

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

IMPORTING THE ESSENTIAL LIBRARIES:-

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\dinesh reddy\Downloads\rainfall.csv")
df
```

Out[3]:

	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	381.1
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	191.1
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.1
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	221.1
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	261.1
...
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	111.1
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	141.1
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	71.1
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	161.1
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	161.1

4116 rows × 19 columns

DATA PREPROCESSING:-

In [4]:

```
df.head()
```

Out[4]:

	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
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
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
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
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 [5]:

```
df.tail()
```

Out[5]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165

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	
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	230.500000
std	33.140898	33.576192	35.922602	47.045473	67.816588	123.220150	234.800000
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	70.400000
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	306.100000
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.900000

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()
```

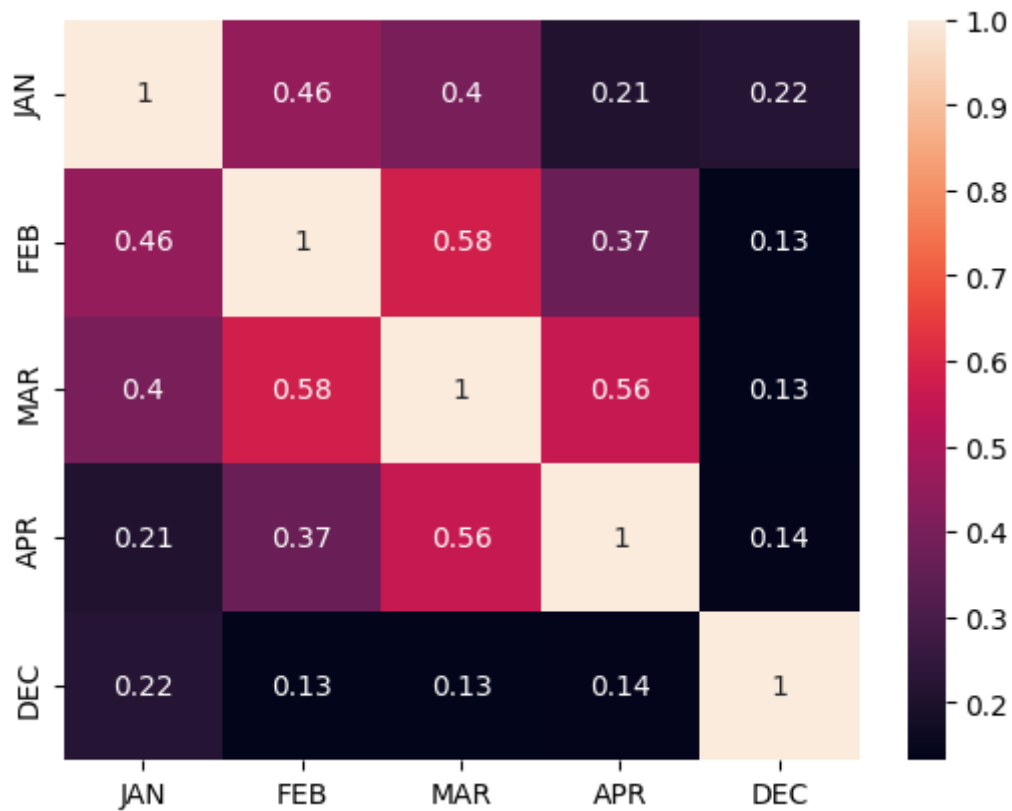
Out[17]:

```
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 [22]:

```
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[22]:

	coefficient
FEB	0.442278

In [23]:

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

0.1793580786264921

In [24]:

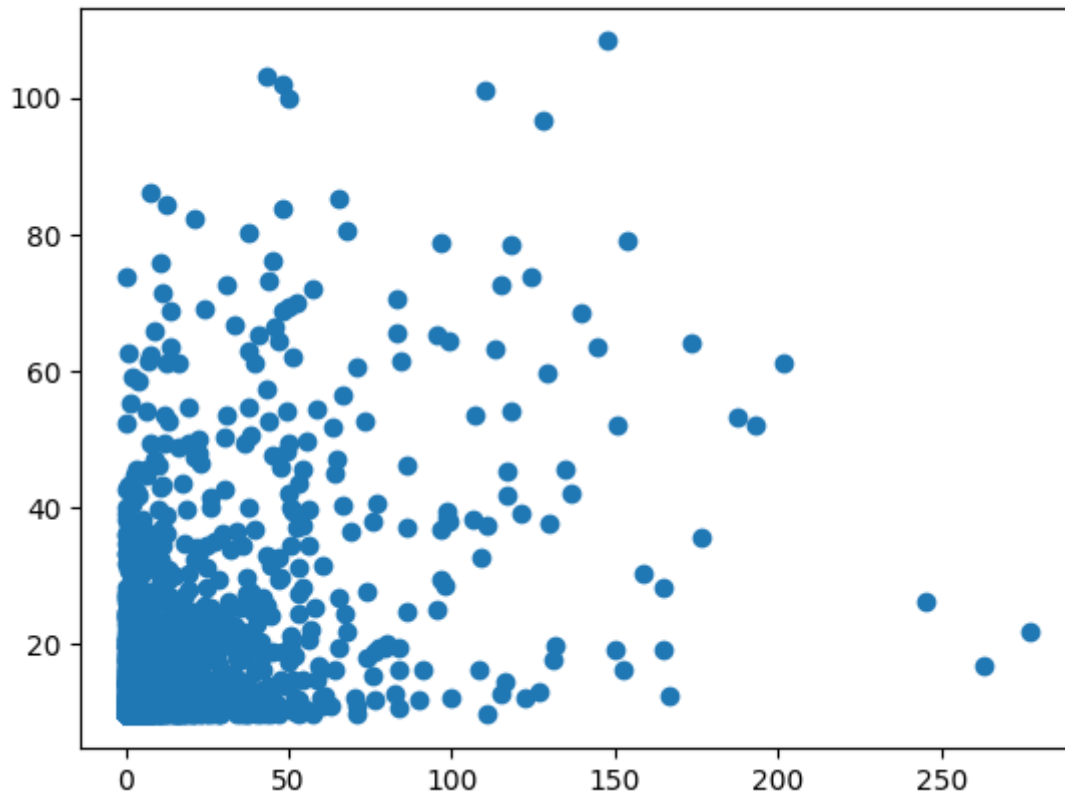
```
predictions=reg.predict(X_test)
```

In [25]:

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

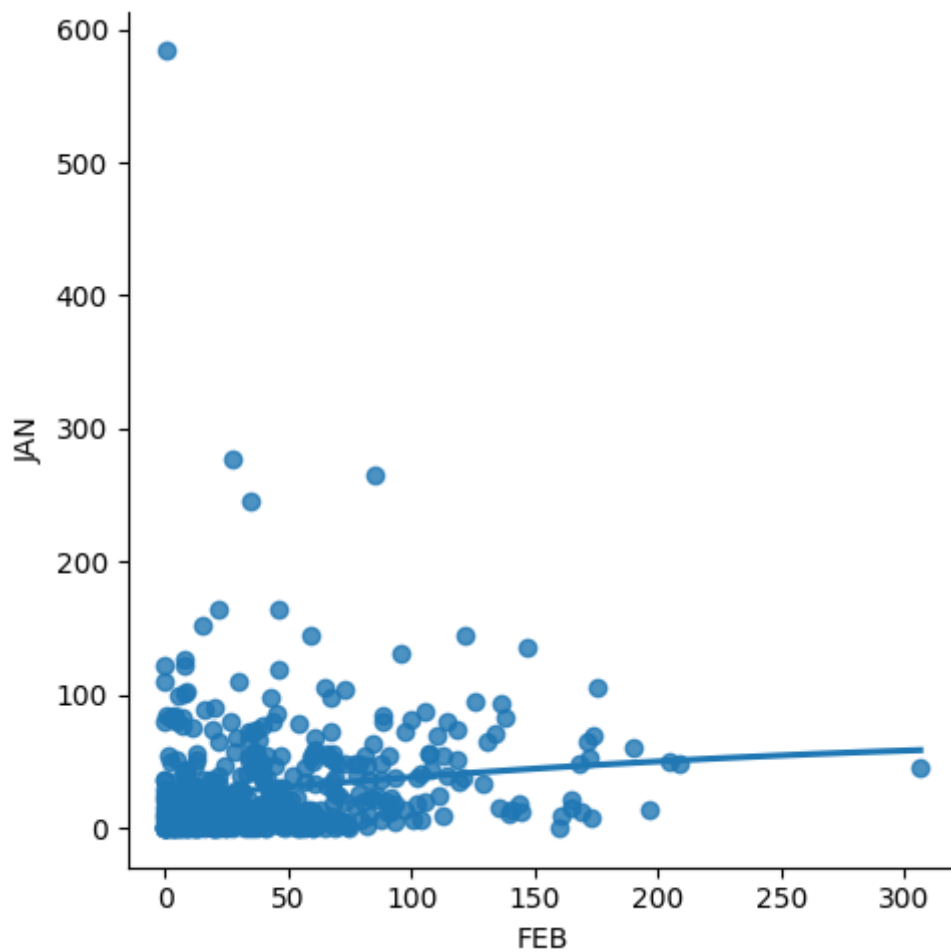
Out[25]:

<matplotlib.collections.PathCollection at 0x1b711d42fb0>



In [26]:

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



In [27]:

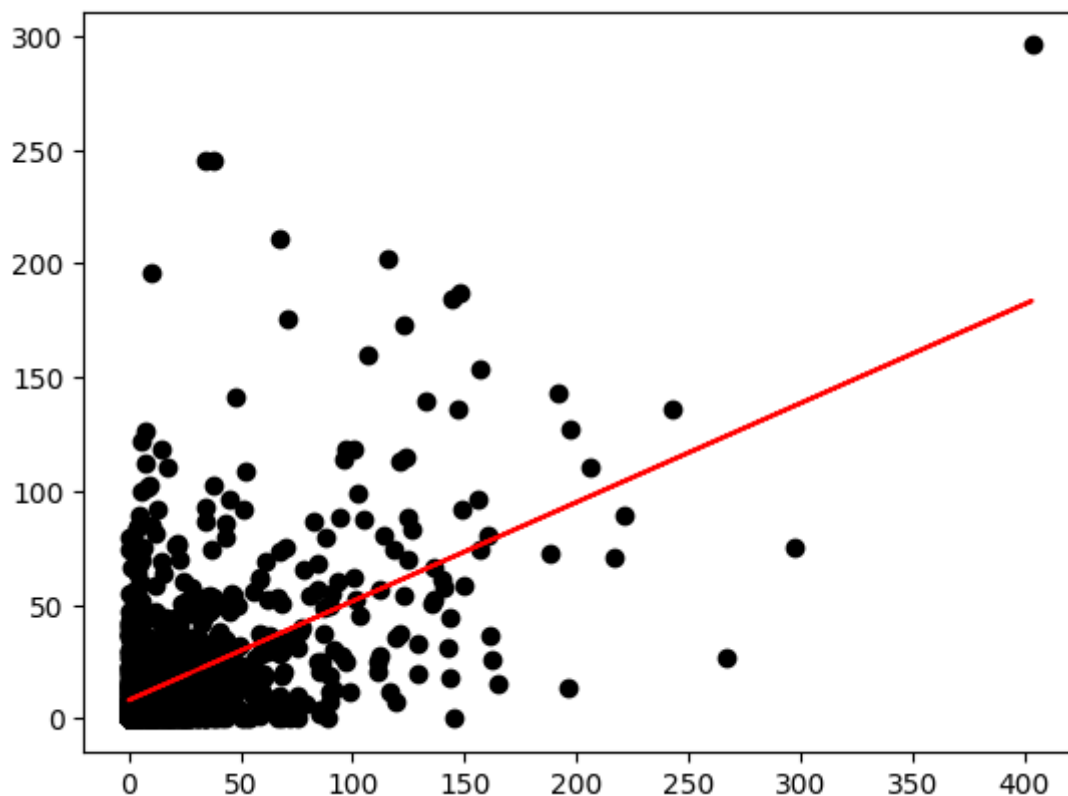
```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)  
reg.fit(X_train,y_train)  
reg.fit(X_test,y_test)
```

Out[27]:

```
LinearRegression  
LinearRegression()
```

In [28]:

```
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 [29]:

```
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: 0.2781088171137377

RIDGE MODEL:-

In [30]:

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

In [31]:

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

In [32]:

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

In [33]:

```
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 [34]:

```
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 [35]:

```
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:

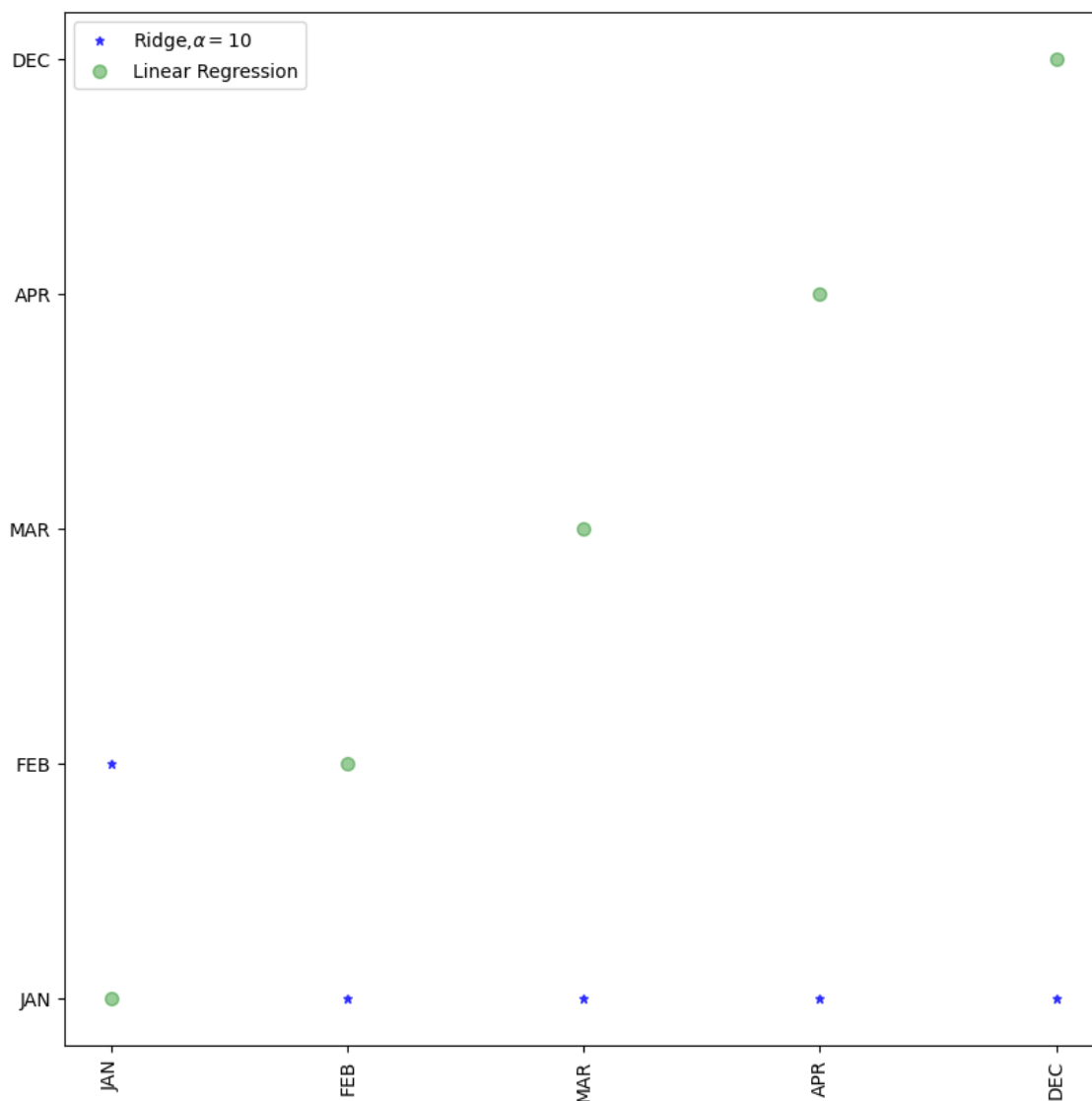
```
the train score for ridge model is0.9999999999874192  
the test score for ridge model is0.99999999998833
```

In [36]:

```
lr=LinearRegression()
```

In [37]:

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



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

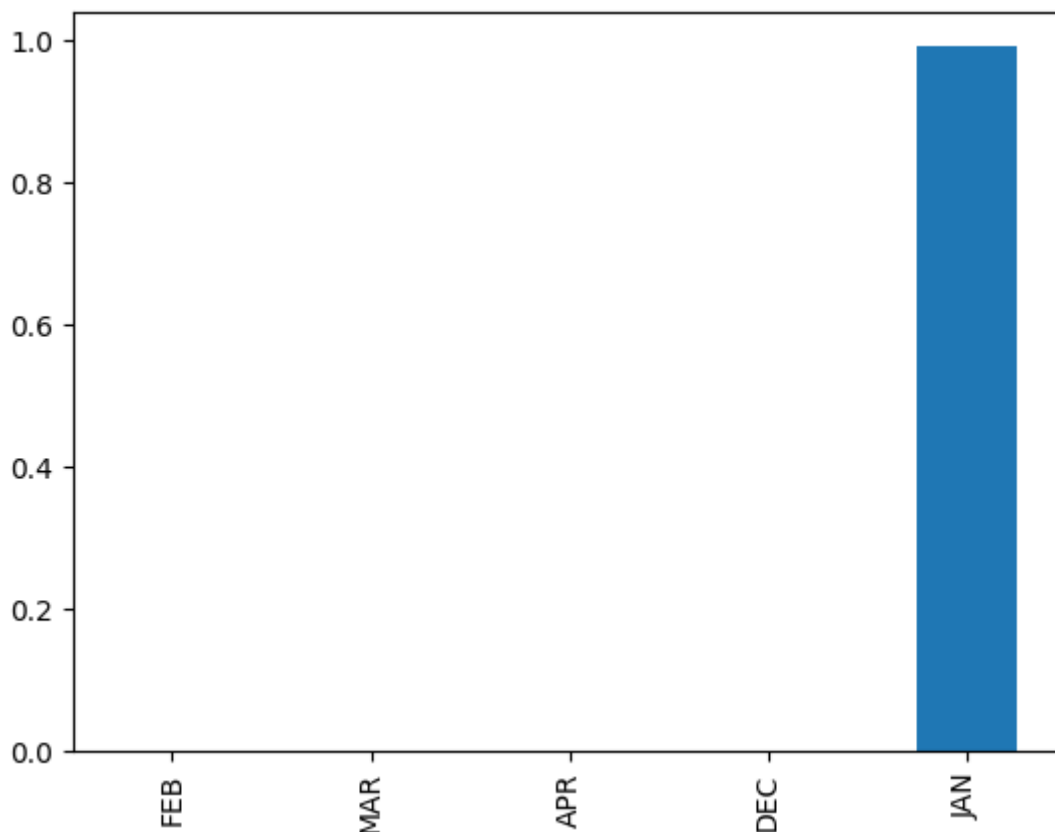
The test score for ls model is0.9999206791315255

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_train)
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))

```

0.9999999999999921

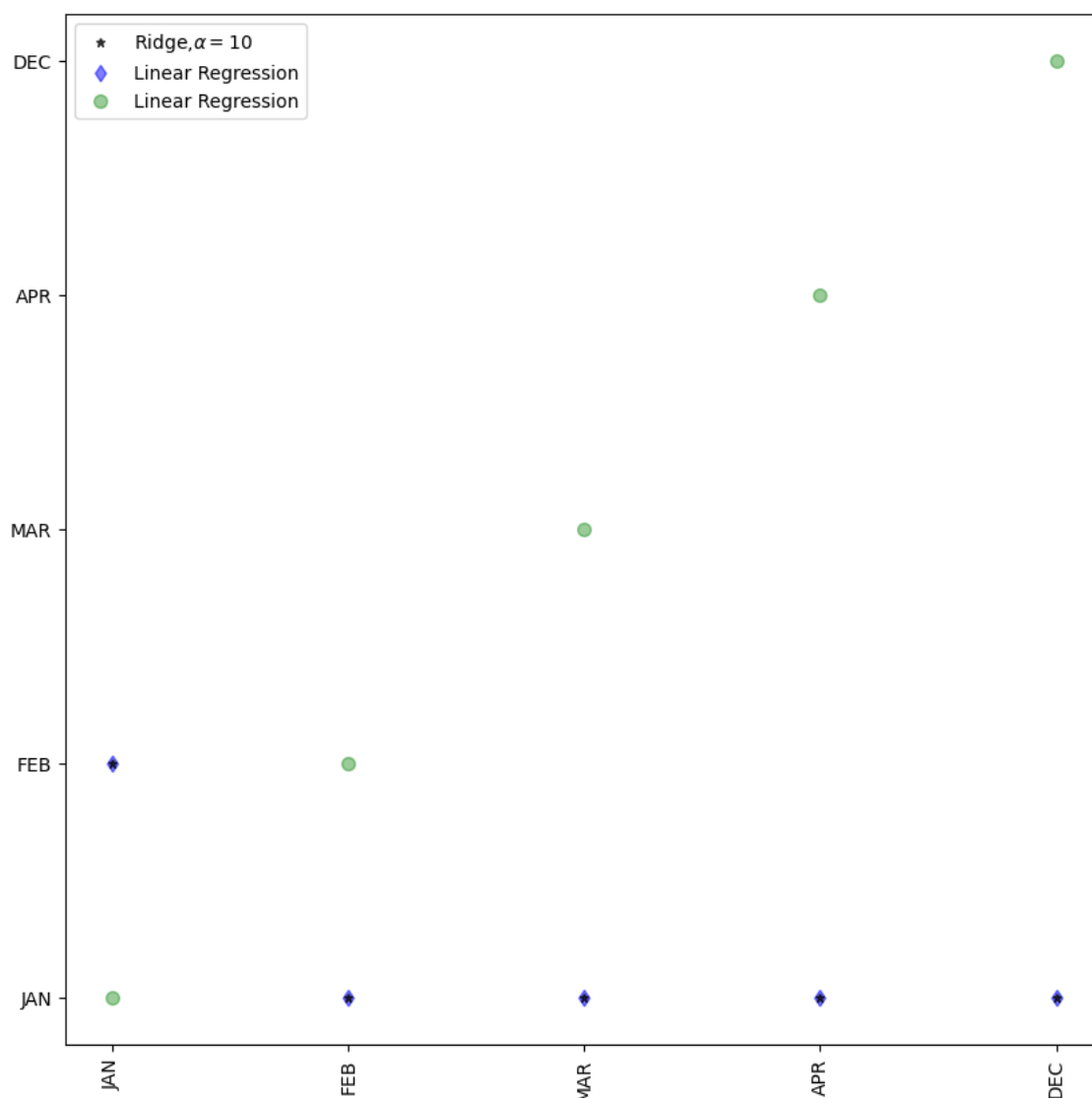
0.9999999999999921

In [41]:

```

plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color='green')
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='Ridge')
plt.xticks(rotation = 90)
plt.legend()
plt.show()

```



ELASTIC NET:-

In [42]:

```
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
```

In [43]:

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

```
0.0008816302333951295
```

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 DATA SET

In []:

In []: