

# Import Libraries

In [33]:



```
!pip install MultiColumnLabelEncoder
```

Collecting MultiColumnLabelEncoder

Downloading MultiColumnLabelEncoder-1.1.3-py3-none-any.whl (14 kB)

Installing collected packages: MultiColumnLabelEncoder

Successfully installed MultiColumnLabelEncoder-1.1.3

In [1]:



```
# Importing important Libraries
import pandas as pd
import numpy as np
from scipy import stats
from prettytable import PrettyTable
import pickle
#import pyforest
from lazypredict.Supervised import LazyRegressor
from pandas.plotting import scatter_matrix

# Scikit-Learn packages
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Neural Network packages
from tensorflow.keras.models import Model, load_model, Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.callbacks import ModelCheckpoint

# Hide warnings
import warnings
```

```
warnings.filterwarnings("ignore")  
  
# plotting  
import seaborn as sns  
import matplotlib.pyplot as plt  
from matplotlib import style  
from matplotlib.gridspec import GridSpec  
%matplotlib inline
```

## Load Dataset

In [2]:

```
df = pd.read_csv("D:/Freelancing/Mortality Detection/Dataset/Mortality-5.csv")
df.head(20)
```

Out[2]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	Deaths22
0	4303	nan	NaN	2017	101	1000	1	1	8	281784	...	43174.00	29856.00
1	4303	nan	NaN	2017	101	1000	2	1	8	292339	...	56037.00	52655.00
2	4303	nan	NaN	2017	101	1001	1	1	8	6198	...	62.00	36.00
3	4303	nan	NaN	2017	101	1001	2	1	8	2516	...	86.00	45.00
4	4303	nan	NaN	2017	101	1002	1	1	8	0	...	0.00	0.00
5	4303	nan	NaN	2017	101	1002	2	1	8	0	...	0.00	0.00
6	4303	nan	NaN	2017	101	1003	1	1	8	1	...	0.00	0.00
7	4303	nan	NaN	2017	101	1003	2	1	8	1	...	0.00	1.00
8	4303	nan	NaN	2017	101	1004	1	1	8	18	...	1.00	0.00

In [3]:



```
#check for datatypes and null values  
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 610184 entries, 0 to 610183  
Data columns (total 39 columns):  
#   Column          Non-Null Count  Dtype  
---  -  
0   Country         610184 non-null int64  
1   Admin1          0 non-null      float64  
2   SubDiv          3931 non-null   object  
3   Year            610184 non-null int64  
4   List            610184 non-null int64  
5   Cause           610184 non-null object  
6   Sex             610184 non-null int64  
7   Frmat           610184 non-null int64  
8   IM_Frmat        610184 non-null int64  
9   Deaths1        610184 non-null int64  
10  Deaths2        608592 non-null float64  
11  Deaths3        608592 non-null float64  
12  Deaths4        594046 non-null float64  
13  Deaths5        594046 non-null float64  
14  Deaths6        594046 non-null float64  
15  Deaths7        608592 non-null float64
```



16	Deaths8	608194	non-null	float64
17	Deaths9	608592	non-null	float64
18	Deaths10	608194	non-null	float64
19	Deaths11	608592	non-null	float64
20	Deaths12	608194	non-null	float64
21	Deaths13	608592	non-null	float64
22	Deaths14	608194	non-null	float64
23	Deaths15	608592	non-null	float64
24	Deaths16	608194	non-null	float64
25	Deaths17	608592	non-null	float64
26	Deaths18	608194	non-null	float64
27	Deaths19	608592	non-null	float64
28	Deaths20	608194	non-null	float64
29	Deaths21	608592	non-null	float64
30	Deaths22	607847	non-null	float64
31	Deaths23	607847	non-null	float64
32	Deaths24	540474	non-null	float64
33	Deaths25	540474	non-null	float64
34	Deaths26	608592	non-null	float64
35	IM_Deaths1	608592	non-null	float64
36	IM_Deaths2	516532	non-null	float64
37	IM_Deaths3	522331	non-null	float64
38	IM_Deaths4	522331	non-null	float64

dtypes: float64(30), int64(7), object(2)

memory usage: 181.6+ MB



In [4]:



```
# check data type of each columns for further processing  
df.dtypes
```

Out[4]:

Country	int64
Admin1	float64
SubDiv	object
Year	int64
List	int64
Cause	object
Sex	int64
Frmat	int64
IM_Frmat	int64
Deaths1	int64
Deaths2	float64
Deaths3	float64
Deaths4	float64
Deaths5	float64
Deaths6	float64
Deaths7	float64
Deaths8	float64
Deaths9	float64
Deaths10	float64

Deaths11	float64
Deaths12	float64
Deaths13	float64
Deaths14	float64
Deaths15	float64
Deaths16	float64
Deaths17	float64
Deaths18	float64
Deaths19	float64
Deaths20	float64
Deaths21	float64
Deaths22	float64
Deaths23	float64
Deaths24	float64
Deaths25	float64
Deaths26	float64
IM_Deaths1	float64
IM_Deaths2	float64
IM_Deaths3	float64
IM_Deaths4	float64

dtype: object



In [5]:



```
# check unique values for each feature vector and output  
df.nunique()
```

Out[5]:

Country	99
Admin1	0
SubDiv	2
Year	4
List	3
Cause	10073
Sex	3
Frmat	6
IM_Frmat	4
Deaths1	5894
Deaths2	766
Deaths3	247
Deaths4	179
Deaths5	151
Deaths6	140
Deaths7	266
Deaths8	280
Deaths9	460
Deaths10	557
Deaths11	627

Deaths12	702
Deaths13	800
Deaths14	911
Deaths15	1070
Deaths16	1266
Deaths17	1500
Deaths18	1714
Deaths19	1875
Deaths20	1918
Deaths21	2156
Deaths22	2365
Deaths23	2531
Deaths24	1805
Deaths25	1243
Deaths26	216
IM_Deaths1	472
IM_Deaths2	341
IM_Deaths3	307
IM_Deaths4	418

dtype: int64

In [6]:



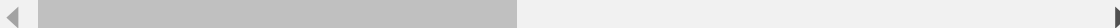
```
df = df.drop(columns= ['Admin1', 'Cause'], axis = 1)
df.head(20)
```

Out[6]:

	Country	SubDiv	Year	List	Sex	Frmate	IM_Frmate	Deaths1	Deaths2	Deaths3	...	D
0	4303	NaN	2017	101	1	1	8	281784	1608.00	133.00	...	4
1	4303	NaN	2017	101	2	1	8	292339	1178.00	99.00	...	5
2	4303	NaN	2017	101	1	1	8	6198	41.00	11.00	...	
3	4303	NaN	2017	101	2	1	8	2516	29.00	7.00	...	
4	4303	NaN	2017	101	1	1	8	0	0.00	0.00	...	
5	4303	NaN	2017	101	2	1	8	0	0.00	0.00	...	
6	4303	NaN	2017	101	1	1	8	1	0.00	0.00	...	
7	4303	NaN	2017	101	2	1	8	1	0.00	0.00	...	
8	4303	NaN	2017	101	1	1	8	18	6.00	0.00	...	
9	4303	NaN	2017	101	2	1	8	4	1.00	0.00	...	
10	4303	NaN	2017	101	1	1	8	1864	1.00	0.00	...	

	Country	SubDiv	Year	List	Sex	Frmate	IM_Frmate	Deaths1	Deaths2	Deaths3	...	D
11	4303	NaN	2017	101	2	1	8	417	0.00	0.00	...	
12	4303	NaN	2017	101	1	1	8	1186	0.00	0.00	...	
13	4303	NaN	2017	101	2	1	8	268	1.00	1.00	...	
14	4303	NaN	2017	101	1	1	8	0	0.00	0.00	...	
15	4303	NaN	2017	101	2	1	8	0	0.00	0.00	...	
16	4303	NaN	2017	101	1	1	8	1	0.00	0.00	...	
17	4303	NaN	2017	101	2	1	8	4	0.00	0.00	...	
18	4303	NaN	2017	101	1	1	8	0	0.00	0.00	...	
19	4303	NaN	2017	101	2	1	8	0	0.00	0.00	...	

20 rows × 37 columns



In [7]:



```
# general overview of dataset characteristics  
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
<b>Country</b>	610184.00	3372.06	969.38	1125.00	2310.00	4010.00	4210.00	5198.00
<b>Year</b>	610184.00	2018.15	0.99	2017.00	2017.00	2018.00	2019.00	2020.00
<b>List</b>	610184.00	103.92	0.32	101.00	104.00	104.00	104.00	104.00
<b>Sex</b>	610184.00	1.50	0.67	1.00	1.00	1.00	2.00	9.00
<b>Frmat</b>	610184.00	0.16	0.63	0.00	0.00	0.00	0.00	9.00
<b>IM_Frmat</b>	610184.00	2.02	2.46	1.00	1.00	1.00	1.00	9.00
<b>Deaths1</b>	610184.00	201.33	7401.58	0.00	1.00	3.00	13.00	1473823.00
<b>Deaths2</b>	608592.00	2.50	110.72	0.00	0.00	0.00	0.00	20964.00
<b>Deaths3</b>	608592.00	0.26	11.90	0.00	0.00	0.00	0.00	2663.00
<b>Deaths4</b>	594046.00	0.15	6.99	0.00	0.00	0.00	0.00	1519.00
<b>Deaths5</b>	594046.00	0.11	4.94	0.00	0.00	0.00	0.00	1119.00

	count	mean	std	min	25%	50%	75%	max
<b>Deaths6</b>	594046.00	0.09	4.00	0.00	0.00	0.00	0.00	873.00
<b>Deaths7</b>	608592.00	0.33	14.70	0.00	0.00	0.00	0.00	2982.00
<b>Deaths8</b>	608194.00	0.37	15.81	0.00	0.00	0.00	0.00	2828.00
<b>Deaths9</b>	608592.00	0.96	51.11	0.00	0.00	0.00	0.00	17763.00
<b>Deaths10</b>	608194.00	1.48	78.95	0.00	0.00	0.00	0.00	24445.00
<b>Deaths11</b>	608592.00	1.83	91.10	0.00	0.00	0.00	0.00	21425.00
<b>Deaths12</b>	608194.00	2.37	113.20	0.00	0.00	0.00	0.00	25135.00
<b>Deaths13</b>	608592.00	3.09	141.96	0.00	0.00	0.00	0.00	34168.00
<b>Deaths14</b>	608194.00	3.91	168.98	0.00	0.00	0.00	0.00	40125.00
<b>Deaths15</b>	608592.00	5.29	215.27	0.00	0.00	0.00	0.00	44424.00
<b>Deaths16</b>	608194.00	7.52	300.88	0.00	0.00	0.00	1.00	63581.00
<b>Deaths17</b>	608592.00	11.07	454.88	0.00	0.00	0.00	1.00	98387.00
<b>Deaths18</b>	608194.00	14.64	595.65	0.00	0.00	0.00	1.00	130870.00
<b>Deaths19</b>	608592.00	17.89	696.98	0.00	0.00	0.00	1.00	150938.00
<b>Deaths20</b>	608194.00	19.15	717.37	0.00	0.00	0.00	1.00	169309.00
<b>Deaths21</b>	608592.00	24.12	900.68	0.00	0.00	0.00	1.00	176496.00
<b>Deaths22</b>	607847.00	28.42	1055.30	0.00	0.00	0.00	1.00	185065.00

	count	mean	std	min	25%	50%	75%	max
<b>Deaths23</b>	607847.00	32.94	1325.49	0.00	0.00	0.00	1.00	268423.00
<b>Deaths24</b>	540474.00	17.83	822.92	0.00	0.00	0.00	1.00	202170.00
<b>Deaths25</b>	540474.00	8.40	474.17	0.00	0.00	0.00	0.00	128337.00
<b>Deaths26</b>	608592.00	0.19	13.85	0.00	0.00	0.00	0.00	3560.00
<b>IM_Deaths1</b>	608592.00	1.01	60.52	0.00	0.00	0.00	0.00	19846.00
<b>IM_Deaths2</b>	516532.00	0.51	23.73	0.00	0.00	0.00	0.00	5676.00
<b>IM_Deaths3</b>	522331.00	0.41	22.23	0.00	0.00	0.00	0.00	5954.00
<b>IM_Deaths4</b>	522331.00	0.83	44.53	-1.00	0.00	0.00	0.00	10658.00

## Data Visualization and Preprocessing

### Look for Missing and NAN Values

In [8]:



```
# check for null or missing values
df.isnull().sum()
```

Out[8]:

Country	0
SubDiv	606253
Year	0
List	0
Sex	0
Frmat	0
IM_Frmat	0
Deaths1	0
Deaths2	1592
Deaths3	1592
Deaths4	16138
Deaths5	16138
Deaths6	16138
Deaths7	1592
Deaths8	1990
Deaths9	1592
Deaths10	1990
Deaths11	1592
Deaths12	1990
Deaths13	1592



Deaths14	1990
Deaths15	1592
Deaths16	1990
Deaths17	1592
Deaths18	1990
Deaths19	1592
Deaths20	1990
Deaths21	1592
Deaths22	2337
Deaths23	2337
Deaths24	69710
Deaths25	69710
Deaths26	1592
IM_Deaths1	1592
IM_Deaths2	93652
IM_Deaths3	87853
IM_Deaths4	87853

dtype: int64

There are several columns that have missing values. We will replace these values with zero

In [9]:



```
df.columns.isna()
```

Out[9]:

```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False])
```

In [10]:



```
# inplace
df.replace(np.nan, 0, inplace=True)
df.head(30)
```

Out[10]:

	Country	SubDiv	Year	List	Sex	Frmate	IM_Frmate	Deaths1	Deaths2	Deaths3	...	Deaths4
0	4303	0	2017	101	1	1	8	281784	1608.00	133.00	...	43174
1	4303	0	2017	101	2	1	8	292339	1178.00	99.00	...	56037
2	4303	0	2017	101	1	1	8	6198	41.00	11.00	...	62
3	4303	0	2017	101	2	1	8	2516	29.00	7.00	...	86
4	4303	0	2017	101	1	1	8	0	0.00	0.00	...	0
5	4303	0	2017	101	2	1	8	0	0.00	0.00	...	0
6	4303	0	2017	101	1	1	8	1	0.00	0.00	...	0
7	4303	0	2017	101	2	1	8	1	0.00	0.00	...	0
8	4303	0	2017	101	1	1	8	18	6.00	0.00	...	1
9	4303	0	2017	101	2	1	8	4	1.00	0.00	...	0
10	4303	0	2017	101	1	1	8	1864	1.00	0.00	...	27

	Country	SubDiv	Year	List	Sex	Frmate	IM_Frmate	Deaths1	Deaths2	Deaths3	...	Deaths
11	4303	0	2017	101	2	1	8	417	0.00	0.00	...	33
12	4303	0	2017	101	1	1	8	1186	0.00	0.00	...	18
13	4303	0	2017	101	2	1	8	268	1.00	1.00	...	11
14	4303	0	2017	101	1	1	8	0	0.00	0.00	...	0
15	4303	0	2017	101	2	1	8	0	0.00	0.00	...	0
16	4303	0	2017	101	1	1	8	1	0.00	0.00	...	0
17	4303	0	2017	101	2	1	8	4	0.00	0.00	...	1
18	4303	0	2017	101	1	1	8	0	0.00	0.00	...	0
19	4303	0	2017	101	2	1	8	0	0.00	0.00	...	0
20	4303	0	2017	101	1	1	8	1	1.00	0.00	...	0
21	4303	0	2017	101	2	1	8	1	1.00	0.00	...	0
22	4303	0	2017	101	1	1	8	32	11.00	8.00	...	0
23	4303	0	2017	101	2	1	8	17	4.00	1.00	...	0
24	4303	0	2017	101	1	1	8	250	10.00	3.00	...	7
25	4303	0	2017	101	2	1	8	160	11.00	3.00	...	14
26	4303	0	2017	101	1	1	8	12	0.00	0.00	...	0
27	4303	0	2017	101	2	1	8	3	0.00	0.00	...	0

	Country	SubDiv	Year	List	Sex	Format	IM_Format	Deaths1	Deaths2	Deaths3	...	Deaths
28	4303	0	2017	101	1	1	8	0	0.00	0.00	...	C
29	4303	0	2017	101	2	1	8	0	0.00	0.00	...	C

30 rows × 37 columns



In [11]:



```
# check for null or missing values  
df.isnull().sum()
```

Out[11]:

Country	0
SubDiv	0
Year	0
List	0
Sex	0
Frmat	0
IM_Frmat	0
Deaths1	0
Deaths2	0
Deaths3	0
Deaths4	0
Deaths5	0
Deaths6	0
Deaths7	0
Deaths8	0
Deaths9	0
Deaths10	0
Deaths11	0
Deaths12	0
Deaths13	0

Deaths14	0
Deaths15	0
Deaths16	0
Deaths17	0
Deaths18	0
Deaths19	0
Deaths20	0
Deaths21	0
Deaths22	0
Deaths23	0
Deaths24	0
Deaths25	0
Deaths26	0
IM_Deaths1	0
IM_Deaths2	0
IM_Deaths3	0
IM_Deaths4	0

dtype: int64

In [12]:



```
#heatmap
plt.figure(figsize=(30,30))
cor_map = df.corr()
sns.heatmap(cor_map, annot=True)
```

Out[12]:

<AxesSubplot:>





Deaths11	-0.0092-0.0012-0.033-0.0073-0.0014	0.013	0.75	0.76	0.65	0.67	0.69	0.7	0.73	0.84	0.93	0.97	1	0.97	0.93	0.91	0.91	0.89	0.85	0.82	0.78	0.76	0.68	0.6	0.46	0.46	0.37	0.62	0.71	0.55	0.44	0.48			
Deaths12	-0.0056-0.0011-0.05	-0.0068-0.0015-0.0017	0.78	0.71	0.62	0.64	0.66	0.67	0.71	0.81	0.84	0.88	0.97	1	0.99	0.98	0.96	0.93	0.9	0.88	0.84	0.79	0.72	0.64	0.49	0.46	0.36	0.67	0.67	0.5	0.41	0.45			
Deaths13	-0.0038-0.0092-0.057-0.0064-0.0027-0.018	0.08	0.69	0.6	0.62	0.65	0.66	0.69	0.79	0.79	0.83	0.93	0.99	1	0.99	0.97	0.95	0.93	0.9	0.87	0.8	0.74	0.66	0.52	0.47	0.37	0.67	0.65	0.48	0.4	0.43				
Deaths14	-0.0039-0.0062-0.058-0.003-0.0035-0.018	0.83	0.69	0.61	0.63	0.66	0.67	0.7	0.79	0.78	0.81	0.91	0.98	0.99	1	0.99	0.97	0.95	0.92	0.89	0.83	0.77	0.7	0.55	0.49	0.39	0.67	0.65	0.49	0.4	0.44				
Deaths15	-0.0039-0.0053-0.053-0.006	7e-05	0.015	0.88	0.72	0.63	0.65	0.67	0.69	0.72	0.81	0.78	0.82	0.91	0.96	0.97	0.99	1	0.99	0.97	0.96	0.93	0.89	0.83	0.75	0.6	0.55	0.45	0.63	0.65	0.52	0.43	0.47		
Deaths16	-0.0035-0.0098-0.05	-0.0059	6e-05	0.014	0.91	0.72	0.63	0.66	0.68	0.69	0.72	0.8	0.77	0.8	0.89	0.93	0.95	0.97	0.99	1	0.99	0.98	0.96	0.92	0.86	0.79	0.64	0.59	0.48	0.57	0.63	0.53	0.46	0.51	
Deaths17	-0.0021-0.0071-0.054-0.0055-0.0096	0.014	0.92	0.67	0.58	0.61	0.63	0.64	0.66	0.74	0.7	0.74	0.85	0.9	0.93	0.95	0.97	0.99	1	1	0.98	0.93	0.88	0.81	0.67	0.6	0.48	0.55	0.58	0.49	0.44	0.48			
Deaths18	-0.0014-0.0045-0.054-0.0051-0.0076-0.013	0.93	0.65	0.56	0.59	0.61	0.62	0.64	0.71	0.67	0.71	0.82	0.88	0.9	0.92	0.96	0.98	1	1	0.99	0.95	0.9	0.84	0.69	0.62	0.5	0.53	0.56	0.47	0.43	0.47				
Deaths19	-0.0007-0.0052-0.054-0.0043-0.0079	0.013	0.96	0.64	0.55	0.57	0.6	0.6	0.62	0.69	0.65	0.69	0.78	0.84	0.87	0.89	0.93	0.96	0.98	0.99	1	0.97	0.95	0.89	0.76	0.67	0.54	0.51	0.54	0.46	0.43	0.47			
Deaths20	-0.0017-0.0041-0.041-0.0032-0.0059	0.0087	0.98	0.65	0.54	0.57	0.59	0.59	0.61	0.68	0.65	0.69	0.76	0.79	0.8	0.83	0.89	0.92	0.93	0.95	0.97	1	0.96	0.93	0.82	0.76	0.64	0.44	0.54	0.48	0.43	0.48			
Deaths21	-0.0016-0.0012-0.049-0.011-0.0095	0.011	0.98	0.56	0.47	0.49	0.51	0.52	0.54	0.6	0.56	0.6	0.68	0.72	0.74	0.77	0.83	0.86	0.88	0.9	0.95	0.96	1	0.98	0.88	0.77	0.63	0.41	0.49	0.4	0.36	0.4			
Deaths22	-0.0034-11e-05-0.046	0.0011	0.0015	0.0089	0.97	0.5	0.42	0.43	0.45	0.46	0.48	0.54	0.49	0.52	0.6	0.64	0.66	0.7	0.75	0.79	0.81	0.84	0.89	0.93	0.98	1	0.94	0.79	0.67	0.38	0.45	0.35	0.31	0.35	
Deaths23	-0.0044-0.0045-0.037	0.0041	0.0046	0.0072	0.88	0.4	0.33	0.34	0.35	0.36	0.38	0.42	0.37	0.4	0.46	0.49	0.52	0.55	0.6	0.64	0.67	0.69	0.76	0.82	0.88	0.94	1	0.71	0.64	0.3	0.35	0.28	0.24	0.28	
Deaths24	-0.1e-05-0.0013-0.012	0.0045-0.0059	0.008	0.81	0.4	0.3	0.31	0.32	0.33	0.34	0.4	0.37	0.4	0.46	0.46	0.47	0.49	0.55	0.59	0.6	0.62	0.67	0.76	0.77	0.79	0.71	1	0.96	0.17	0.34	0.28	0.25	0.29		
Deaths25	-0.0018-0.006-0.0039-0.0059-0.0043-0.0022	0.022	0.7	0.34	0.25	0.26	0.27	0.27	0.29	0.34	0.3	0.33	0.37	0.36	0.37	0.39	0.45	0.48	0.48	0.5	0.54	0.64	0.63	0.67	0.64	0.96	1	0.11	0.29	0.24	0.22	0.26			
Deaths26	-0.008-0.0049-0.036	0.0075	0.0053	0.022	0.46	0.42	0.34	0.34	0.35	0.36	0.38	0.47	0.56	0.58	0.62	0.67	0.67	0.67	0.63	0.57	0.55	0.53	0.51	0.44	0.41	0.38	0.3	0.17	0.11	1	0.59	0.18	0.12	0.11	
IM_Deaths1	-0.011-0.0023-0.018-0.009-0.009-0.0022-0.024	0.024	0.54	0.7	0.54	0.52	0.53	0.54	0.56	0.67	0.71	0.71	0.71	0.67	0.65	0.65	0.65	0.63	0.58	0.56	0.54	0.54	0.49	0.45	0.35	0.34	0.29	0.59	1	0.24	0.18	0.19			
IM_Deaths2	-0.013-0.00022-0.017-0.0034-0.0022-0.0082	0.082	0.45	0.81	0.79	0.79	0.79	0.79	0.79	0.76	0.63	0.59	0.55	0.5	0.48	0.49	0.52	0.53	0.49	0.47	0.46	0.48	0.4	0.35	0.28	0.28	0.24	0.18	0.24	1	0.87	0.85			
IM_Deaths3	-0.016-0.00053-0.018-0.0016-0.0028-0.007	0.007	0.4	0.81	0.84	0.84	0.84	0.81	0.77	0.71	0.53	0.47	0.44	0.41	0.4	0.4	0.43	0.46	0.44	0.43	0.43	0.43	0.36	0.31	0.24	0.25	0.22	0.12	0.16	0.87	1	0.96			
IM_Deaths4	-0.016-0.0091-0.002-0.0011-0.003-0.0071	0.071	0.45	0.82	0.89	0.89	0.88	0.86	0.83	0.75	0.55	0.5	0.48	0.45	0.43	0.44	0.47	0.51	0.48	0.47	0.47	0.48	0.4	0.35	0.28	0.29	0.26	0.11	0.19	0.85	0.96	1			
Country	Year	Lat	Sex	frmt	IM_fmt	Deaths1	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths10	Deaths11	Deaths12	Deaths13	Deaths14	Deaths15	Deaths16	Deaths17	Deaths18	Deaths19	Deaths20	Deaths21	Deaths22	Deaths23	Deaths24	Deaths25	Deaths26	IM_Deaths1	IM_Deaths2	IM_Deaths3	IM_Deaths4



In [13]:



```
# check data type of each columns for further processing
df.dtypes
```

Out[13]:

Country	int64
SubDiv	object
Year	int64
List	int64
Sex	int64
Frmat	int64
IM_Frmat	int64
Deaths1	int64
Deaths2	float64
Deaths3	float64
Deaths4	float64
Deaths5	float64
Deaths6	float64
Deaths7	float64
Deaths8	float64
Deaths9	float64
Deaths10	float64
Deaths11	float64
Deaths12	float64
Deaths13	float64

Deaths14	float64
Deaths15	float64
Deaths16	float64
Deaths17	float64
Deaths18	float64
Deaths19	float64
Deaths20	float64
Deaths21	float64
Deaths22	float64
Deaths23	float64
Deaths24	float64
Deaths25	float64
Deaths26	float64
IM_Deaths1	float64
IM_Deaths2	float64
IM_Deaths3	float64
IM_Deaths4	float64

dtype: object

Heatmap shows correlation of each attribute values amongst each other.

In [14]:



```
output_columns=['Deaths1','Deaths2','Deaths3','Deaths4','Deaths5','Deaths6','Deaths7','Deaths8','Deaths9','Deaths10','Deaths11','Deaths12','Deaths13','Deaths14','Deaths15','Deaths16','Deaths17','Deaths18','Deaths19','Deaths20','Deaths21','Deaths22','Deaths23','Deaths24','Deaths25','Deaths26']
```

In [15]:



```
numerical_features = [features for features in df.columns if len(df[features].unique())!=3]  
categorical_features = [features for features in df.columns if features not in numerical_features]
```

In [16]:



```
numerical_features
```

Out[16]:

```
['Country',  
 'Year',  
 'Frmат',  
 'IM_Frmат',  
 'Deaths1',  
 'Deaths2',  
 'Deaths3',  
 'Deaths4',  
 'Deaths5',  
 'Deaths6',  
 'Deaths7',  
 'Deaths8',  
 'Deaths9',  
 'Deaths10',  
 'Deaths11',  
 'Deaths12',  
 'Deaths13',  
 'Deaths14',  
 'Deaths15',  
 'Deaths16',  
 'Deaths17',
```

```
'Deaths18',  
'Deaths19',  
'Deaths20',  
'Deaths21',  
'Deaths22',  
'Deaths23',  
'Deaths24',  
'Deaths25',  
'Deaths26',  
'IM_Deaths1',  
'IM_Deaths2',  
'IM_Deaths3',  
'IM_Deaths4']
```

In [17]:



```
categorical_features
```

Out[17]:

```
['SubDiv', 'List', 'Sex']
```

## Split Dataset into Train and Test Set

In [18]:



```
# split dataset into train and test set
X = df.drop(columns=output_columns, axis = 1)
Y = df[output_columns]
X.head()
```

Out[18]:

	Country	SubDiv	Year	List	Sex	Frmat	IM_Frmat	IM_Deaths1	IM_Deaths2	IM_Deaths3	I
0	4303	0	2017	101	1	1	8	1608.00	0.00	0.00	
1	4303	0	2017	101	2	1	8	1178.00	0.00	0.00	
2	4303	0	2017	101	1	1	8	41.00	0.00	0.00	
3	4303	0	2017	101	2	1	8	29.00	0.00	0.00	
4	4303	0	2017	101	1	1	8	0.00	0.00	0.00	



In [19]:

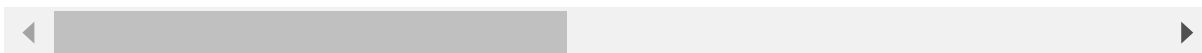


```
Y.head()
```

Out[19]:

	Deaths1	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths
0	281784	1608.00	133.00	87.00	77.00	60.00	214.00	254.00	633.00	1492.00
1	292339	1178.00	99.00	59.00	47.00	36.00	177.00	148.00	257.00	416.00
2	6198	41.00	11.00	7.00	4.00	7.00	7.00	7.00	10.00	41.00
3	2516	29.00	7.00	4.00	5.00	3.00	6.00	5.00	13.00	27.00
4	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

5 rows × 26 columns



In [20]:



```
# Dataset is split into 80:20 ratio in which 80% of the total is allocated for training set
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=24)
```



In [21]:



```
X_train.dtypes
```

Out[21]:

```
Country      int64
SubDiv       object
Year         int64
List         int64
Sex          int64
Frm          int64
IM_Frm       int64
IM_Deaths1   float64
IM_Deaths2   float64
IM_Deaths3   float64
IM_Deaths4   float64
dtype: object
```

```
le = MultiColumnLabelEncoder() encoded_dataframe = le.fit_transform(dataframe)
```

[Note: columns argument can also be passed if we want encoding only for certain columns. By default it will be none and it will encode all the categorical columns]

In [22]:



```
class MultiColumnLabelEncoder:
    def __init__(self, columns = None):
        self.columns = columns

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:
                output[col] = LabelEncoder().fit_transform(output[col])
        else:
            for colname, col in output.iteritems():
                output[colname] = LabelEncoder().fit_transform(col)
        return output

    def fit_transform(self, X, y=None):
        return self.fit(X, y).transform(X)
```

In [23]:



```
#MultiColumnLabelEncoder(columns = ['SubDiv', 'Cause']).fit_transform(X_train)
```

In [24]:



```
# Normalize input feature vector using standard scalar  
le = LabelEncoder()  
X_train['SubDiv'] = le.fit_transform(X_train['SubDiv'].astype(str))  
X_test['SubDiv'] = le.fit_transform(X_test['SubDiv'].astype(str))
```

In [25]:



```
# Normalize input feature vector using standard scalar  
scalar = StandardScaler()  
X_train = scalar.fit_transform(X_train)  
X_test = scalar.fit_transform(X_test)
```

In [26]:



```
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)

# print shape
print("x train Shape",X_train.shape)
print("y train Shape",y_train.shape)
print("x test Shape",X_test.shape)
print("y test Shape",y_test.shape)
```

```
x train Shape (488147, 11)
y train Shape (488147, 26)
x test Shape (122037, 11)
y test Shape (122037, 26)
```

## Train Linear Regression Model

In [27]:



```
x_train = X_train  
x_test = X_test
```

In [28]:



```
## Train Linear Regression Model

linear_model = LinearRegression()
linear_model.fit(x_train,y_train)
pred = linear_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_linear = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_linear,2))

rmse_linear = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_linear,2))

mae_linear = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_linear,2))

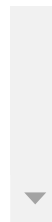
r2_linear = r2_score(y_train,pred)
print ("R2: ",np.round(r2_linear,2))

print ("Score (train): ",np.round(linear_model.score(x_train, y_train),2))
```

Performace of trained model on Training Data



```
=====
MSE: 1349387.55
RMSE: 1161.63
MAE: 27.85
R2: 0.58
Score (train): 0.58
```



In [30]:



```
pred = linear_model.predict(x_test)
print("Performace of trained model on Testing Data")
print("=====")

mse_linear = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_linear,2))

rmse_linear = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_linear,2))

mae_linear = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_linear,2))

r2_linear = r2_score(y_test,pred)
print ("R2: ",np.round(r2_linear,2))

print ("Score (test): ",np.round(linear_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

=====

MSE: 1336808.71

RMSE: 1156.2

MAE: 27.8

R2: 0.59

Score (test): 0.59



# **Train GradientBoosting Regressor**

In [33]:



```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.multioutput import MultiOutputRegressor
## Train GradientBoosting Regression Model

gbr_model = GradientBoostingRegressor()
gbr_model=MultiOutputRegressor(gbr_model)
gbr_model.fit(x_train,y_train)
pred = gbr_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_gbr = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_gbr,2))

rmse_gbr = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_gbr,2))

mae_gbr = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_gbr,2))

r2_gbr = r2_score(y_train,pred)
print ("R2: ",np.round(r2_gbr,2))

print ("Score (train): ",np.round(gbr_model.score(x_train, y_train),2))
```

# Performace of trained model on Training Data

=====

MSE: 238888.23

RMSE: 488.76

MAE: 15.39

R2: 0.92

Score (train): 0.92

In [34]:



```
pred = gbr_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_gbr = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_gbr,2))

rmse_gbr = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_gbr,2))

mae_gbr = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_gbr,2))

r2_gbr = r2_score(y_test,pred)
print ("R2: ",np.round(r2_gbr,2))

print ("Score (test): ",np.round(gbr_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

=====

MSE: 366270.29

RMSE: 605.2

MAE: 16.96



R2: 0.79  
Score (test): 0.79



In [35]:



```
# set path to save model here
```

```
pickle.dump(gbr_model,open('D:/Freelancing/Mortality Detection/Saved Model/gbr.pkl','wb'))
```

## Train Ridge Regression Model

In [36]:



```
ridge_model = Ridge()
ridge_model.fit(x_train,y_train)
pred = ridge_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_ridge = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_ridge,2))

rmse_ridge = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_ridge,2))

mae_ridge = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_ridge,2))

r2_ridge = r2_score(y_train,pred)
print ("R2: ",np.round(r2_ridge,2))

print ("Score (train): ",np.round(ridge_model.score(x_train, y_train),2))
```

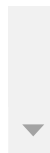
Performace of trained model on Training Data

=====

MSE: 1349387.55



RMSE: 1161.63  
MAE: 27.85  
R2: 0.58  
Score (train): 0.58



In [37]:



```
pred = ridge_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_gbr = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_gbr,2))

rmse_gbr = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_gbr,2))

mae_gbr = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_gbr,2))

r2_gbr = r2_score(y_test,pred)
print ("R2: ",np.round(r2_gbr,2))

print ("Score (test): ",np.round(ridge_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

```
=====
MSE: 1336810.4
RMSE: 1156.21
MAE: 27.8
```





R2: 0.59

Score (test): 0.59



## Train Lasso Regression Model

In [38]:



```
lasso_model = Lasso()
lasso_model.fit(x_train,y_train)
pred = lasso_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_lasso = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_lasso,2))

rmse_lasso = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_lasso,2))

mae_lasso = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_lasso,2))

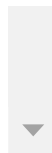
r2_lasso = r2_score(y_train,pred)
print ("R2: ",np.round(r2_lasso,2))

print ("Score (train): ",np.round(lasso_model.score(x_train, y_train),2))
```

```
Performace of trained model on Training Data
=====
MSE:  1349428.81
```



RMSE: 1161.65  
MAE: 26.8  
R2: 0.57  
Score (train): 0.57



In [39]:



```
pred = lasso_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_gbr = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_gbr,2))

rmse_gbr = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_gbr,2))

mae_gbr = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_gbr,2))

r2_gbr = r2_score(y_test,pred)
print ("R2: ",np.round(r2_gbr,2))

print ("Score (test): ",np.round(lasso_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

```
=====
MSE: 1337422.39
RMSE: 1156.47
MAE: 26.78
```



R2: 0.58

Score (test): 0.58



## Train Random Forest Regressor

In [42]:



```
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor(n_estimators = 300)
rf_model.fit(x_train,y_train)
pred = rf_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_rf = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_rf,2))

rmse_rf = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_rf,2))

mae_rf = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_rf,2))

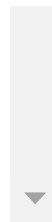
r2_rf = r2_score(y_train,pred)
print ("R2: ",np.round(r2_rf,2))

print ("Score (train): ",np.round(rf_model.score(x_train, y_train),2))
```

Performace of trained model on Training Data



```
=====
MSE: 103814.92
RMSE: 322.2
MAE: 11.58
R2: 0.95
Score (train): 0.95
```



In [43]:



```
pred = rf_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_gbr = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_gbr,2))

rmse_gbr = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_gbr,2))

mae_gbr = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_gbr,2))

r2_gbr = r2_score(y_test,pred)
print ("R2: ",np.round(r2_gbr,2))

print ("Score (test): ",np.round(rf_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

```
=====
MSE:  428002.18
RMSE:  654.22
MAE:  15.88
```





R2: 0.74  
Score (test): 0.74



In [45]:



```
# set path to save model here
```

```
pickle.dump(rf_model,open('D:/Freelancing/Mortality Detection/Saved Model/rf.pkl','wb'))
```

## Train Decision Tree Regressor

In [46]:



```
from sklearn.tree import DecisionTreeRegressor

dt_model = DecisionTreeRegressor()
dt_model.fit(x_train,y_train)
pred = dt_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_rf = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_rf,2))

rmse_rf = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_rf,2))

mae_rf = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_rf,2))

r2_rf = r2_score(y_train,pred)
print ("R2: ",np.round(r2_rf,2))

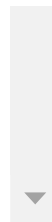
print ("Score (train): ",np.round(dt_model.score(x_train, y_train),2))
```

Performace of trained model on Training Data



=====

MSE: 65196.21  
RMSE: 255.34  
MAE: 9.94  
R2: 0.98  
Score (train): 0.98



In [47]:



```
pred = dt_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_dt = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_dt,2))

rmse_dt = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_dt,2))

mae_dt = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_dt,2))

r2_dt = r2_score(y_test,pred)
print ("R2: ",np.round(r2_dt,2))

print ("Score (test): ",np.round(dt_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

```
=====
MSE:  651022.45
RMSE:  806.86
MAE:  16.47
```



R2: 0.62

Score (test): 0.62



## Train Extra Tree Regressor

In [49]:



```
from sklearn.ensemble import ExtraTreesRegressor

et_model = ExtraTreesRegressor()
et_model.fit(x_train,y_train)
pred = et_model.predict(x_train)

print("Performace of trained model on Training Data")
print("=====")

mse_et = mean_squared_error(y_train,pred)
print("MSE: ",np.round(mse_et,2))

rmse_et = np.sqrt(mean_squared_error(y_train, pred))
print("RMSE: ",np.round(rmse_et,2))

mae_et = mean_absolute_error(y_train,pred)
print("MAE: ",np.round(mae_et,2))

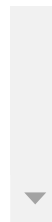
r2_et = r2_score(y_train,pred)
print ("R2: ",np.round(r2_et,2))

print ("Score (train): ",np.round(et_model.score(x_train, y_train),2))
```

Performace of trained model on Training Data



```
=====
MSE: 65196.21
RMSE: 255.34
MAE: 9.94
R2: 0.98
Score (train): 0.98
```



In [51]:



```
pred = et_model.predict(x_test)

print("Performace of trained model on Testing Data")
print("=====")

mse_et = mean_squared_error(y_test,pred)
print("MSE: ",np.round(mse_et,2))

rmse_et = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE: ",np.round(rmse_et,2))

mae_et = mean_absolute_error(y_test,pred)
print("MAE: ",np.round(mae_et,2))

r2_et = r2_score(y_test,pred)
print ("R2: ",np.round(r2_et,2))

print ("Score (test): ",np.round(et_model.score(x_test, y_test),2))
```

Performace of trained model on Testing Data

```
=====
MSE:  526791.79
RMSE:  725.8
MAE:  15.75
```





R2: 0.83  
Score (test): 0.83



In [52]:



```
# set path to save model here
```

```
pickle.dump(et_model,open('D:/Freelancing/Mortality Detection/Saved Model/et.pkl','wb'))
```

## Application Phase

In [57]:



```
# Take input from the user
country = int (input("Enter country: "))
subDiV = input ("Enter SubDiV: ")
cause = input ("Cause of death: ")
year = int (input("Enter Year (Year to which data refer): "))
List = int (input("Enter List of ICD revision used : "))
gender = int (input("Enter Gender (1 male, 2 female and 9 sex unspecified): "))
Frmат = int (input ("Enter Frmat (Age-group format for breakdown of deaths at 0-95+ yrs): "))
IM_Frmat = int (input ("Enter IM_Frmat (Age format for breakdown of infant deaths (0 year))"))
IM_deaths1 = float(input ("Enter Number of Infant deaths at age 0 day: "))
IM_deaths2 = float(input ("Enter Number of Infant deaths at age 1-6 day: "))
IM_deaths3 = float(input ("Enter Number of Infant deaths at age 7-27 day: "))
IM_deaths4 = float(input ("Enter Number of Infant deaths at age 28-364 day: "))
```

Enter country: 4303

Enter SubDiV: 0

Cause of death: 1000

Enter Year (Year to which data refer): 2017

Enter List of ICD revision used : 101

Enter Gender (1 male, 2 female and 9 sex unspecified): 1

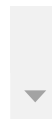
Enter Frmat (Age-group format for breakdown of deaths at 0-95+ yrs): 1

Enter IM\_Frmat (Age format for breakdown of infant deaths (0 year)): 8

Enter Number of Infant deaths at age 0 day: 20



Enter Number of Infant deaths at age 1-6 day: 10  
Enter Number of Infant deaths at age 7-27 day: 5  
Enter Number of Infant deaths at age 28-364 day: 2





```
user_input = pd.DataFrame({ 'Country': [country], 'SubDiv': [subDiv], 'Year': [year], 'List':  
                             , 'Frmат': [Frmат], 'IM_Frmат': [IM_Frmат], 'IM_Deaths1': [IM_deaths  
                             'IM_Deaths3': [IM_deaths3], 'IM_Deaths4': [IM_deaths4]})  
  
print("\n\nUser Input Feature Vector:")  
print("=====\n")  
print(user_input)
```

=====

	Country	SubDiV	Year	List	Sex	Frmat	IM_Frmat	IM_Deaths1	IM_Deaths2
0	4303	0	2017	101	1	1	8	20.00	10.00
	IM_Deaths3	IM_Deaths4							
0	5.00	2.00							



In [59]:



```
user_input.dtypes
```

Out[59]:

```
Country      int64
SubDiV       object
Year         int64
List         int64
Sex          int64
Frm          int64
IM_Frm       int64
IM_Deaths1   float64
IM_Deaths2   float64
IM_Deaths3   float64
IM_Deaths4   float64
dtype: object
```

In [60]:



```
# Load trained model
```

```
model = pickle.load(open('D:/Freelancing/Mortality Detection/Saved Model/et.pkl','rb')) # s
```

In [62]:



```
#le = LabelEncoder()  
user_input['SubDiV'] = le.transform(user_input['SubDiV'].astype(str))
```

In [63]:



```
# convert into numpy arrays  
user_input = np.array(user_input)
```

In [64]:



```
pred = model.predict(user_input)

print("Predicted Values: ")
print("=====\n")
print("Deaths 1 = ",pred[0][0])
print("Deaths 2 = ",pred[0][1])
print("Deaths 3 = ",pred[0][2])
print("Deaths 4 = ",pred[0][3])
print("Deaths 5 = ",pred[0][4])
print("Deaths 6 = ",pred[0][5])
print("Deaths 7 = ",pred[0][6])
print("Deaths 8 = ",pred[0][7])
print("Deaths 9 = ",pred[0][8])
print("Deaths 10 = ",pred[0][9])
print("Deaths 11 = ",pred[0][10])
print("Deaths 12 = ",pred[0][11])
print("Deaths 13 = ",pred[0][12])
print("Deaths 14 = ",pred[0][13])
print("Deaths 15 = ",pred[0][14])
print("Deaths 16 = ",pred[0][15])
print("Deaths 17 = ",pred[0][16])
print("Deaths 18 = ",pred[0][17])
print("Deaths 19 = ",pred[0][18])
print("Deaths 20 = ",pred[0][19])
print("Deaths 21 = ",pred[0][20])
```

```
print("Deaths 22 = ",pred[0][21])
print("Deaths 23 = ",pred[0][22])
print("Deaths 24 = ",pred[0][23])
print("Deaths 25 = ",pred[0][24])
print("Deaths 26 = ",pred[0][25])
```

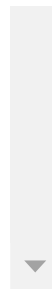
Predicted Values:

=====

Deaths 1 = 151866.48  
Deaths 2 = 1109.07  
Deaths 3 = 83.67  
Deaths 4 = 37.56  
Deaths 5 = 29.45  
Deaths 6 = 20.98  
Deaths 7 = 95.98  
Deaths 8 = 102.85  
Deaths 9 = 231.08  
Deaths 10 = 392.78  
Deaths 11 = 582.49  
Deaths 12 = 850.64  
Deaths 13 = 1180.75  
Deaths 14 = 1592.06  
Deaths 15 = 2355.79  
Deaths 16 = 3725.59  
Deaths 17 = 5903.05  
Deaths 18 = 8097.23



Deaths 19 = 10819.33  
Deaths 20 = 13095.52  
Deaths 21 = 19587.78  
Deaths 22 = 24903.24  
Deaths 23 = 41795.13  
Deaths 24 = 9941.38  
Deaths 25 = 5330.45  
Deaths 26 = 2.63



In [67]:



```
# Use pretty table to show detail analysis
x = PrettyTable()
print("\nDetailed Performance of all Models")
print("=====\n")
x.field_names=["Model", "MSE", "MAE", "RMSE", "R2"]
x.add_row(["Linear Regression", np.round(mse_linear,2), np.round(mae_linear,2), np.round(rmse_linear,2), np.round(r2_linear,2)])
x.add_row(["Gadient Boosting Regression", 366270.29, 605.2, 16.96, 0.79])
x.add_row(["Ridge Regression", np.round(mse_ridge,2), np.round(mae_ridge,2), np.round(rmse_ridge,2), np.round(r2_ridge,2)])
x.add_row(["Lasso Regression", np.round(mse_lasso,2), np.round(mae_lasso,2), np.round(rmse_lasso,2), np.round(r2_lasso,2)])
x.add_row(["Random Forest Regression", 428002.18, 654.22, 15.88, 0.74])
x.add_row(["Decision Tree Regression", np.round(mse_dt,2), np.round(mae_dt,2), np.round(rmse_dt,2), np.round(r2_dt,2)])
x.add_row(["Extra Regression", np.round(mse_et,2), np.round(mae_et,2), np.round(rmse_et,2), np.round(r2_et,2)])

print(x)

print("\nBest Model")
print("=====\n")
y = PrettyTable()
y.field_names=["Model", "MSE", "MAE", "RMSE", "R2"]
y.add_row(["Extra Regression", np.round(mse_et,2), np.round(mae_et,2), np.round(rmse_et,2), np.round(r2_et,2)])
print(y)
```



Detailed Performance of all Models

=====

Model	MSE	MAE	RMSE	R2
Linear Regression	1336808.71	27.8	1156.2	0.59
Gadient Boosting Regression	366270.29	605.2	16.96	0.79
Ridge Regression	1349387.55	27.85	1161.63	0.58
Lasso Regression	1349428.81	26.8	1161.65	0.57
Random Forest Regression	428002.18	654.22	15.88	0.74
Decision Tree Regression	651022.45	16.47	806.86	0.62
Extra Regression	526791.79	15.75	725.8	0.83

Best Model

=====

Model	MSE	MAE	RMSE	R2
Extra Regression	526791.79	15.75	725.8	0.83



