Problem statement:To predict How Best the DataFits,To Predict the accuracy of the Rainfall based on the given features

1)Data collection

In [1]:

```
#Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [2]:

```
data=pd.read_csv(r"C:\Users\chinta pavani\Documents\rainfall in india 1901
data
```

Out[2]:

	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	3
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	1
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	1
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	2
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	2
...	...	...	...	...	...	...	...	...	...	...	...	
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	1
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	1
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	1
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	1

4116 rows × 19 columns

2)Data Cleaning and Preprocessing

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

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	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 [4]:
```
data.tail()
```

Out[4]:

	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 [5]:
```
data.shape
```

Out[5]: (4116, 19)

In [6]:

```
data.describe
```

Out[6]:

```
<bound method NDFrame.describe of                    SUBDIVISION  YEAR
JAN    FEB   MAR    APR    MAY    JUN
0     ANDAMAN & NICOBAR ISLANDS  1901  49.2   87.1  29.2    2.3  528.8  5
17.5  \
1     ANDAMAN & NICOBAR ISLANDS  1902   0.0  159.8  12.2    0.0  446.1  5
37.1
2     ANDAMAN & NICOBAR ISLANDS  1903  12.7  144.0   0.0    1.0  235.1  4
79.9
3     ANDAMAN & NICOBAR ISLANDS  1904   9.4   14.7   0.0  202.4  304.5  4
95.1
4     ANDAMAN & NICOBAR ISLANDS  1905   1.3    0.0   3.3   26.9  279.5  6
28.7
...                         ...   ...   ...    ...   ...    ...    ...
...
4111               LAKSHADWEEP  2011   5.1    2.8   3.1   85.9  107.2  1
53.6
4112               LAKSHADWEEP  2012  19.2    0.1   1.6   76.8   21.2  3
27.0
4113               LAKSHADWEEP  2013  26.2   34.4  37.5    5.3   88.3  4
26.2
4114               LAKSHADWEEP  2014  53.2   16.1   4.4   14.9   57.4  2
44.1
4115               LAKSHADWEEP  2015   2.2    0.5   3.7   87.1  133.1  2
96.6

        JUL    AUG    SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May
0     365.1  481.1  332.6  388.5  558.2   33.6  3373.2    136.3    560.3
\
1     228.9  753.7  666.2  197.2  359.0  160.5  3520.7    159.8    458.3
2     728.4  326.7  339.0  181.2  284.4  225.0  2957.4    156.7    236.1
3     502.0  160.1  820.4  222.2  308.7   40.1  3079.6     24.1    506.9
4     368.7  330.5  297.0  260.7   25.4  344.7  2566.7      1.3    309.7
...     ...    ...    ...    ...    ...    ...     ...      ...      ...
4111  350.2  254.0  255.2  117.4  184.3   14.9  1533.7      7.9    196.2
4112  231.5  381.2  179.8  145.9   12.4    8.8  1405.5     19.3     99.6
4113  296.4  154.4  180.0   72.8   78.1   26.7  1426.3     60.6    131.1
4114  116.1  466.1  132.2  169.2   59.0   62.3  1395.0     69.3     76.7
4115  257.5  146.4  160.4  165.4  231.0  159.0  1642.9      2.7    223.9

      Jun-Sep  Oct-Dec
0      1696.3    980.3
1      2185.9    716.7
2      1874.0    690.6
3      1977.6    571.0
4      1624.9    630.8
...       ...      ...
4111   1013.0    316.6
4112   1119.5    167.1
4113   1057.0    177.6
4114    958.5    290.5
4115    860.9    555.4

[4116 rows x 19 columns]>
```

In [7]:
```
data.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          4112 non-null   float64
 3   FEB          4113 non-null   float64
 4   MAR          4110 non-null   float64
 5   APR          4112 non-null   float64
 6   MAY          4113 non-null   float64
 7   JUN          4111 non-null   float64
 8   JUL          4109 non-null   float64
 9   AUG          4112 non-null   float64
 10  SEP          4110 non-null   float64
 11  OCT          4109 non-null   float64
 12  NOV          4105 non-null   float64
 13  DEC          4106 non-null   float64
 14  ANNUAL       4090 non-null   float64
 15  Jan-Feb      4110 non-null   float64
 16  Mar-May      4107 non-null   float64
 17  Jun-Sep      4106 non-null   float64
 18  Oct-Dec      4103 non-null   float64
dtypes: float64(17), int64(1), object(1)
memory usage: 611.1+ KB
```

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

Out[8]:
```
SUBDIVISION     0
YEAR            0
JAN             4
FEB             3
MAR             6
APR             4
MAY             3
JUN             5
JUL             7
AUG             4
SEP             6
OCT             7
NOV            11
DEC            10
ANNUAL         26
Jan-Feb         6
Mar-May         9
Jun-Sep        10
Oct-Dec        13
dtype: int64
```

In [9]:
```
data.fillna(method="ffill",inplace=True)
```

In [10]:
```
data.isnull().sum()
```

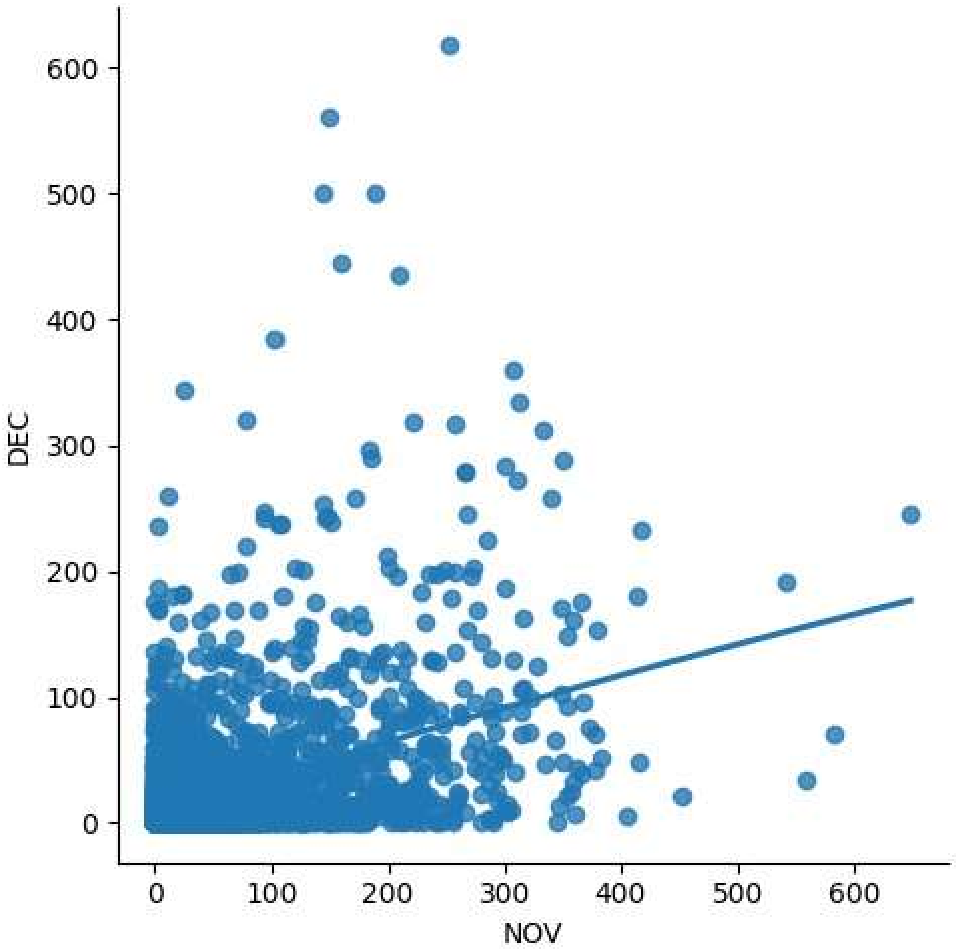
Out[10]:
```
SUBDIVISION    0
YEAR           0
JAN            0
FEB            0
MAR            0
APR            0
MAY            0
JUN            0
JUL            0
AUG            0
SEP            0
OCT            0
NOV            0
DEC            0
ANNUAL         0
Jan-Feb        0
Mar-May        0
Jun-Sep        0
Oct-Dec        0
dtype: int64
```

In [11]:
```
data['YEAR'].value_counts()
```

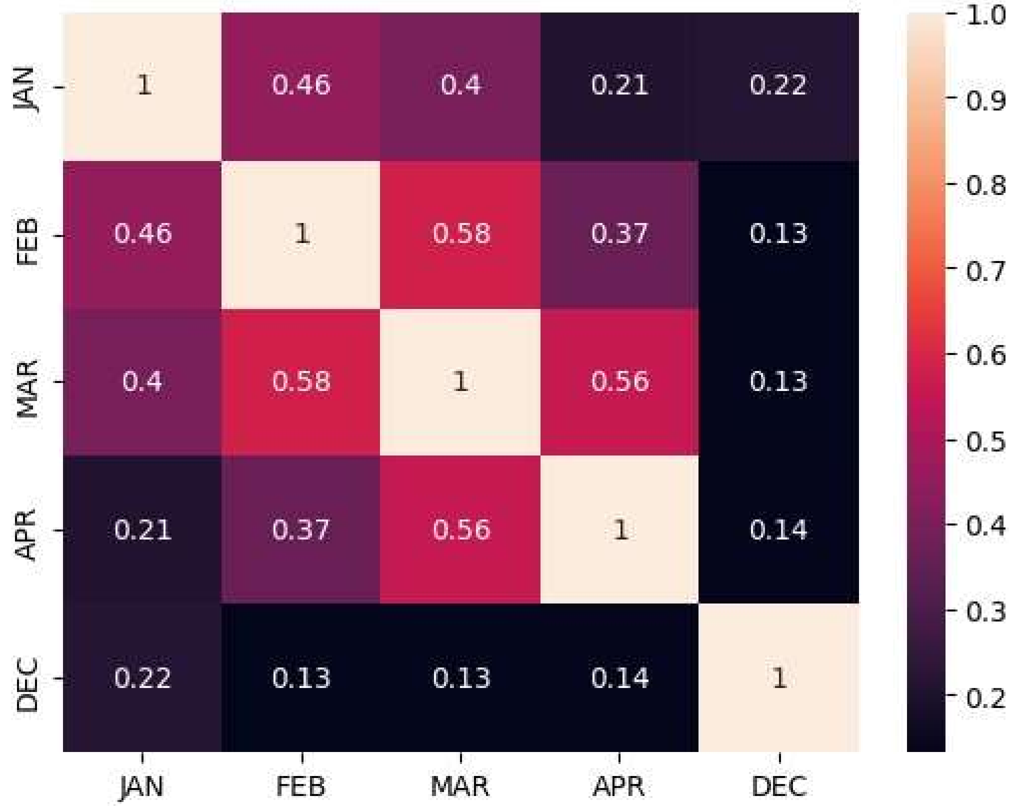
Out[11]:
```
YEAR
1963    36
2002    36
1976    36
1975    36
1974    36
        ..
1915    35
1918    35
1954    35
1955    35
1909    34
Name: count, Length: 115, dtype: int64
```

3)Exploratory Data Analysis

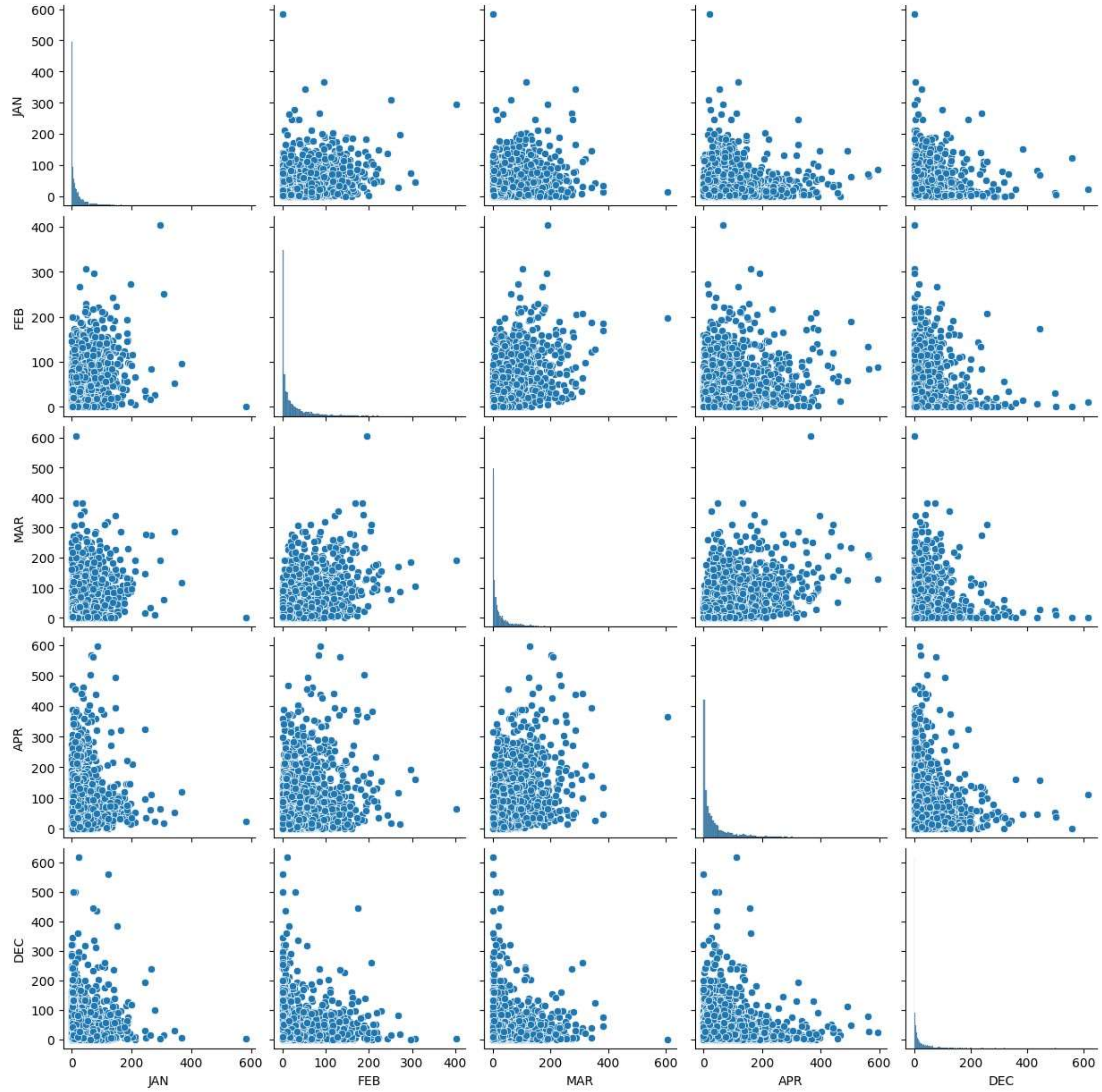
In [13]:
```
sns.lmplot(x='NOV',y='DEC',order=2,data=data,ci=None)
plt.show()
```



In [14]:
```
df=data[['JAN','FEB','MAR','APR','DEC']]
sns.heatmap(df.corr(),annot=True)
plt.show()
```



In [15]:
```
sns.pairplot(df)
plt.show()
```



4)Training our Model

In [16]:
```
x=np.array(df['FEB']).reshape(-1,1)
y=x=np.array(df['JAN']).reshape(-1,1)
```

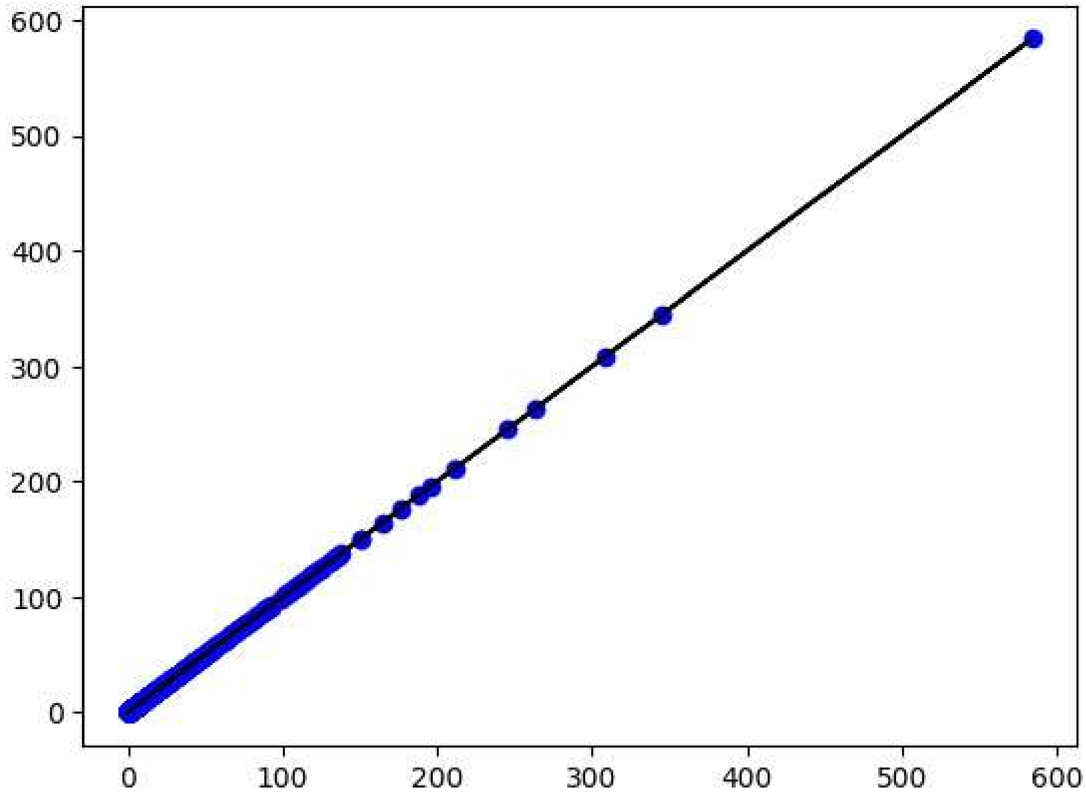
In [17]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30)
```

In [18]:
```
lin=LinearRegression()
lin.fit(x_train,y_train)
print(lin.score(x_train,y_train))
```

```
1.0
```

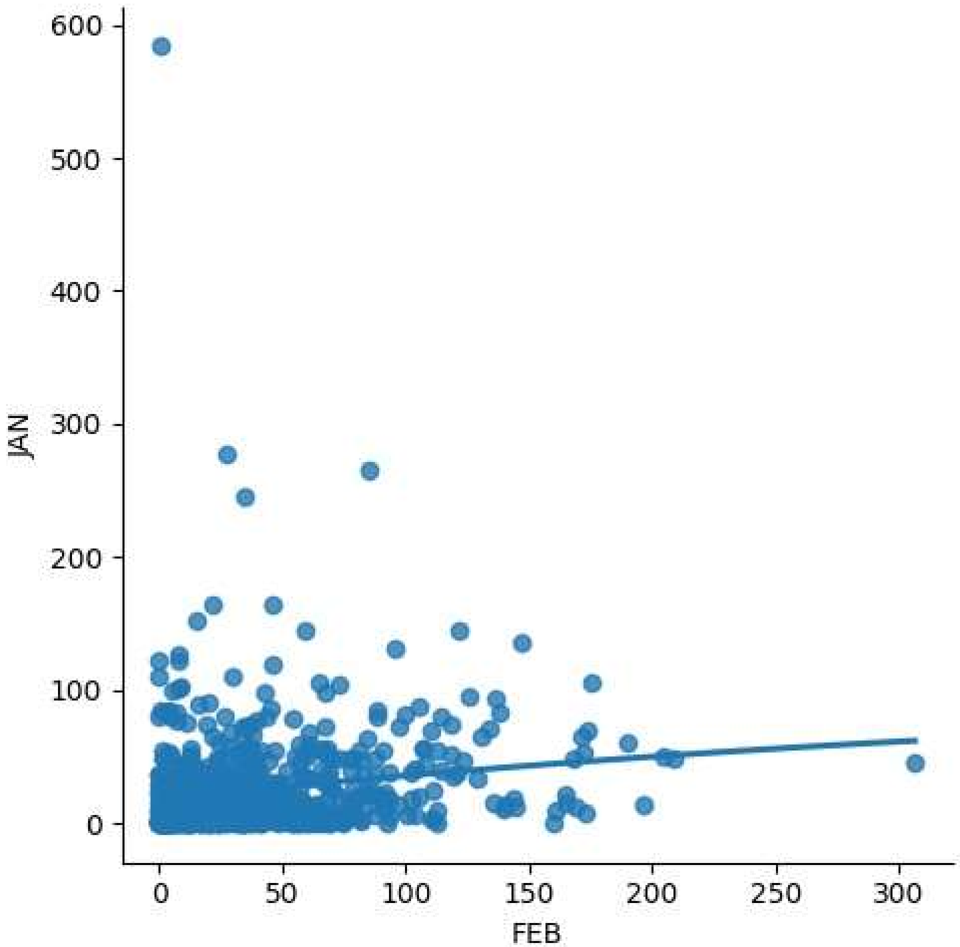
5)Exploring our Results

In [19]:
```
y_pred=lin.predict(x_test)
plt.scatter(x_test,y_test,color='blue')
plt.plot(x_test,y_pred,color='black')
plt.show()
```



7)Working with subset of data

In [20]:
```
df700=df[:][:700]
sns.lmplot(x='FEB',y='JAN',order=2,ci=None,data=df700)
plt.show()
```



In [21]:
```
df700.fillna(method='ffill',inplace=True)
```

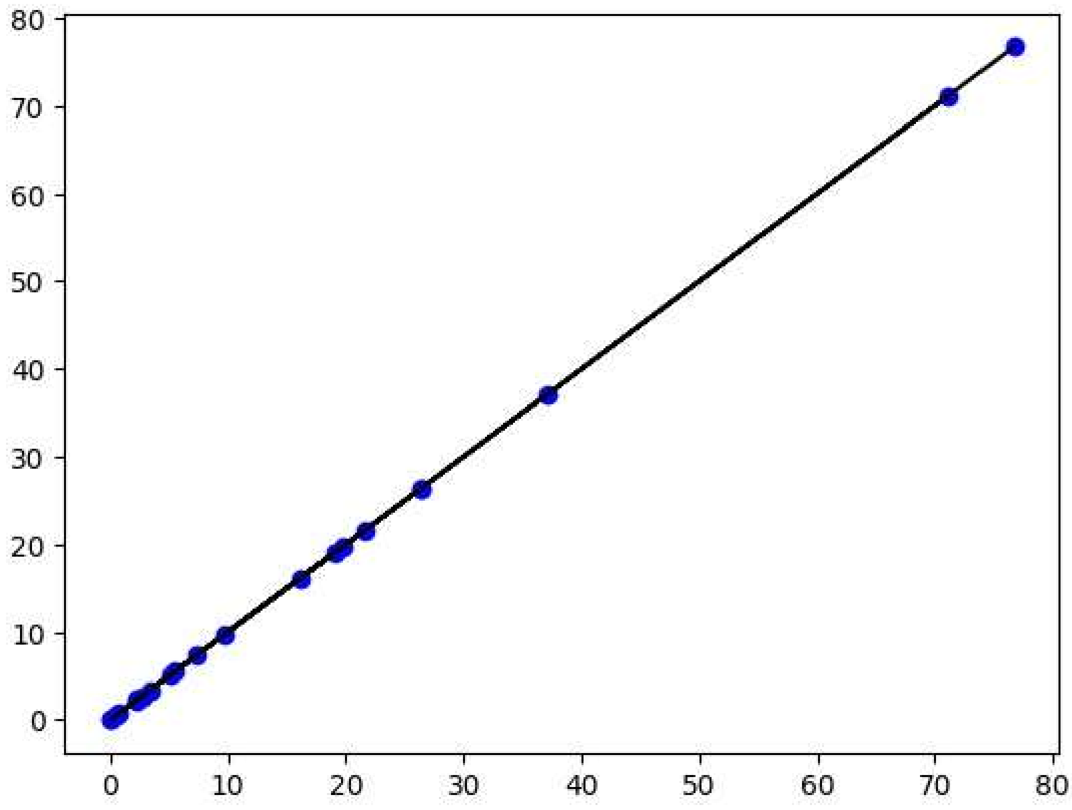
In [22]:
```
x=np.array(df700['FEB']).reshape(-1,1)
y=x=np.array(df700['JAN']).reshape(-1,1)
```

In [23]:
```
df700.dropna(inplace=True)
```

In [24]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.03)
lr=LinearRegression()
lr.fit(x_train,y_train)
print(lr.score(x_test,y_test))
```

```
1.0
```

In [25]:
```
y_pred=lr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



In [26]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

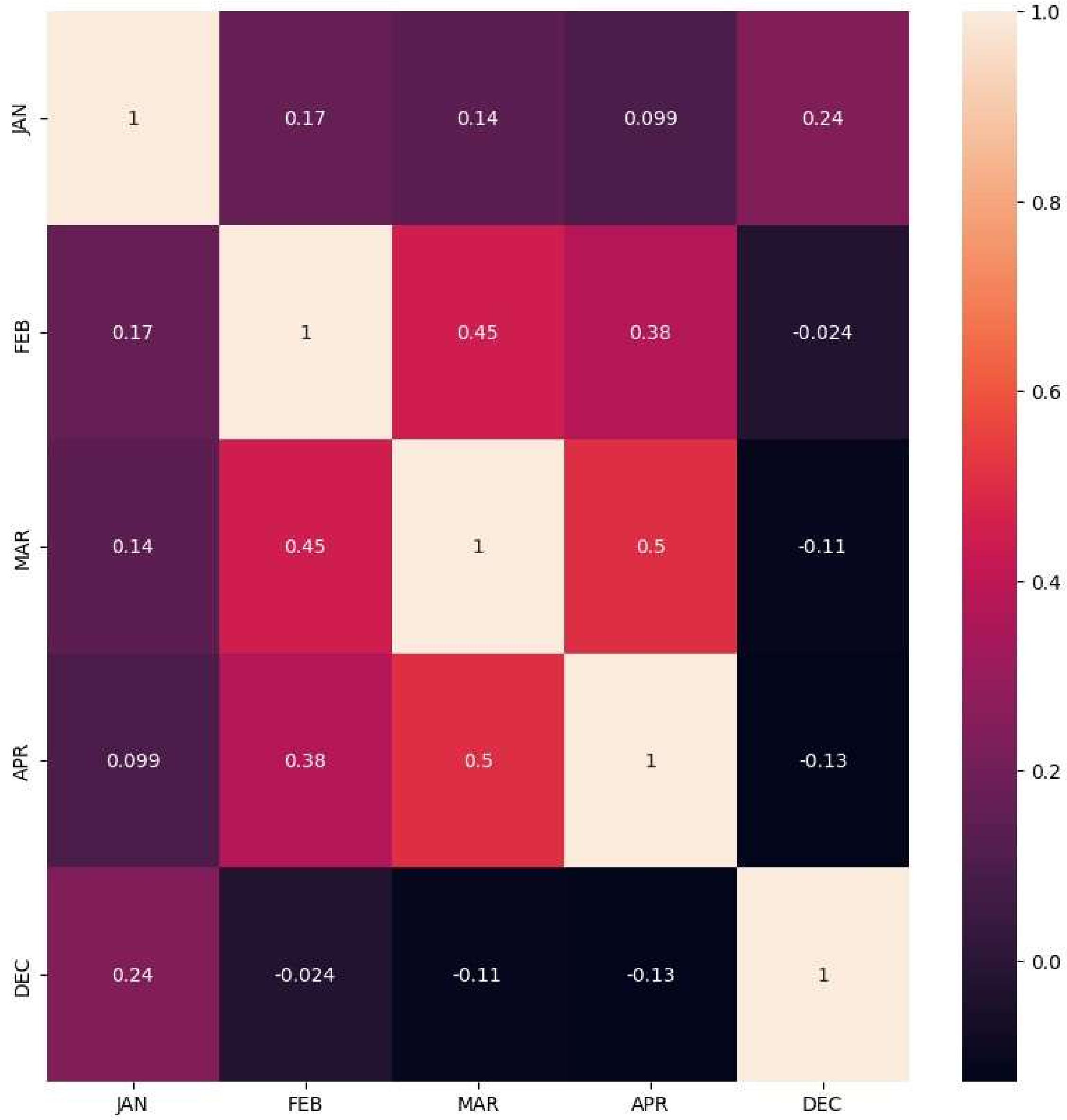
In [27]:
```
lr=LinearRegression()
lr.fit(x_train,y_train)
y_pred=lr.predict(x_test)
r2=r2_score(y_test,y_pred)
print("R2 score:",r2)
```

```
R2 score: 1.0
```

Ridge Regression

In [28]:
```
#Importing Libraries
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

In [29]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df700.corr(),annot=True)
plt.show()
```



In [30]:
```
features=df.columns[0:5]
target=df.columns[-5]
```

In [31]:
```
x=df[features].values
y=df[target].values
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_s
print("The dimension of X_train is {}".format(x_train.shape))
print("The dimension of X_test is {}".format(x_test.shape))
```

```
The dimension of X_train is (2881, 5)
The dimension of X_test is (1235, 5)
```

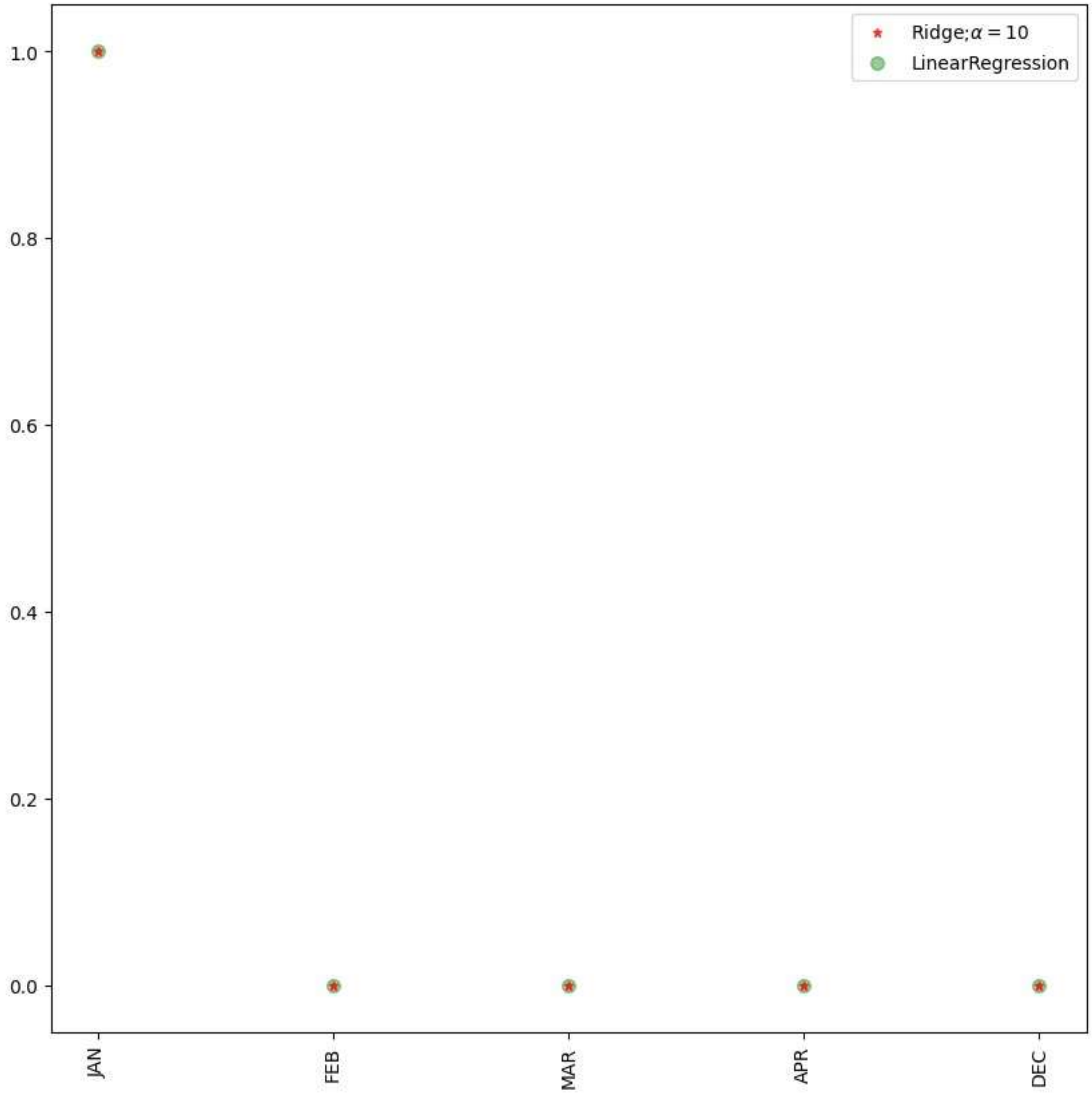
In [32]:
```
lr = LinearRegression()
#Fit model
lr.fit(x_train, y_train)
#predict
actual = y_test
train_score_lr = lr.score(x_train, y_train)
test_score_lr = lr.score(x_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".format(train_score_lr))
print("The test score for lr model is {}".format(test_score_lr))
```

```
Linear Regression Model:

The train score for lr model is 1.0
The test score for lr model is 1.0
```

In [33]:
```
ridgeReg = Ridge(alpha=10)
ridgeReg.fit(x_train,y_train)
#train and test scorefor ridge regression
train_score_ridge = ridgeReg.score(x_train, y_train)
test_score_ridge = ridgeReg.score(x_test, y_test)
print("\nRidge 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 is 0.9999999999856335
The test score for ridge model is 0.9999999999840021
```

In [34]:
```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",mar
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker="o",markersiz
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Lasso Regression

In [35]:
```
#Importing Libraries
lasso= Lasso(alpha=10)
lasso.fit(x_train,y_train)
#train and test scorefor ridge regression
train_score_ls = lasso.score(x_train, y_train)
test_score_ls= lasso.score(x_test, y_test)
print("\nLasso Model:\n")
print("The train score for lasso model is {}".format(train_score_ls))
print("The test score for lasso model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for lasso model is 0.9999147271297208
The test score for lasso model is 0.9999147248375002
```

In [36]:
```
plt.figure(figsize=(10,10))
```

Out[36]:
```
<Figure size 1000x1000 with 0 Axes>

<Figure size 1000x1000 with 0 Axes>
```

In [37]:
```
from sklearn.linear_model import LassoCV
```

In [38]:
```
#using the linear cv model
from sklearn.linear_model import RidgeCV
#cross validation
ridge_cv=RidgeCV(alphas =[0.0001,0.001,0.01,0.1,1,10]).fit(x_train,y_train
#score
print(ridge_cv.score(x_train,y_train))
print(ridge_cv.score(x_test,y_test))
```

```
0.999999999261034
0.9999999993719254
```

In [40]:
```
#using the linear cv model
from sklearn.linear_model import LassoCV
#cross validation
lasso_cv=LassoCV(alphas =[0.0001,0.001,0.01,0.1,1,10]).fit(x_train,y_train
#score
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999915
0.9999999999999915
```

Elastic Regression

In [41]:
```
from sklearn.linear_model import ElasticNet
```

In [42]:
```
el=ElasticNet()
el.fit(x_train,y_train)
print(el.coef_)
print(el.intercept_)
el.score(x,y)
```

```
[9.99044548e-01 1.38835344e-05 4.58897515e-05 0.00000000e+00
 0.00000000e+00]
0.01656567968369771
```

Out[42]:
```
0.9999991435191248
```

In [43]:
```
y_pred_elastic=el.predict(x_train)
```

In [44]:
```
mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
print(mean_squared_error)
```

```
0.0009226812593703956
```

CONCLUSION:

The given data is "Rain fall pridection".here we need to find the best fit model.As per the given data set I had applyed different types of models...in which different type of models got different type of accyuracies

The accuracy of the Linear Regression is 1.0

The accuracy of the Ridge Model is 0.9999999999856

The accuracy of the Lasso Model is 0.20

The accuracy of the ElasticNet Regression is 0.99999914, comparing to all the models,Ridge Regression got the Highest Accuracy

In [ ]: