PROBLEM STATEMENT:- TO PREDICT THE RAIFALL 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\Welcome\Downloads\rainfall.csv")
df
```

Out[2]:

	STATE_UT_NAME	DISTRICT	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG
0	ANDAMAN And NICOBAR ISLANDS	NICOBAR	107.3	57.9	65.2	117.0	358.5	295.5	285.0	271.9
1	ANDAMAN And NICOBAR ISLANDS	SOUTH ANDAMAN	43.7	26.0	18.6	90.5	374.4	457.2	421.3	423.1
2	ANDAMAN And NICOBAR ISLANDS	N & M ANDAMAN	32.7	15.9	8.6	53.4	343.6	503.3	465.4	460.9
3	ARUNACHAL PRADESH	LOHIT	42.2	80.8	176.4	358.5	306.4	447.0	660.1	427.8
4	ARUNACHAL PRADESH	EAST SIANG	33.3	79.5	105.9	216.5	323.0	738.3	990.9	711.2
...	...	...	...	...	...	...	...	...	...	...
636	KERALA	IDUKKI	13.4	22.1	43.6	150.4	232.6	651.6	788.9	527.3
637	KERALA	KASARGOD	2.3	1.0	8.4	46.9	217.6	999.6	1108.5	636.3
638	KERALA	PATHANAMTHITTA	19.8	45.2	73.9	184.9	294.7	556.9	539.9	352.7
639	KERALA	WAYANAD	4.8	8.3	17.5	83.3	174.6	698.1	1110.4	592.9
640	LAKSHADWEEP	LAKSHADWEEP	20.8	14.7	11.8	48.9	171.7	330.2	287.7	217.5

641 rows × 19 columns

```
In [3]: df.head()
```

Out[3]:

	STATE_UT_NAME	DISTRICT	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC
0	ANDAMAN And NICOBAR ISLANDS	NICOBAR	107.3	57.9	65.2	117.0	358.5	295.5	285.0	271.9	354.8	326.
1	ANDAMAN And NICOBAR ISLANDS	SOUTH ANDAMAN	43.7	26.0	18.6	90.5	374.4	457.2	421.3	423.1	455.6	301.
2	ANDAMAN And NICOBAR ISLANDS	N & M ANDAMAN	32.7	15.9	8.6	53.4	343.6	503.3	465.4	460.9	454.8	276.
3	ARUNACHAL PRADESH	LOHIT	42.2	80.8	176.4	358.5	306.4	447.0	660.1	427.8	313.6	167.
4	ARUNACHAL PRADESH	EAST SIANG	33.3	79.5	105.9	216.5	323.0	738.3	990.9	711.2	568.0	206.

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

Out[4]:

	STATE_UT_NAME	DISTRICT	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	
636	KERALA	IDUKKI	13.4	22.1	43.6	150.4	232.6	651.6	788.9	527.3	3
637	KERALA	KASARGOD	2.3	1.0	8.4	46.9	217.6	999.6	1108.5	636.3	2
638	KERALA	PATHANAMTHITTA	19.8	45.2	73.9	184.9	294.7	556.9	539.9	352.7	2
639	KERALA	WAYANAD	4.8	8.3	17.5	83.3	174.6	698.1	1110.4	592.9	2
640	LAKSHADWEEP	LAKSHADWEEP	20.8	14.7	11.8	48.9	171.7	330.2	287.7	217.5	1

In [5]:
```
df.isnull().any()
```

Out[5]:
```
STATE_UT_NAME    False
DISTRICT         False
JAN              False
FEB              False
MAR              False
APR              False
MAY              False
JUN              False
JUL              False
AUG              False
SEP              False
OCT              False
NOV              False
DEC              False
ANNUAL           False
Jan-Feb          False
Mar-May          False
Jun-Sep          False
Oct-Dec          False
dtype: bool
```

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

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
STATE_UT_NAME    0
DISTRICT         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]:

	JAN	FEB	MAR	APR	MAY	JUN	JUL	
count	641.000000	641.000000	641.000000	641.000000	641.000000	641.000000	641.000000	6
mean	18.355070	20.984399	30.034789	45.543214	81.535101	196.007332	326.033697	2
std	21.082806	27.729596	45.451082	71.556279	111.960390	196.556284	221.364643	1
min	0.000000	0.000000	0.000000	0.000000	0.900000	3.800000	11.600000	
25%	6.900000	7.000000	7.000000	5.000000	12.100000	68.800000	206.400000	1
50%	13.300000	12.300000	12.700000	15.100000	33.900000	131.900000	293.700000	2
75%	19.200000	24.100000	33.200000	48.300000	91.900000	226.600000	374.800000	3
max	144.500000	229.600000	367.900000	554.400000	733.700000	1476.200000	1820.900000	15

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 641 entries, 0 to 640
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   STATE_UT_NAME  641 non-null    object 
 1   DISTRICT       641 non-null    object 
 2   JAN            641 non-null    float64
 3   FEB            641 non-null    float64
 4   MAR            641 non-null    float64
 5   APR            641 non-null    float64
 6   MAY            641 non-null    float64
 7   JUN            641 non-null    float64
 8   JUL            641 non-null    float64
 9   AUG            641 non-null    float64
 10  SEP            641 non-null    float64
 11  OCT            641 non-null    float64
 12  NOV            641 non-null    float64
 13  DEC            641 non-null    float64
 14  ANNUAL         641 non-null    float64
 15  Jan-Feb        641 non-null    float64
 16  Mar-May        641 non-null    float64
 17  Jun-Sep        641 non-null    float64
 18  Oct-Dec        641 non-null    float64
dtypes: float64(17), object(2)
memory usage: 95.3+ KB
```

In [10]:
```
df.columns
```

Out[10]:
```
Index(['STATE_UT_NAME', 'DISTRICT', '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]:
```
(641, 19)
```

In [12]:
```
df['ANNUAL'].value_counts()
```

Out[12]:
```
ANNUAL
747.1     9
2080.0    4
1336.5    3
1824.8    3
2814.4    3
         ..
1037.6    1
907.2     1
944.5     1
1003.3    1
3253.1    1
Name: count, Length: 591, dtype: int64
```

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

Out[13]:
```
Jan-Feb
32.7     9
18.2     5
21.4     5
0.8      5
17.5     5
        ..
107.7    1
87.0     1
101.0    1
135.2    1
65.0     1
Name: count, Length: 399, dtype: int64
```

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

Out[14]:
```
Mar-May
43.5     9
27.9     5
36.6     4
468.6    4
40.4     3
        ..
16.3     1
23.3     1
49.6     1
20.5     1
232.4    1
Name: count, Length: 511, dtype: int64
```

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

Out[15]:
```
Jun-Sep
636.2     9
1386.1    4
385.0     3
1122.3    3
1308.0    3
         ..
916.9     1
923.5     1
790.3     1
840.7     1
998.5     1
Name: count, Length: 592, dtype: int64
```

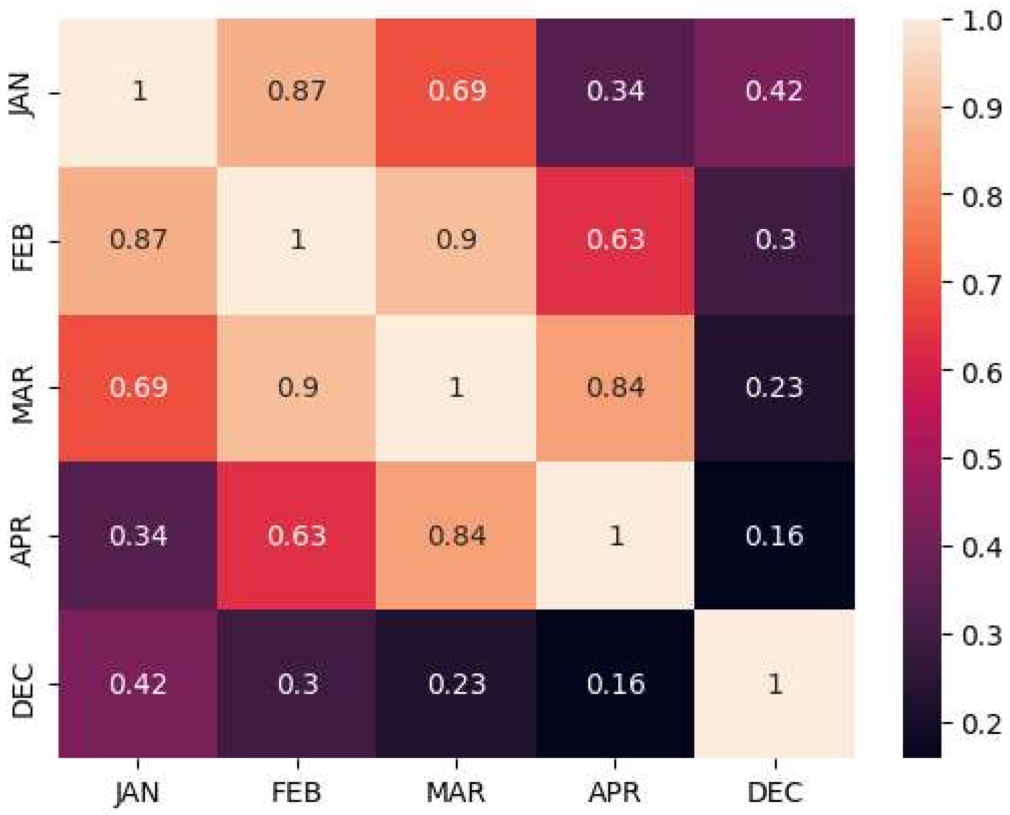
In [16]:
```
df['Oct-Dec'].value_counts()
```

Out[16]:
```
Oct-Dec
34.7     9
174.8    4
49.6     3
27.7     3
183.7    3
        ..
82.8     1
55.2     1
65.6     1
54.0     1
333.6    1
Name: count, Length: 524, dtype: int64
```

EXPLORATARY DATA ANALYSIS:-

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"]
```

LINEAR REGRESSION:-

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=
```

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_
```

```
3.6728680241521268
```

Out[21]:

	coefficient
FEB	0.715365

In [22]:

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

```
0.6855837686354153
```

In [23]:

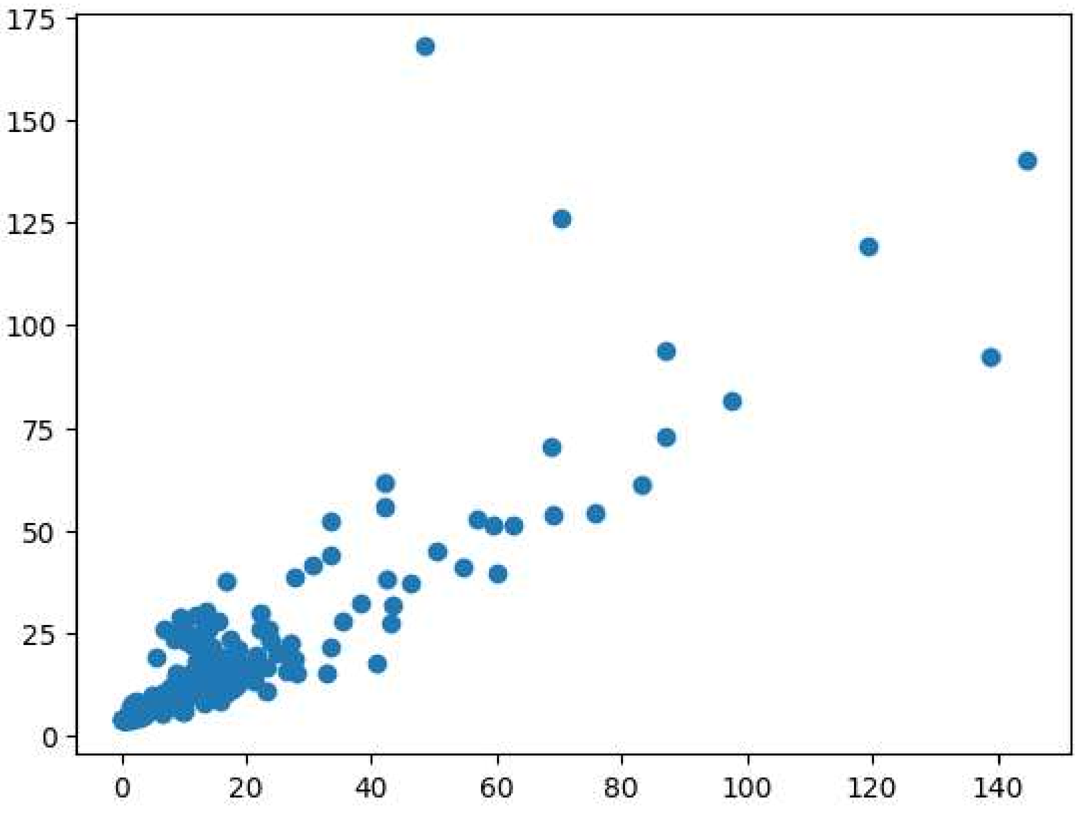
```
predictions=reg.predict(X_test)
```

In [24]:

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

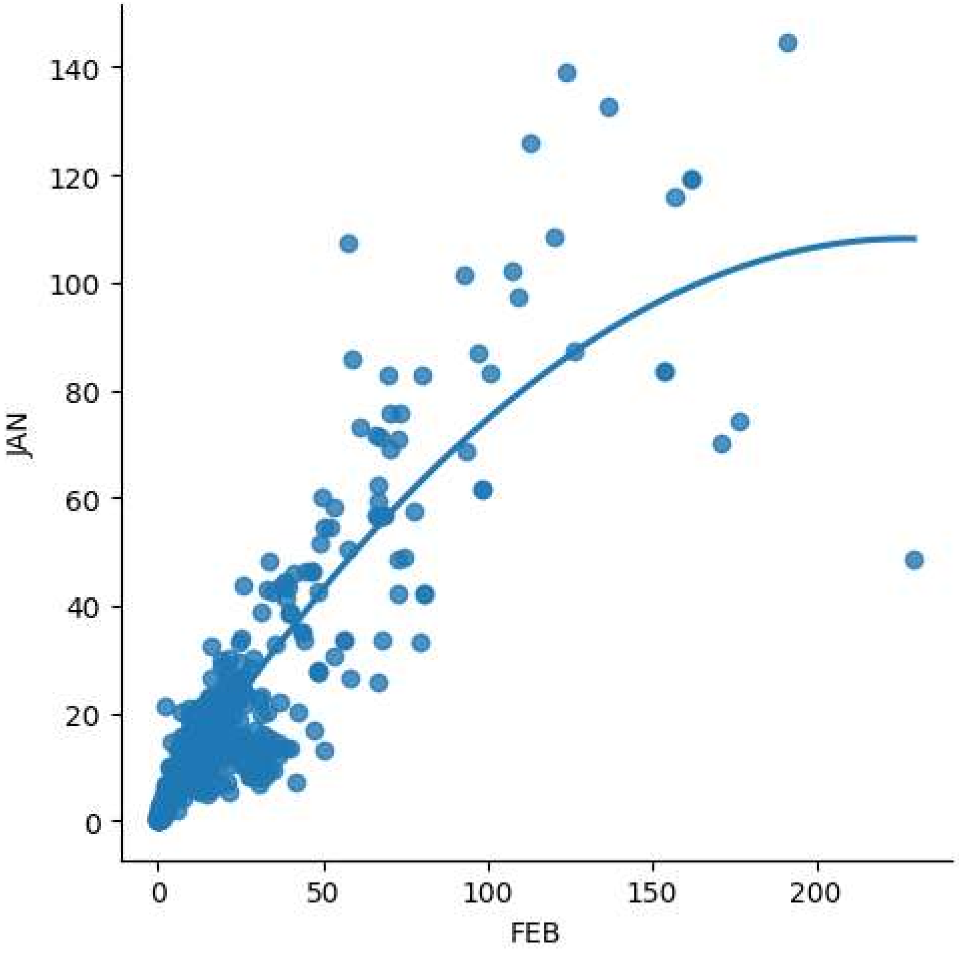
Out[24]:

```
<matplotlib.collections.PathCollection at 0x1cd24d58c10>
```



In [25]:

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



In [26]:

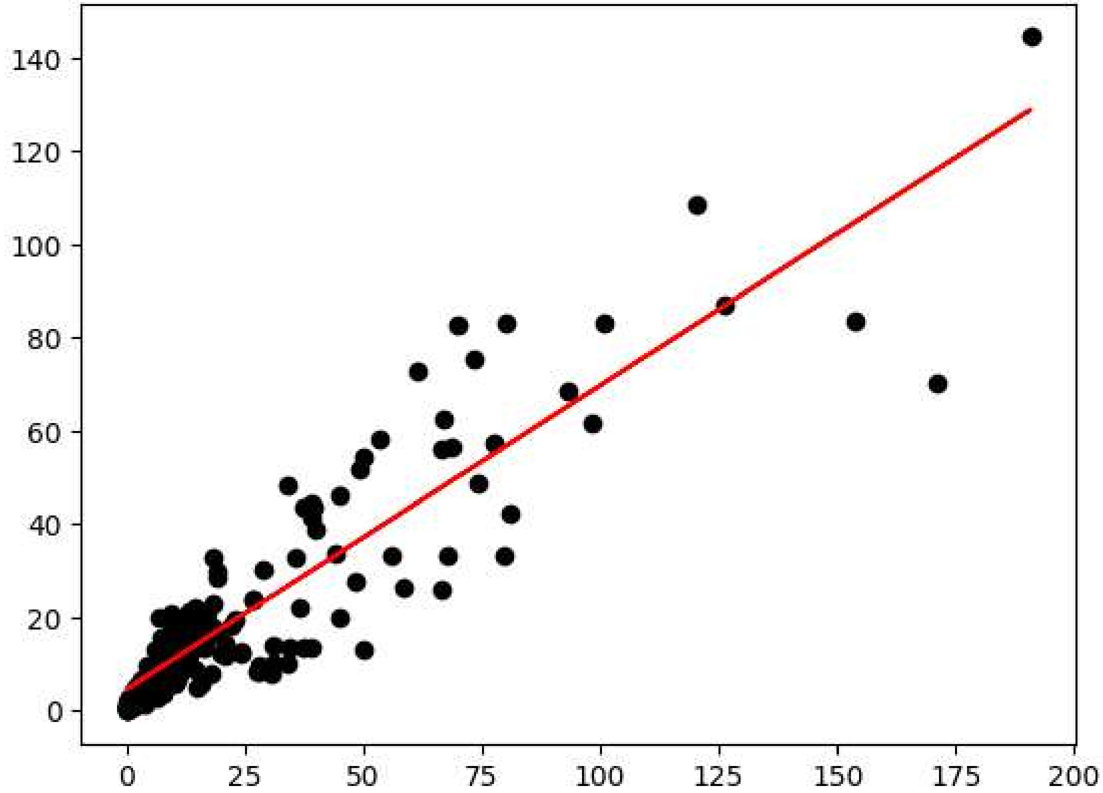
```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)
reg.fit(X_train,y_train)
reg.fit(X_test,y_test)
```

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: 0.8131357285061002
```

RIDGE MODEL

In [29]:

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

In [30]:

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

In [31]:
```
x=np.array(df['JAN']).reshape(-1,1)
y=np.array(df['FEB']).reshape(-1,1)
```

In [32]:
```
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=1
```

In [33]:
```
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)
```

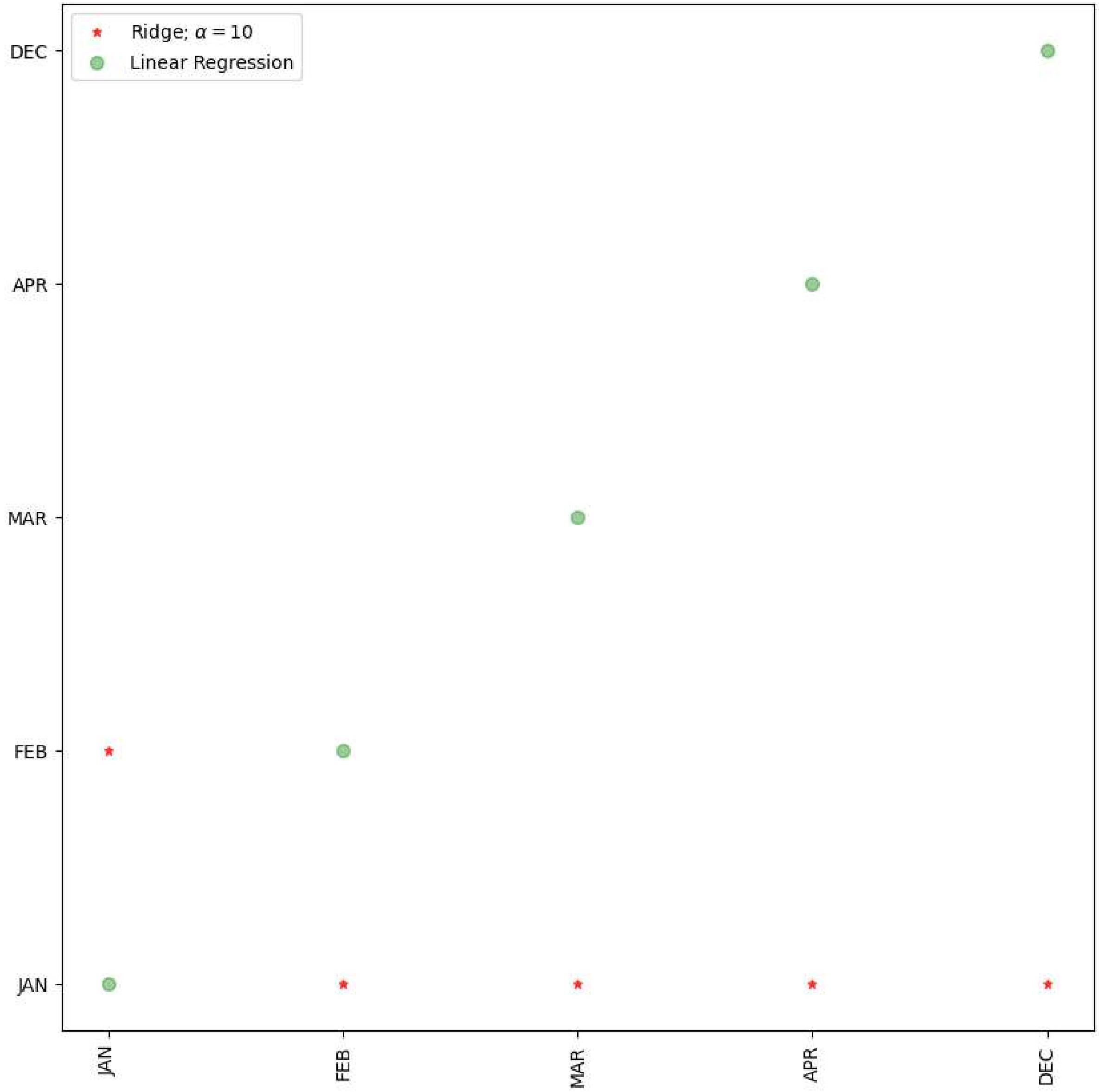
In [34]:
```
print("\n Ridge Model:\n")
print("the train score for ridge model is{}".format(train_score_ridge))
print("the test score for ridge model is{}".format(test_score_ridge))
```

```
 Ridge Model:

the train score for ridge model is0.9999999792491524
the test score for ridge model is0.9999999887465535
```

In [35]:
```
lr=LinearRegression()
```

In [36]:

```
plt.figure(figsize = (10, 10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
#plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color=
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color='gre
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



LASSO MODEL

In [37]:

```
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))
```

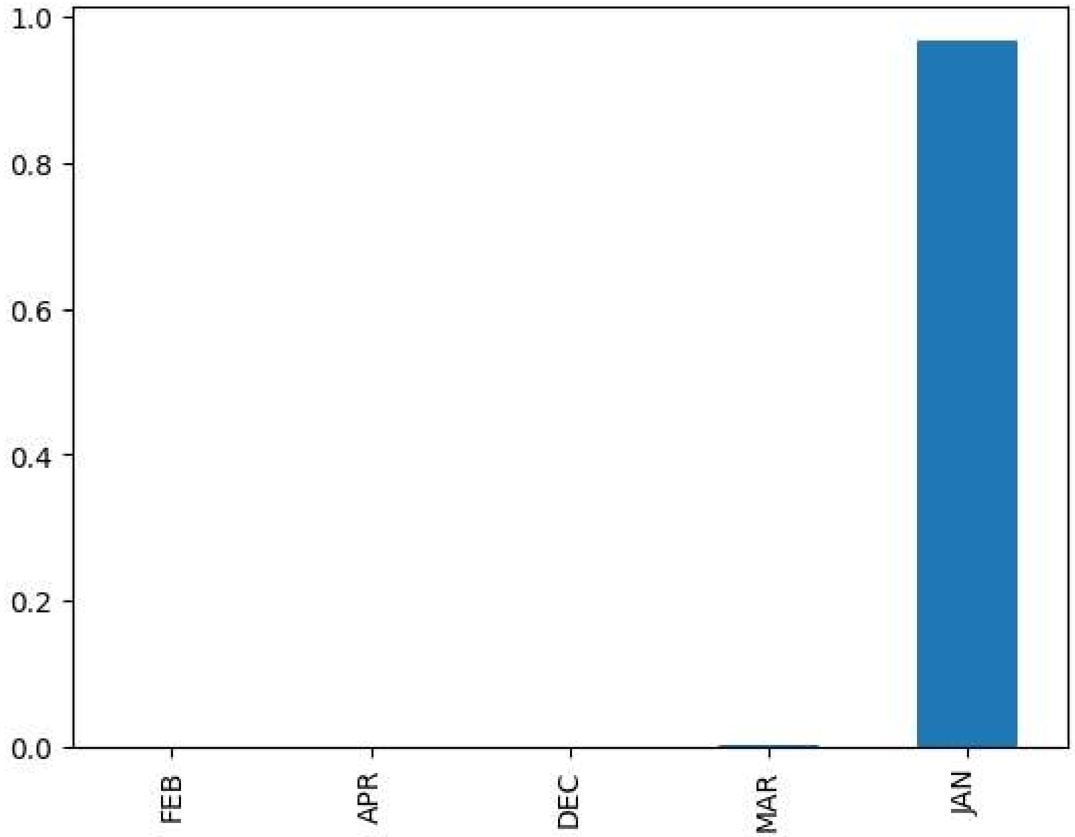
```

 Lasso Model:

The train score for ls model is 0.99912857000705
The test score for ls model is0.9991969731663574
```

In [38]:

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

Out[38]:

```
<Axes: >
```



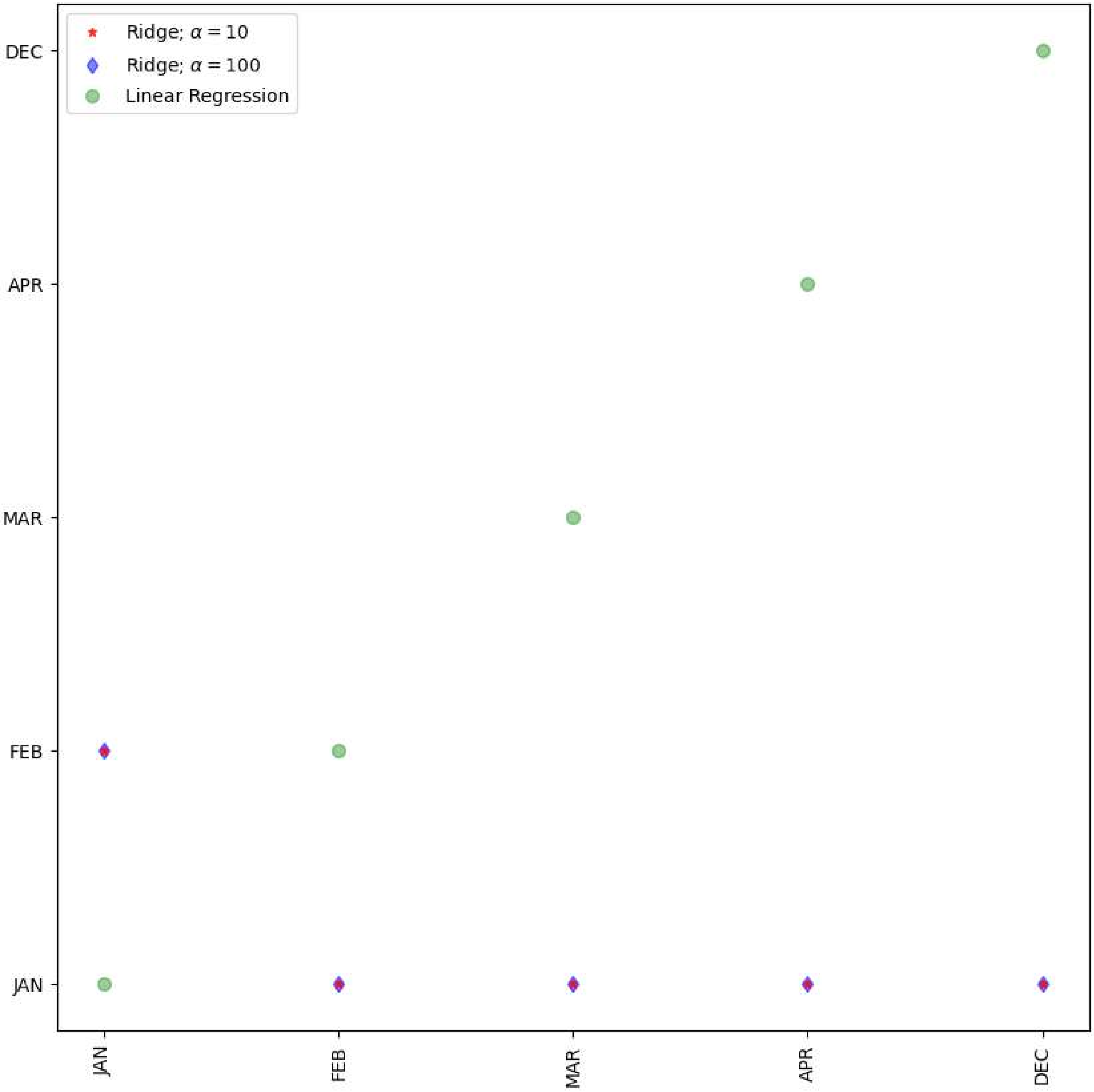
In [39]:

```
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_
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999198
0.9999999999999254
```

In [40]:

```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersi
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,colc
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="gre
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



ELASTIC NET

In [44]:

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

```
[ 9.93078025e-01  4.17330119e-03  0.00000000e+00 -2.56844715e-04
  4.33064019e-04]
0.04331617537314614
0.9999905490942288
```

In [45]:

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

```
0.004278888506659526
```

CONCLUSION:-

THE SCORE OF LINEAR REGRESSION IS :-0.8131357285061002 THE SCORE OF RIDGE MODEL IS :- 0.9999999887465535 THE SCORE OF LASSO MODEL IS :- 0.999999999999992 THE SCORE OF ELASTIC NET IS :-0.004278888506659526 *AMONG ALL MODELS LASSO YEILD HIGHEST ACCURACY.SO,WE PREFER LASSO MODEL FOR THIS DATA SET*