```
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 [80]:

```
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 [81]:

```
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:

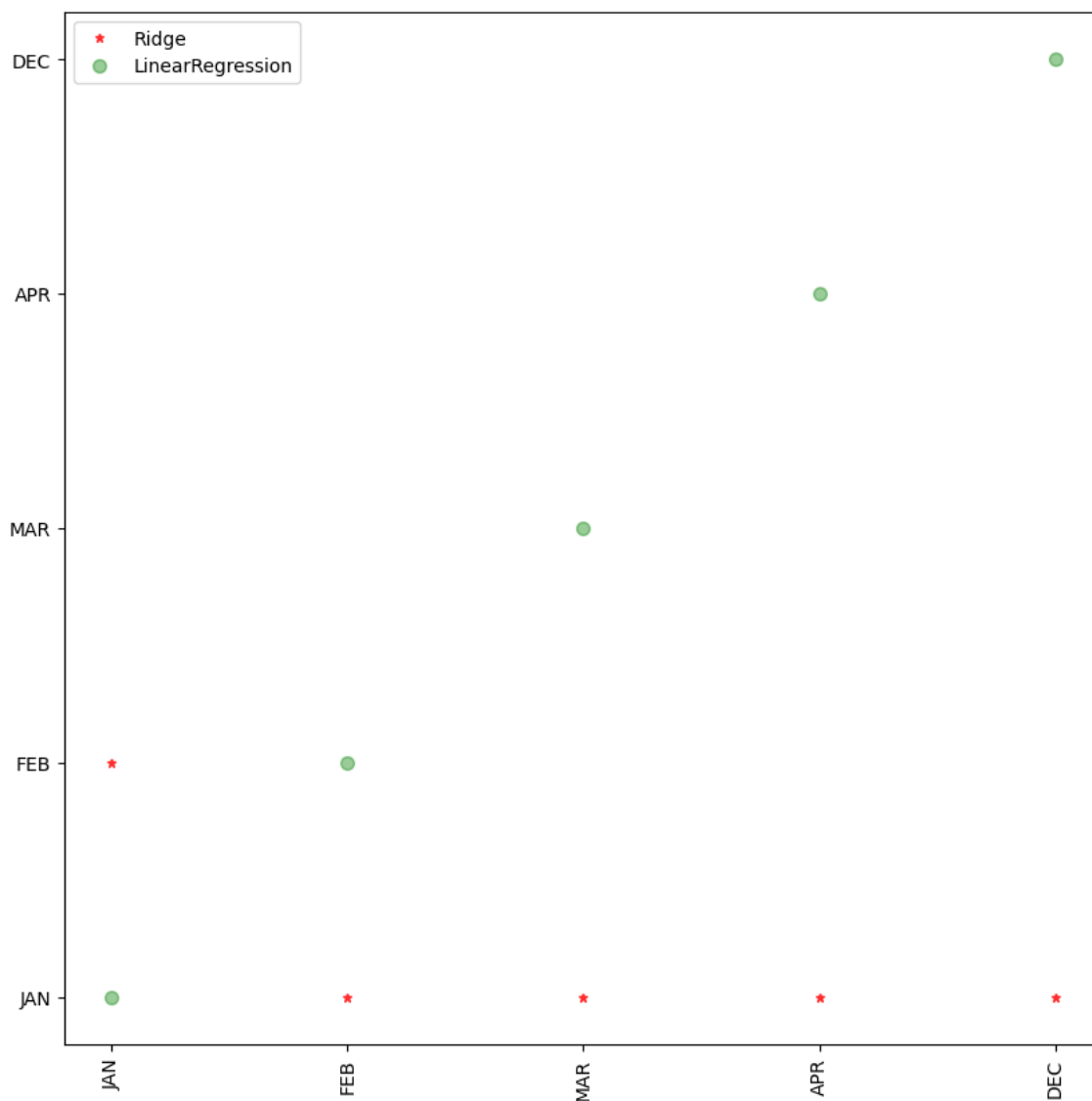
```
the train score for ridge model is0.9999999999874192
the test score for ridge model is0.99999999998833
```

In [82]:

