In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df=pd.read_csv("18_world-data-2023.csv")
df.fillna(0,inplace=True)
df
```

Out[2]:

	Country	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Ma C
0	Afghanistan	60	AF	58.10%	652,230	323,000	32.49	93.0	Ka
1	Albania	105	AL	43.10%	28,748	9,000	11.78	355.0	Tira
2	Algeria	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algi
3	Andorra	164	AD	40.00%	468	0	7.20	376.0	Andorra Ve
4	Angola	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luan
...	...	...	...	...	...	...	...	...	
190	Venezuela	32	VE	24.50%	912,050	343,000	17.88	58.0	Carac
191	Vietnam	314	VN	39.30%	331,210	522,000	16.75	84.0	Ha
192	Yemen	56	YE	44.60%	527,968	40,000	30.45	967.0	San
193	Zambia	25	ZM	32.10%	752,618	16,000	36.19	260.0	Lusa
194	Zimbabwe	38	ZW	41.90%	390,757	51,000	30.68	263.0	Hara

195 rows × 35 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 35 columns):
 #   Column                                   Non-Null Count  Dtype  
---  ------                                   --------------  -----  
 0   Country                                  195 non-null    object 
 1   Density
(P/Km2)                          195 non-null    object 
 2   Abbreviation                             195 non-null    object 
 3   Agricultural Land( %)                    195 non-null    object 
 4   Land Area(Km2)                           195 non-null    object 
 5   Armed Forces size                        195 non-null    object 
 6   Birth Rate                               195 non-null    float64
 7   Calling Code                             195 non-null    float64
 8   Capital/Major City                       195 non-null    object 
 9   Co2-Emissions                            195 non-null    object 
 10  CPI                                      195 non-null    object 
 11  CPI Change (%)                           195 non-null    object 
 12  Currency-Code                            195 non-null    object 
 13  Fertility Rate                           195 non-null    float64
 14  Forested Area (%)                        195 non-null    object 
 15  Gasoline Price                           195 non-null    object 
 16  GDP                                      195 non-null    object 
 17  Gross primary education enrollment (%)   195 non-null    object 
 18  Gross tertiary education enrollment (%)  195 non-null    object 
 19  Infant mortality                         195 non-null    float64
 20  Largest city                             195 non-null    object 
 21  Life expectancy                          195 non-null    float64
 22  Maternal mortality ratio                 195 non-null    float64
 23  Minimum wage                             195 non-null    object 
 24  Official language                        195 non-null    object 
 25  Out of pocket health expenditure         195 non-null    object 
 26  Physicians per thousand                  195 non-null    float64
 27  Population                               195 non-null    object 
 28  Population: Labor force participation (%)  195 non-null    object 
 29  Tax revenue (%)                          195 non-null    object 
 30  Total tax rate                           195 non-null    object 
 31  Unemployment rate                        195 non-null    object 
 32  Urban_population                         195 non-null    object 
 33  Latitude                                 195 non-null    float64
 34  Longitude                                195 non-null    float64
dtypes: float64(9), object(26)
memory usage: 53.4+ KB
```

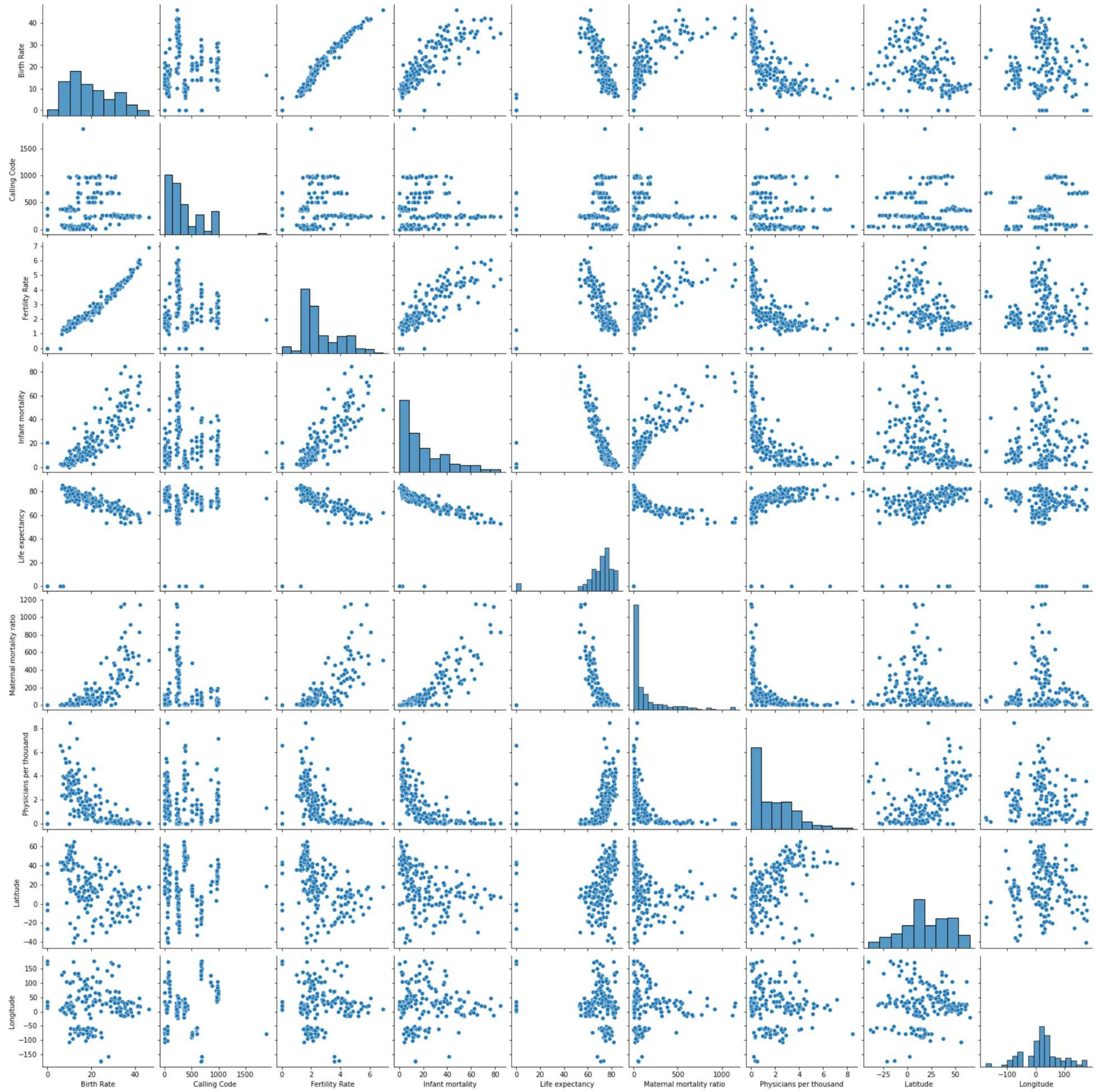
In [4]:
```
df.describe()
```

Out[4]:

	Birth Rate	Calling Code	Fertility Rate	Infant mortality	Life expectancy	Maternal mortality ratio	Physicians per thousand	Latitude
count	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000
mean	19.592974	358.697436	2.601282	20.676410	69.314359	148.876923	1.773795	18.994442
std	10.397534	323.434462	1.355777	19.594644	16.133643	228.717593	1.688826	23.939018
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-40.900557
25%	10.675000	81.500000	1.625000	5.000000	66.150000	9.000000	0.245000	4.372880
50%	17.800000	255.000000	2.200000	13.700000	72.800000	43.000000	1.300000	17.189877
75%	28.445000	506.500000	3.565000	31.550000	77.250000	175.000000	2.875000	40.106102
max	46.080000	1876.000000	6.910000	84.500000	85.400000	1150.000000	8.420000	64.963051

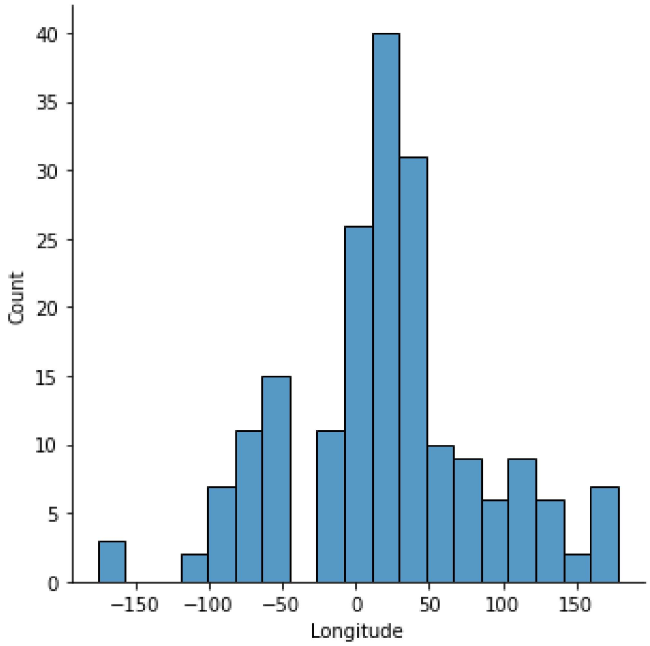
In [5]:
```
sns.pairplot(df)
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x2184d7addc0>



In [6]:
```
sns.displot(df['Longitude'])
```

Out[6]:
```
<seaborn.axisgrid.FacetGrid at 0x2184fd86790>
```



In [7]:
```
df1=df.drop(['Country'],axis=1)
df1
```

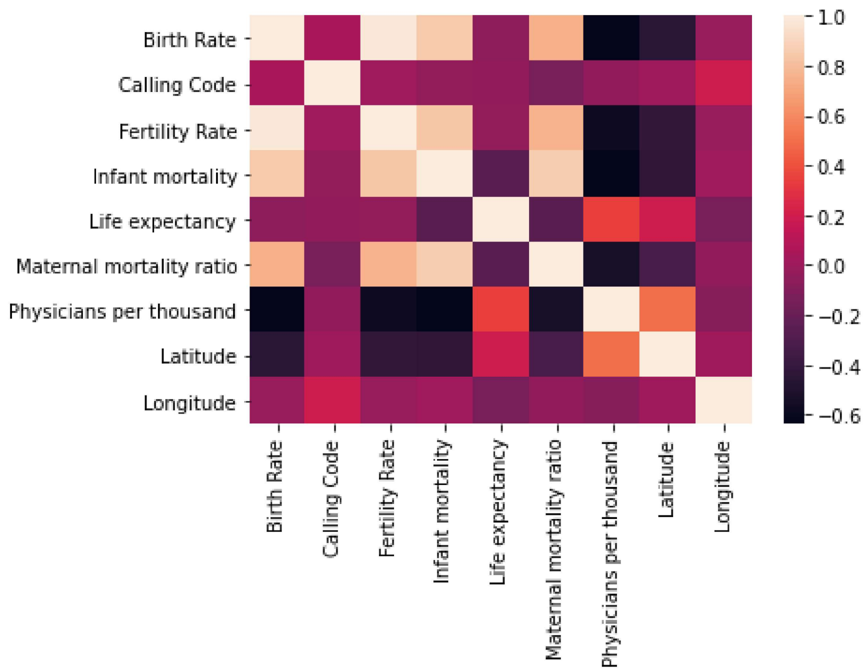
Out[7]:

	Density\n(P/Km2)	Abbreviation	Agricultural Land(%)	Land Area(Km2)	Armed Forces size	Birth Rate	Calling Code	Capital/Major City	Co Emissio
0	60	AF	58.10%	652,230	323,000	32.49	93.0	Kabul	8,6
1	105	AL	43.10%	28,748	9,000	11.78	355.0	Tirana	4,5
2	18	DZ	17.40%	2,381,741	317,000	24.28	213.0	Algiers	150,0
3	164	AD	40.00%	468	0	7.20	376.0	Andorra la Vella	4
4	26	AO	47.50%	1,246,700	117,000	40.73	244.0	Luanda	34,6
...	...	...	...	...	...	...	...	...	
190	32	VE	24.50%	912,050	343,000	17.88	58.0	Caracas	164,1
191	314	VN	39.30%	331,210	522,000	16.75	84.0	Hanoi	192,6
192	56	YE	44.60%	527,968	40,000	30.45	967.0	Sanaa	10,6
193	25	ZM	32.10%	752,618	16,000	36.19	260.0	Lusaka	5,1
194	38	ZW	41.90%	390,757	51,000	30.68	263.0	Harare	10,9

195 rows × 34 columns

In [8]:
```
sns.heatmap(df1.corr())
```

Out[8]: <AxesSubplot:>



In [9]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [10]:
```
y=df['Longitude']
x=df1.drop(['Longitude','Abbreviation','Agricultural Land( %)','Land Area(Km2)','Armed
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
print(x_train)
```

```
     Birth Rate  Calling Code   Latitude
190       17.88          58.0   6.423750
105       41.54         223.0  17.570692
154       17.10         248.0  -4.679574
152       34.52         221.0  14.497401
165       15.83          94.0   7.873054
..          ...           ...        ...
27        39.01         257.0  -3.373056
16        10.30          32.0  50.503887
73         0.00         379.0  41.902916
23        13.92          55.0 -14.235004
157       10.60         421.0  48.669026

[136 rows x 3 columns]
```

In [11]:
```
model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
```

Out[11]: 11.085740356550236

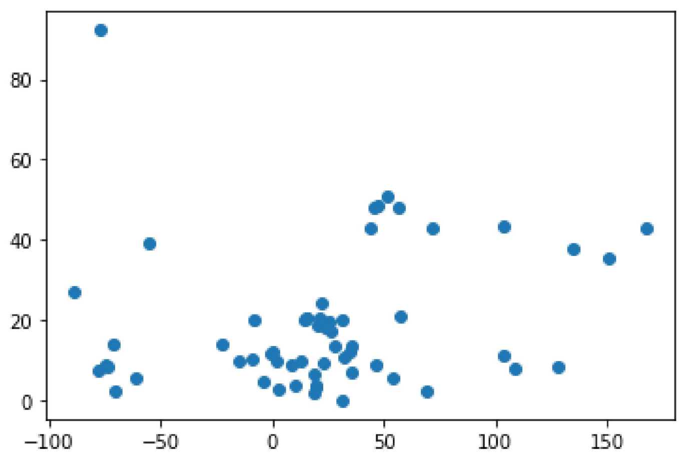
In [12]:
```
coeff=pd.DataFrame(model.coef_,x.columns,columns=["Coefficient"])
coeff
```

Out[12]:

	Coefficient
Birth Rate	-0.320364
Calling Code	0.047229
Latitude	-0.127072

In [13]:
```
prediction=model.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[13]: <matplotlib.collections.PathCollection at 0x21852125a60>



In [14]:
```
model.score(x_test,y_test)
```

Out[14]: 0.003921725830336453

In [15]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [16]:
```
rr = Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[16]: Ridge(alpha=10)

In [17]:
```
rr.score(x_test,y_test)
```

Out[17]: 0.0039329137307800854

In [18]:
```
la = Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[18]: Lasso(alpha=10)

In [19]:
```
la.score(x_test,y_test)
```

Out[19]: 0.009611494267665388

In [20]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
print(en.coef_)
print(en.intercept_)
print(en.predict(x_test))
print(en.score(x_test,y_test))
from sklearn import metrics
print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
[-0.31032468  0.04720037 -0.12413397]
10.840855658686868
[ 5.43752531 48.42471327 42.71879915  8.81853357 43.60305383 24.0367542
 38.80275824  2.64600812  8.9939488  47.91008766 50.70612272 35.45293817
 11.01018304 20.41420935  6.92816362  9.87989343 13.69221578  2.50788548
  5.61318929  6.87450685 27.20688905  8.26783546 10.03799384  3.49619554
 47.9475763  11.72545888 13.97328858  3.15337859 17.38290986  9.13973656
 20.62163358 14.05523827 10.91788959  2.01042378  3.70648427  3.85418879
 10.6930735  20.07164009 19.87956289  8.34624545 10.13011985 37.65969699
  4.9711875  20.32813595 43.29406037 19.71917194 20.50526372  0.26915615
 12.27864679  7.86263266  7.51489203  9.54397631 12.33410349 13.51266428
 43.19364334 92.14450706 18.35334401 21.0575571  18.83283546]
0.004320887974378906
Mean Absolute Error: 37.66836110039882
Mean Squared Error: 3100.045426966432
Root Mean Squared Error: 55.67805157300704
```