```
lr=LinearRegression()
```

In [83]:

```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color="red")
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="green",label="LinearRegression")
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



In [84]:

```
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

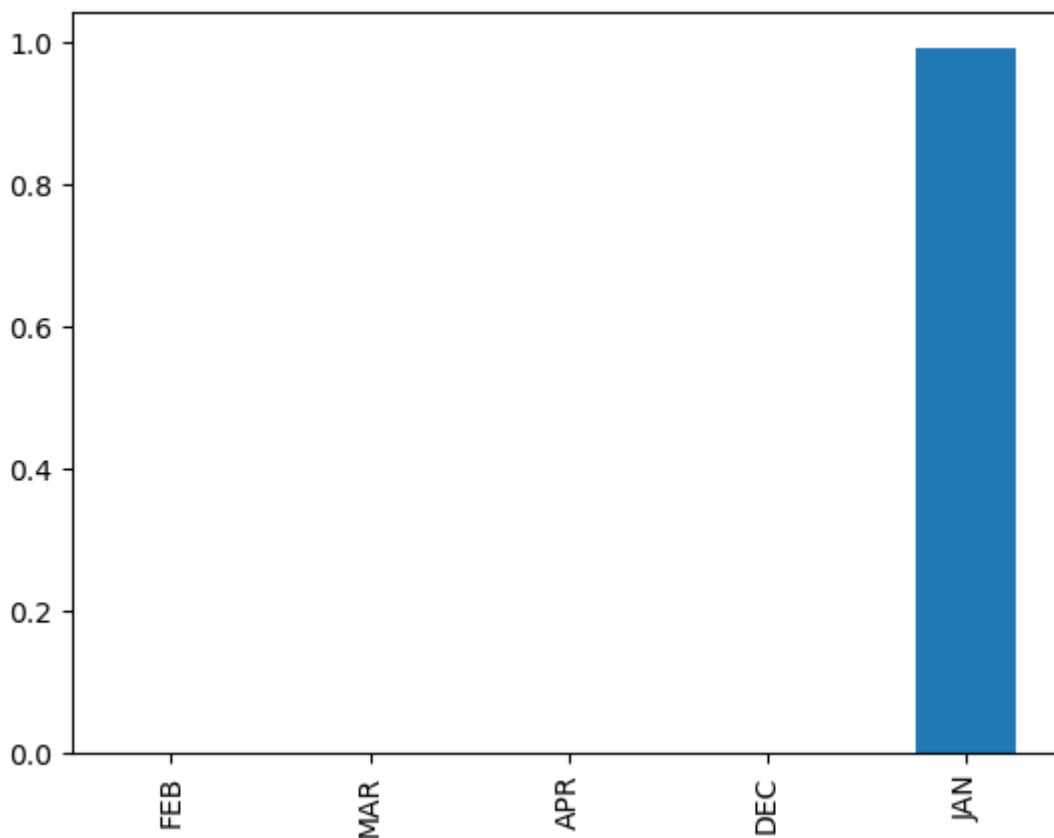
The test score for ls model is 0.9999206791315255

In [85]:

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

Out[85]:

<Axes: >



In [86]:

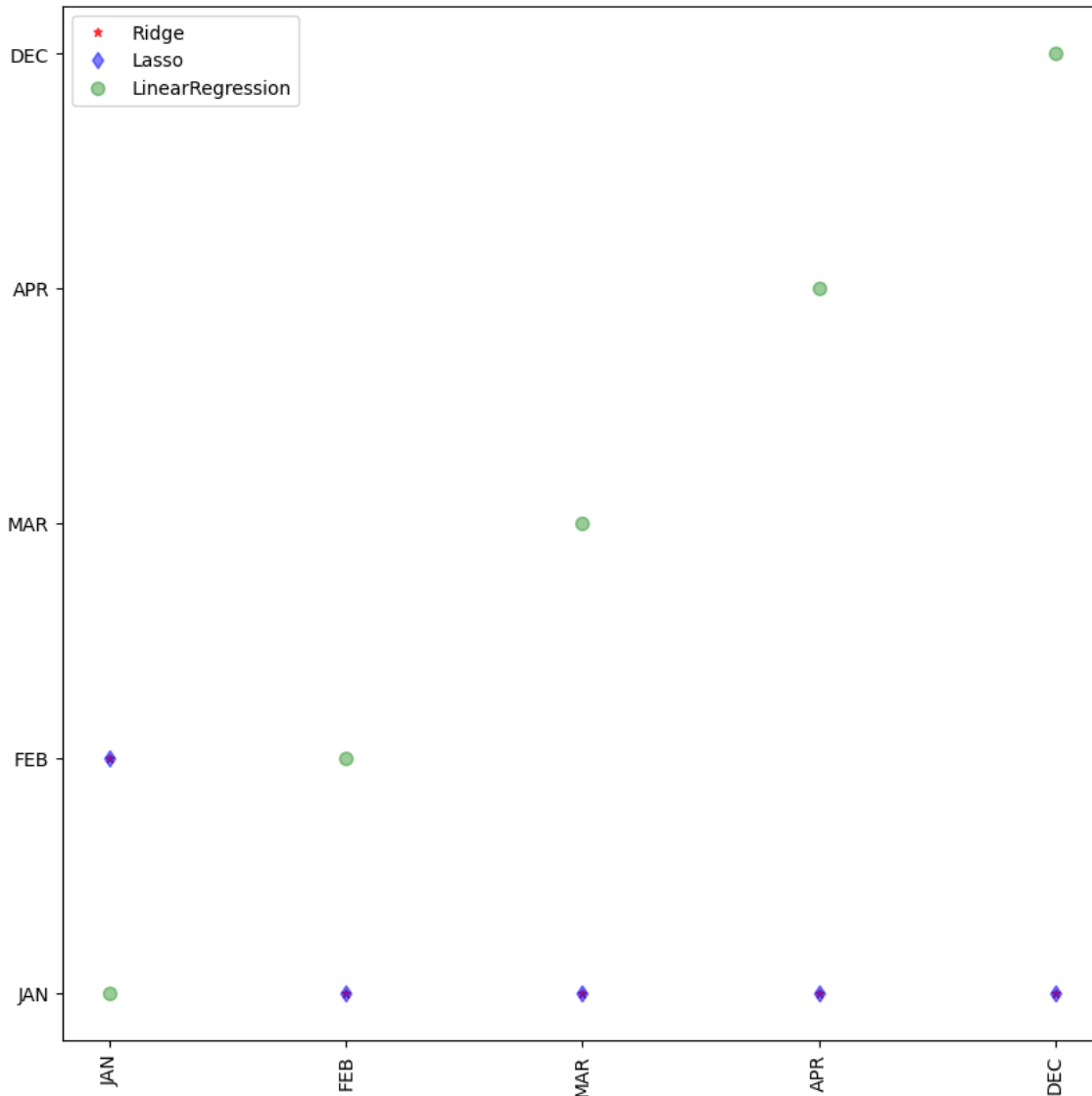
```
from sklearn.linear_model import LassoCV
lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,10],random_state=0).fit(x_train,y_train)
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

0.9999999999999921

0.9999999999999921

In [87]:

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



In [88]:

```
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]
0.016258606966616185
0.9999992160905338
```

In [90]:

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

0.0008816302333954943

CONCLUSION:

AMONG ALL MODELS LASSO YEILD HIGHEST ACCURACY.SO,WE PREFER LASSO MODEL FOR THIS DATA SET

In []:

In []: