Causes of accidents in different ages -2018

॥ वसुधैव कुटुम्बकम् ॥

PROJECT REPORT SUBMITTED TO
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FOR PARTIAL FULFILLMENT OF THE M.Sc. DEGREE

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Sourav Khot

Abstract:

This is an analysis done on the 2018 accidents data, before 2019 we don’t know about covid-19 at that time there were some main causes of present from that death of human can be happened, that can be due to road accidents, Heart attacks, Firearm, poisoning, snake bite, and many more from that person’s valuable life was gone. For their prevention and to know more details about data we have done some analysis that helps us solve that problem and take some precautions about it. For that, we have used different python libraries and software like tableau that helps to visualize and a database like PostgreSQL that helps us store and manage data. That helps to take some future decisions and avoid such accidents and causes that take humans’ life.

Introduction:

In this report, we analyse the data collected from India’s government site where data contains different types of accidents and death information in 2018. The data includes total male, female, and transgender accidents between the years 2017-18. The report will examine the trends in vehicle accident rates, heart attack rates, and many more causes that affected human deaths. Also for the last some years, because of covid-19 humans are aware of different spreading diseases and other causes that affect human deaths and destroy their families from this analysis we can provide better security to different construction projects that can reduce accidents and save laborers’ life. This is the main motive behind this project recently saw that most accidental deaths happen the road accidents as some predictions have in this project.

Dataset Details:

Data Sources:

This data is collected from the Indian government site

Dataset Name:

NCRB-ADSI-2018-Table-1.7

Source: https://data.gov.in/

Dataset size: 62 X 31

This data is static because it's just 2018 year data that will be not changing anymore.

Dataset columns:

Columns of the dataset are as follows:

```
In [13]: df.columns

Out[13]: Index(['Sl. No.', 'Cause', 'Below 14 years - Male', 'Below 14 years - Female',
         'Below 14 years - Transgender', 'Below 14 years - Total',
         '14 and Above - Below 18 years - Male',
         '14 and Above - Below 18 years - Female',
         '14 and Above - Below 18 years - Transgender',
         '14 and Above - Below 18 years - Total',
         '18 and Above - Below 30 years - Male',
         '18 and Above - Below 30 years - Female',
         '18 and Above - Below 30 years - Transgender',
         '18 and Above - Below 30 years - Total',
         '30 and Above - Below 45 years - Male',
         '30 and Above - Below 45 years - Female',
         '30 and Above - Below 45 years - Transgender',
         '30 and Above - Below 45 years - Total',
         '45 and Above - Below 60 years - Male',
         '45 and Above - Below 60 years - Female',
         '45 and Above - Below 60 years - Transgender',
         '45 and Above - Below 60 years - Total', '60 years & Above - Male',
         '60 years & Above - Female', '60 years & Above - Transgender',
         '60 years & Above - Total', 'Total - Male', 'Total - Female',
         'Total - Transgender', 'Total - Total', 'Total - Percentage Share'],
        dtype='object')
```

And in this Cause column contains main accident type and their subtype for main accident type they have given some number they are as follows.

```
In [40]: cause=data.iloc[:,1]
         cause

Out[40]: 0                                      Air Crash
         1                                 Ship Accidents
         2                   Collapse of Structure (Total)
         3     3.1 Collapse of Dwelling House/Residential Bui...
         4         3.2 Collapse of Official/ Commercial Building
                                ...
         57                                   Suffocation
         58                                 Drug Overdose
         59                         Other than above Causes
         60                              Causes Not Known
         61                                         Total
         Name: Cause, Length: 62, dtype: object
```

These subtypes of causes are present:

Sl. No.	Cause
1	Air Crash
2	Ship Accidents
3	Collapse of Structure (Total)
3	3.1 Collapse of Dwelling House/Residential Building
3	3.2 Collapse of Official/ Commercial Building
3	3.3 Collapse of Dam
3	3.4 Collapse of Bridge
3	3.5 Others
4	Drowning (Total)
4	4.1 Boat Capsize
4	4.2 Accidental Falls into Waterbody
4	4.3 Other Cases
5	Electrocution
6	Accidental Explosion (Total)
6	6.1 Domestic Gas Cylinder
6	6.2 Industrial Boiler/ Gas Cylinder Explosion
6	6.3 Ammunition Explosion in Armed Forces/Police/CPMF
6	6.4 Other
7	Falls (Total)
7	7.1 Fall from Height

7	7.2 Fall from Vehicles (Automobile like Bus, Trucks, etc.)
7	7.3 Fall into Manhole
7	7.4 Fall into Pit
7	7.5 Fall into Borewell
7	7.6 Others
8	Factory/Machine Accidents
9	Accidental Fire (Total)
9	9.1 Electrical Short circuit
9	9.2 Riot/Agitation
9	9.3 Fireworks
9	9.4 Cooking Gas Cylinder/Stove Burst
9	9.5 Other Causes
10	Firearm
11	Mines or Quarry Disaster
12	Traffic Accidents (Total)
12	12.1 Road Accidents
12	12.2 Railway Crossing Accidents
12	12.3 Railway Accidents
13	Stampede
14	Sudden Deaths (Total)
14	14.1 Industrial Accidents
14	14.2 Heart Attack
14	14.3 Others
15	Deaths of Women during Pregnancy (Total)
15	15.1 Due to Abortions
15	15.2 Other than Abortions
16	Deaths Due to Consumption of Illicit/Spurious Liquor
17	Killed / Injured by Animals
18	Poisoning (Total)
18	18.1 Food Poisoning
18	18.2 Accidental Intake of Insecticides/Pesticides
18	18.3 Poisonous Gases (Total)
18	18.3.1 Carbon Monoxide (CO) Gas
18	18.3.2 Other Poisonous Gases
18	18.4 Snake Bite
18	18.5 Animal/Reptiles/Insects Bite
18	18.6 Other
19	Suffocation
20	Drug Overdose
21	Other than above Causes
22	Causes Not Known
Total	Total

From above indexes are as follows:

- 3 ➢ Collapse of Structure subtypes
- 4 ➢ Drowning subtypes
- 6 ➢ Accidental Explosion subtypes
- 7 ➢ Falls subtypes
- 9 ➢ Accidental Fire (Total)
- 12 ➢ Traffic Accidents (Total)
- 14 ➢ Sudden Deaths (Total)
- 15 ➢ Deaths of Women during Pregnancy (Total)
- 18 ➢ Poisoning (Total)

As per indexing will be assigning for overall data.
For all of these causes different ages of males, females and trans genders accident cases data are present as well that data will be distributed in the different ages like below 14 males accidents, age 14 to age 18 males accidents, Total male, Total Female like these attributes are present in the data.

Libraries:

Here are some libraries are used in these project

- Pandas:- This library is useful for reading data in .csv format.
- Numpy:- This library is used for doing some numeric operations in data.
- Matplotlib:- This library is used for visualizing the data their sub-package is used that named a pyplot from that we can draw different graphs.
- Seaborn:- This library is also used for visualization.
- Psycopg2:- This library is used to connect databases with python or a server.

Data Cleaning and Preprocessing:

This dataset is collected from a government site so there will be no missing values found so there will be no need to handling with missing values some rows contains the total of the accident deaths and the main type of accident that rows are discarded and taken the data for that python language is used. If those rows are present then we cannot visualize data properly and make an analysis.

```
In [4]: df=data.copy()
        df.drop([2],axis=0,inplace=True)
        df.drop([8,13,18,26,34,39,43,48,61],axis=0,inplace=True)
        df   #used for cleaning purpose
```

		Monoxide (CO) Gas													
53	18	18.3.2 Other Poisonous Gases	3	2	0	5	2	4	0	6	...	30	5	2	0	7
54	18	18.4 Snake Bite	600	445	0	1045	376	279	0	655	...	1857	450	323	0	773
55	18	18.5 Animal/Reptiles/Insects Bite	60	32	0	92	39	24	0	63	...	180	68	35	0	103
56	18	18.6 Other	63	45	0	108	119	98	0	217	...	659	177	84	0	261
57	19	Suffocation	61	35	0	96	59	60	0	119	...	442	134	39	0	173
58	20	Drug Overdose	9	7	0	16	14	10	0	24	...	206	70	25	0	95
59	21	Other than above Causes	1452	1068	1	2521	1721	878	0	2599	...	14477	5973	1804	1	7778
60	22	Causes Not Known	295	161	2	458	555	280	0	835	...	3597	1267	350	0	1617

52 rows × 31 columns

After, that we reduced data and gave name **df,** and their preprocessing operations were done as follows:

For understanding data size and shape we used these queries

```
In [12]: print(df.size) #fpr checking size of the data
         print(df.shape)  #for checking shape of the data

1612
(52, 31)
```

Dataset sample or starting and ending dataset points:

In [5]:
```
df.head()     # for showing first five rows of dataset
```
Out[5]:

	Sl. No.	Cause	Below 14 years - Male	Below 14 years - Female	Below 14 years - Transgender	Below 14 years - Total	14 and Above - Below 18 years - Male	14 and Above - Below 18 years - Female	14 and Above - Below 18 years - Transgender	14 and Above - Below 18 years - Total	...	45 and Above - Below 60 years - Total	60 years & Above - Male	60 years & Above - Female	60 years & Above - Transgender	60 years & Above - Total	Total - Male	T Fe
0	1	Air Crash	0	0	0	0	0	0	0	0	...	11	0	0	0	0	13	
1	2	Ship Accidents	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	3	3.1 Collapse of Dwelling House/Residential Bui...	80	60	0	140	54	35	0	89	...	244	78	62	0	140	862	
4	3	3.2 Collapse of Official/ Commercial Building	3	0	0	3	1	0	0	1	...	15	3	0	0	3	47	
5	3	3.3 Collapse of Dam	0	0	0	0	1	0	0	1	...	0	0	0	0	0	6	

5 rows × 31 columns

In [6]:
```
data.tail()    #for calculating last five rows of datasets
```
Out[6]:

	Sl. No.	Cause	Below 14 years - Male	Below 14 years - Female	Below 14 years - Transgender	Below 14 years - Total	14 and Above - Below 18 years - Male	14 and Above - Below 18 years - Female	14 and Above - Below 18 years - Transgender	14 and Above - Below 18 years - Total	...	45 and Above - Below 60 years - Total	60 years & Above - Male	60 years & Above - Female	60 years & Above - Transgender	60 years & Above - Total	Total - Male	Tot Fem
57	19	Suffocation	61	35	0	96	59	60	0	119	...	442	134	39	0	173	1422	4
58	20	Drug Overdose	9	7	0	16	14	10	0	24	...	206	70	25	0	95	720	1
59	21	Other than above Causes	1452	1068	1	2521	1721	878	0	2599	...	14477	5973	1804	1	7778	45003	13
60	22	Causes Not Known	295	161	2	458	555	280	0	835	...	3597	1267	350	0	1617	11500	31
61	Total	Total	10917	5488	3	16408	19039	6082	0	25121	...	87319	31178	9625	1	40804	325767	79

5 rows × 31 columns

Also for checking the datatypes of columns and for total missing values, we try different queries that are mentioned in the project.

For checking total missing values in the data we have done the following queries:

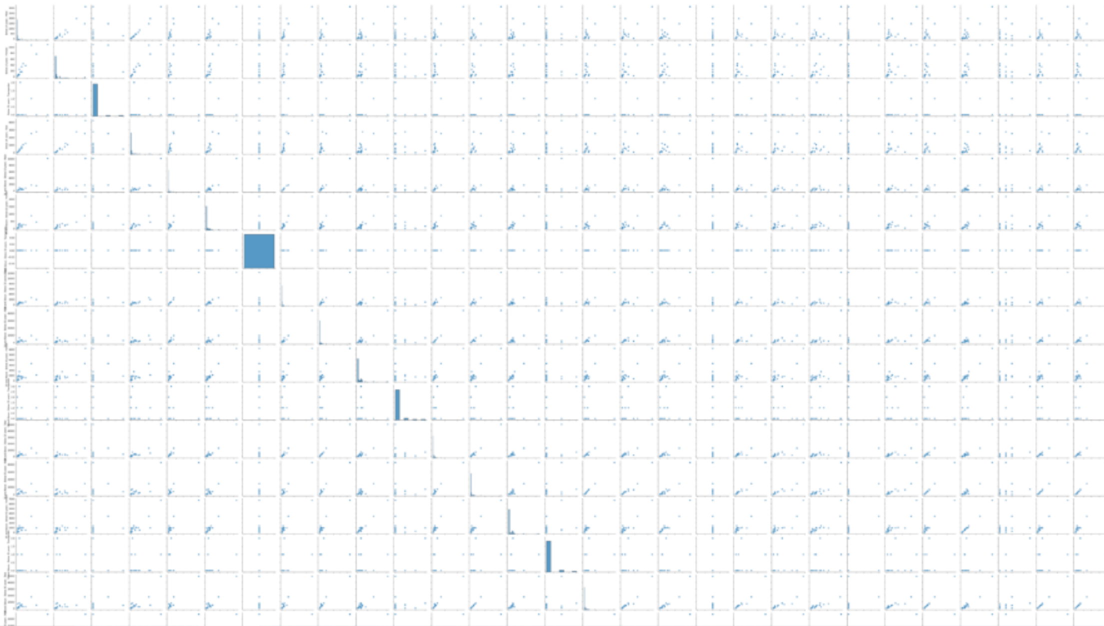
```
In [8]: df.isnull().sum()    #for checking how much null values present in data sets
Out[8]: Sl. No.                                        0
        Cause                                          0
        Below 14 years - Male                          0
        Below 14 years - Female                        0
        Below 14 years - Transgender                   0
        Below 14 years - Total                         0
        14 and Above - Below 18 years - Male           0
        14 and Above - Below 18 years - Female         0
        14 and Above - Below 18 years - Transgender    0
        14 and Above - Below 18 years - Total          0
        18 and Above - Below 30 years - Male           0
        18 and Above - Below 30 years - Female         0
        18 and Above - Below 30 years - Transgender    0
        18 and Above - Below 30 years - Total          0
        30 and Above - Below 45 years - Male           0
        30 and Above - Below 45 years - Female         0
        30 and Above - Below 45 years - Transgender    0
        30 and Above - Below 45 years - Total          0
        45 and Above - Below 60 years - Male           0
        45 and Above - Below 60 years - Female         0
        45 and Above - Below 60 years - Transgender    0
        45 and Above - Below 60 years - Total          0
        60 years & Above - Male                        0
        60 years & Above - Female                      0
        60 years & Above - Transgender                 0
        60 years & Above - Total                       0
        Total - Male                                   0
        Total - Female                                 0
        Total - Transgender                            0
        Total - Total                                  0
        Total - Percentage Share                       0
        dtype: int64
```

And in case any missing value is present for checking we can use the following query:

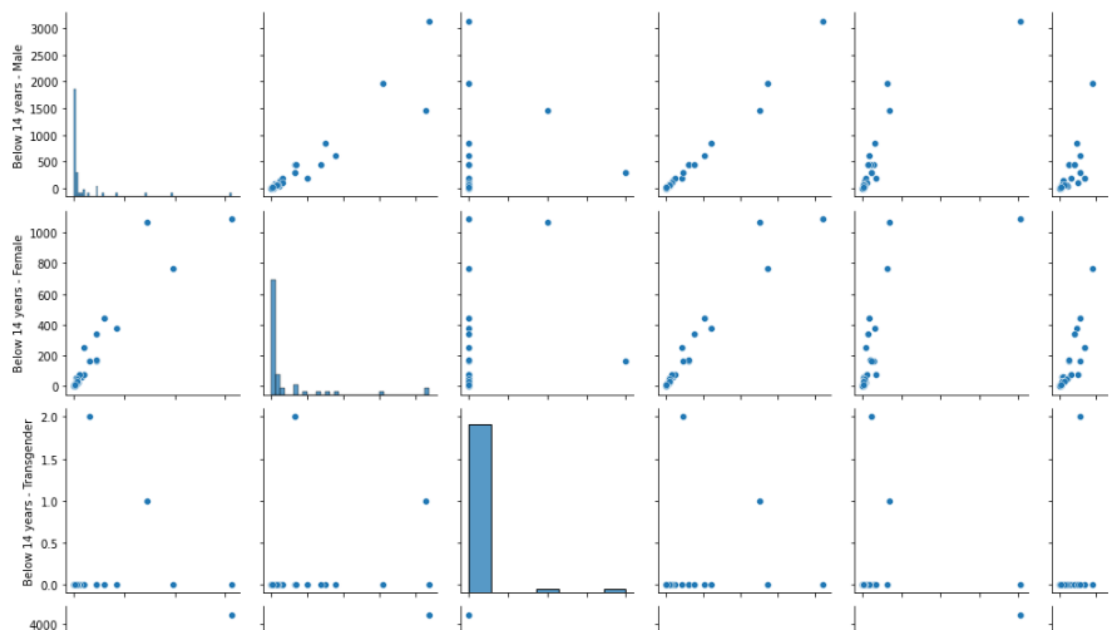
```
In [7]: df.isnull()  #for checking at which place null value is
```

For understanding the relationship between columns or variable we used the seaborne pair plot as follows:

```
In [21]: sns.pairplot(df,kind="scatter")          #to plot subplots of data
         plt.show()
```



```
In [21]: sns.pairplot(df,kind="scatter")          #to plot subplots of data
         plt.show()
```

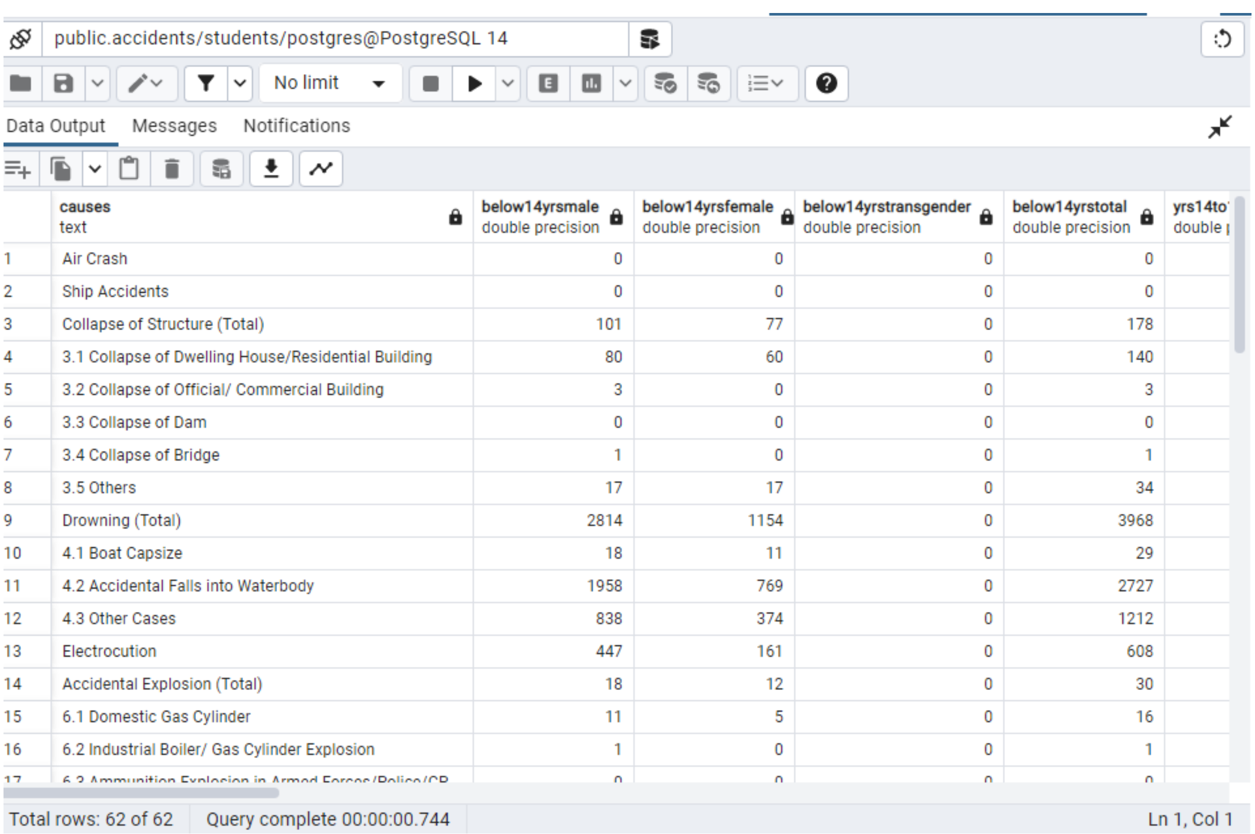


Also for **data storage**, we used **PostgreSQL** for their connection we used the **Psycopg2** library and this storage is very useful not to just store data but also helps to do some operations on data like Alter, drop and many more this database is useful to do DCL operations like GRANT and REVOKE that are useful for the giving and getting data access and DML operations also used with this database they are doing operations like DROP, TRUNCATE, and for many more operation we can join two tables with these using different types of keys and joins.

For connection the following queries are used:

```
In [7]: conn = ps.connect("dbname=students user=postgres password=souravk28")    #for connecting
        cursor=conn.cursor()          #for cursor/operator connection
        cursor.execute("DROP TABLE IF EXISTS accidents")
```

This is the view of the pgAdmin4 where we see the connected database



	causes text	below14yrsmale double precision	below14yrsfemale double precision	below14yrstransgender double precision	below14yrstotal double precision	yrs14to' double p
1	Air Crash	0	0	0	0	
2	Ship Accidents	0	0	0	0	
3	Collapse of Structure (Total)	101	77	0	178	
4	3.1 Collapse of Dwelling House/Residential Building	80	60	0	140	
5	3.2 Collapse of Official/ Commercial Building	3	0	0	3	
6	3.3 Collapse of Dam	0	0	0	0	
7	3.4 Collapse of Bridge	1	0	0	1	
8	3.5 Others	17	17	0	34	
9	Drowning (Total)	2814	1154	0	3968	
10	4.1 Boat Capsize	18	11	0	29	
11	4.2 Accidental Falls into Waterbody	1958	769	0	2727	
12	4.3 Other Cases	838	374	0	1212	
13	Electrocution	447	161	0	608	
14	Accidental Explosion (Total)	18	12	0	30	
15	6.1 Domestic Gas Cylinder	11	5	0	16	
16	6.2 Industrial Boiler/ Gas Cylinder Explosion	1	0	0	1	
17	6.3 Ammunition Explosion in Armed Forces/Police/CP	0	0	0	0	

We have tried one query related to PostgreSQL and their output will have come like ththisnd we can write so many queries like these to get different outputs.

Query | Query History | Scratch Pad

```
select * from accidents where causes like 'S%'
```

Data Output | Messages | Notifications

	causes text	below14yrsmale double precision	below14yrsfemale double precision	below14yrstransgender double precision	below14yrstotal double precision	yrs14to18male double precision	yrs14to18female double precision
1	Ship Accidents	0	0	0	0	0	0
2	Stampede	0	0	0	0	0	0
3	Sudden Deaths (Total)	474	368	0	842	433	233
4	Suffocation	61	35	0	96	59	60

Data Analysis:

Data Information: -

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

<class 'pandas.core.frame.DataFrame'>
Int64Index: 52 entries, 0 to 60
Data columns (total 31 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   Sl. No.                                   52 non-null     object
 1   Cause                                     52 non-null     object
 2   Below 14 years - Male                     52 non-null     int64
 3   Below 14 years - Female                   52 non-null     int64
 4   Below 14 years - Transgender              52 non-null     int64
 5   Below 14 years - Total                    52 non-null     int64
 6   14 and Above - Below 18 years - Male      52 non-null     int64
 7   14 and Above - Below 18 years - Female    52 non-null     int64
 8   14 and Above - Below 18 years - Transgender 52 non-null   int64
 9   14 and Above - Below 18 years - Total     52 non-null     int64
 10  18 and Above - Below 30 years - Male      52 non-null     int64
 11  18 and Above - Below 30 years - Female    52 non-null     int64
 12  18 and Above - Below 30 years - Transgender 52 non-null   int64
 13  18 and Above - Below 30 years - Total     52 non-null     int64
 14  30 and Above - Below 45 years - Male      52 non-null     int64
 15  30 and Above - Below 45 years - Female    52 non-null     int64
 16  30 and Above - Below 45 years - Transgender 52 non-null   int64
 17  30 and Above - Below 45 years - Total     52 non-null     int64
 18  45 and Above - Below 60 years - Male      52 non-null     int64
 19  45 and Above - Below 60 years - Female    52 non-null     int64
 20  45 and Above - Below 60 years - Transgender 52 non-null   int64
 21  45 and Above - Below 60 years - Total     52 non-null     int64
 22  60 years & Above - Male                   52 non-null     int64
 23  60 years & Above - Female                 52 non-null     int64
 24  60 years & Above - Transgender            52 non-null     int64
 25  60 years & Above - Total                  52 non-null     int64
 26  Total - Male                              52 non-null     int64
 27  Total - Female                            52 non-null     int64
 28  Total - Transgender                       52 non-null     int64
 29  Total - Total                             52 non-null     int64
 30  Total - Percentage Share                  52 non-null     float64
dtypes: float64(1), int64(28), object(2)
memory usage: 13.0+ KB
```

Statistical description:

Statistical description contains all columns statistics counts, mean value of the total column, median of column, as well as other statistical terms like standard deviation, 25% first quartile, 75% third quartile and maximum value of the data.

```
In [16]: df.describe()
```

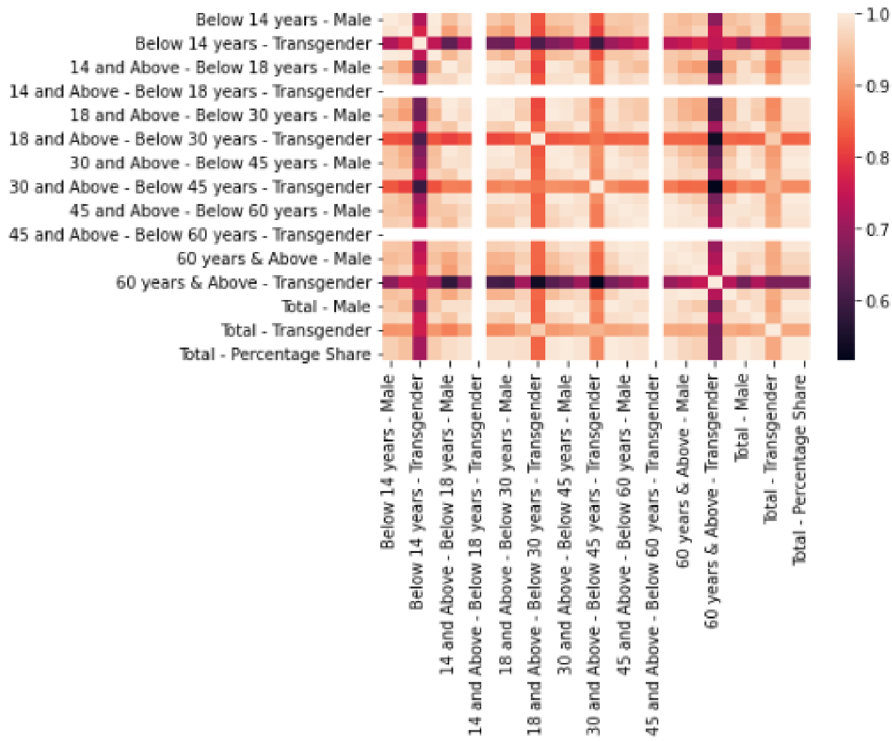
Out[16]:

	Below 14 years - Male	Below 14 years - Female	Below 14 years - Transgender	Below 14 years - Total	14 and Above - Below 18 years - Male	14 and Above - Below 18 years - Female	14 and Above - Below 18 years - Transgender	14 and Above - Below 18 years - Total	18 and Above - Below 30 years - Male	18 and Above - Below 30 years - Female	...	45 and Above Below 6 years - Tota
count	52.000000	52.000000	52.000000	52.000000	52.000000	52.000000	52.0	52.000000	52.000000	52.000000	...	52.00000
mean	210.000000	105.576923	0.057692	315.634615	366.192308	117.038462	0.0	483.230769	1707.730769	405.423077	...	1679.82692
std	548.165425	241.143627	0.307645	779.236907	1424.463023	328.597433	0.0	1742.499800	6233.359942	989.064746	...	4478.31808
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.000000	...	0.00000
25%	3.000000	2.000000	0.000000	5.000000	5.000000	2.750000	0.0	6.000000	24.500000	9.000000	...	22.00000
50%	17.500000	11.000000	0.000000	26.000000	25.500000	12.000000	0.0	36.500000	161.500000	48.000000	...	137.50000
75%	83.250000	60.500000	0.000000	147.000000	141.500000	98.750000	0.0	198.250000	932.500000	413.750000	...	1095.00000
max	3132.000000	1090.000000	2.000000	4222.000000	10112.000000	2177.000000	0.0	12289.000000	44005.000000	6192.000000	...	27229.00000

8 rows × 29 columns

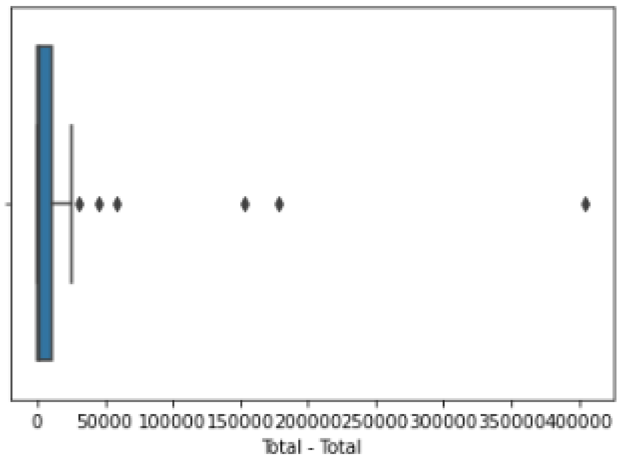
Checking the correlation between two variables we used a seaborn heatmap:

```
In [15]: sns.heatmap(data.corr())
         plt.show()
```



And we calculated the box plot for column ‘Total-Total’ but here the outliers present road accidents means in India public mostly uses the roadways for transportation because of those most accidents happened and due to the outliers boxplot will be not formed properly.

```
In [17]: sns.boxplot(x=data["Total - Total"])
         plt.show()
```



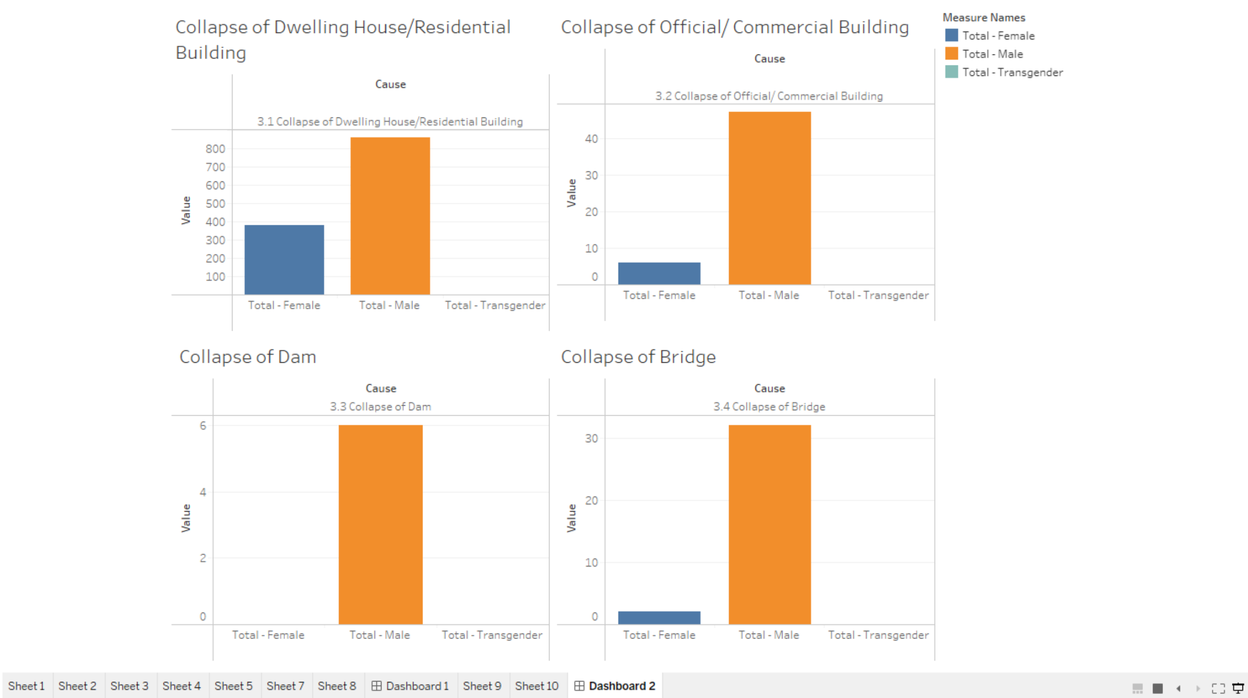
In this plot we, can see the minimum value as 0 and outliers are coming like value 40000 and 18000 like these.

And **Machine learning** models will not happen with the data because if we build a model, the model cannot give higher accuracy or their score will be low if we built those that are not useful because the data are small in size from that data we cannot predict or do any operations. And also lack of diversity is present in the data.

Another main result is poor data quality in these small data there are so many outliers and small values that are not able to predict the model that why we can because of insufficient data we cannot predict the model.

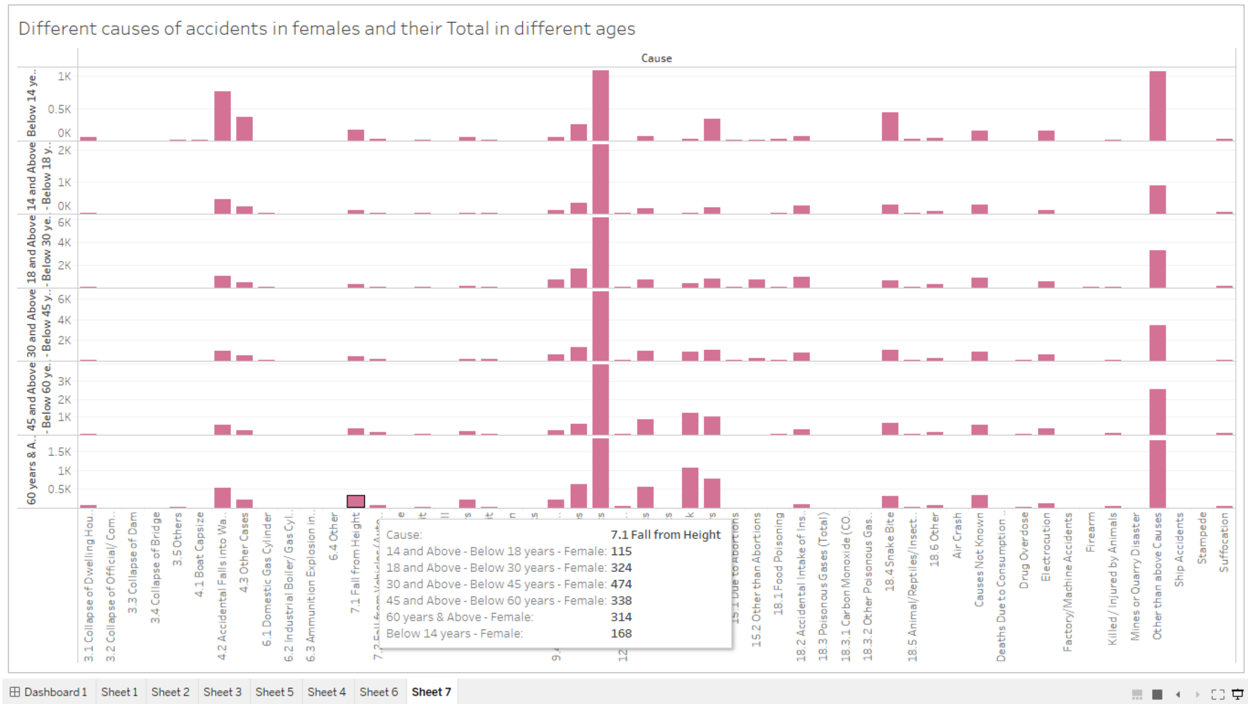
Data Visualization:

Data visualization was done on software like tableau and python from data visualization we can predict and easily visualize and analyze the data for that different plots drawn with different attributes.



Here is the visualization done on parameter structure collapse these 4 subtypes of collapse accidents in which cases happened the collapse of dwelling house total of females are death 379 and the total number of males was death is 862 in 3rd graph we see that death happened because of the collapse of a dam in males is 6 were females deaths are 0 from that we can understand at these places death happened of male workers or staff they are working near this area. From this, we can see that most of the deaths happened in males as compared to females and transgenders.

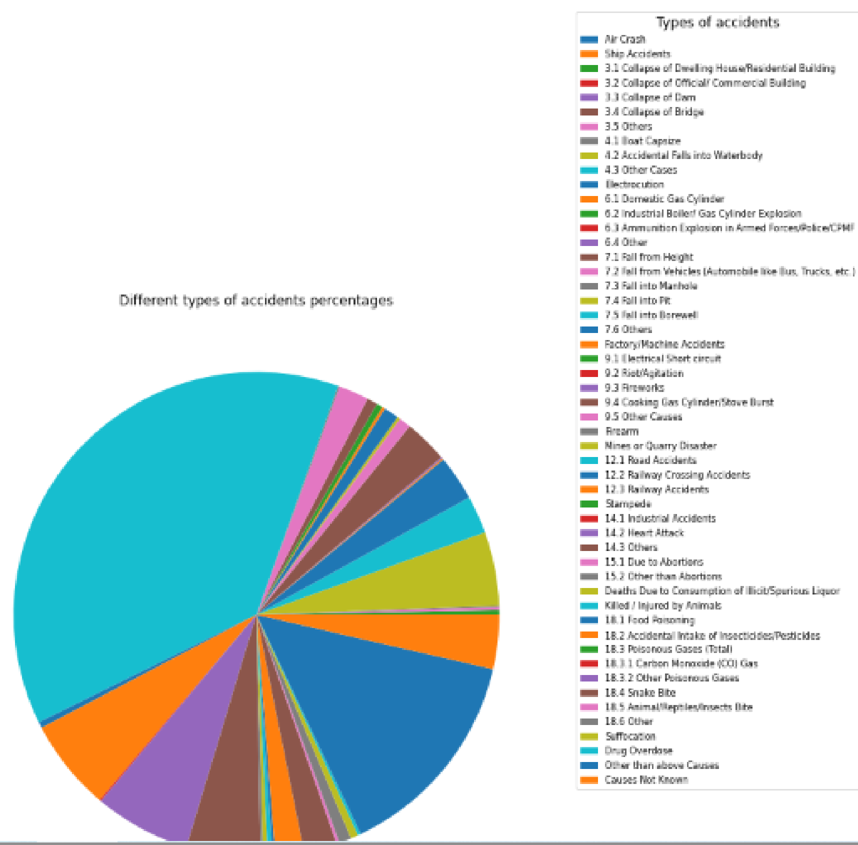
Most of the deaths in female in 2018 happened because of road accidents:



From the above graph we can visualize most of the deaths in females happened due to road accidents and deaths happened due to falling from height is more in the age group 30 and above – below 45 years that are 478 these ages are female workers age that is mostly working at construction site female their death will be occurring due to these cause because small age females death and aged female deaths are as compare to low than middle ones for here safety we can give more protection tools to that workers to reduce the accidents.

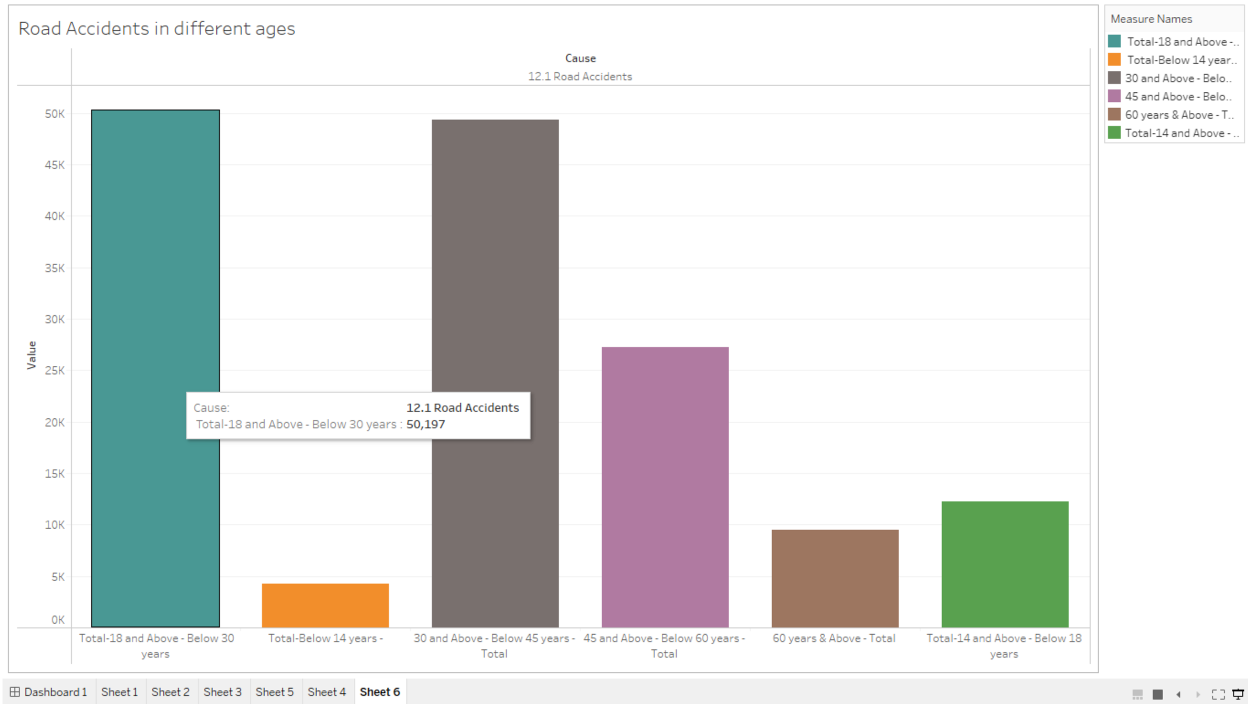
For we know more accidents happened in which area we can visualize it through the pie chart that helps us to easily visualize the data.

```
In [20]: fig = plt.figure(1005, figsize=(10,10))
         plt.pie(df['Total - Percentage Share'])
         plt.title("Different types of accidents percentages")
         plt.legend(df['Cause'], loc="best",fontsize=8, bbox_to_anchor=(-0.5,-0.5,2,2),title="Types of accidents",
                    title_fontsize="large")
         plt.show()
```



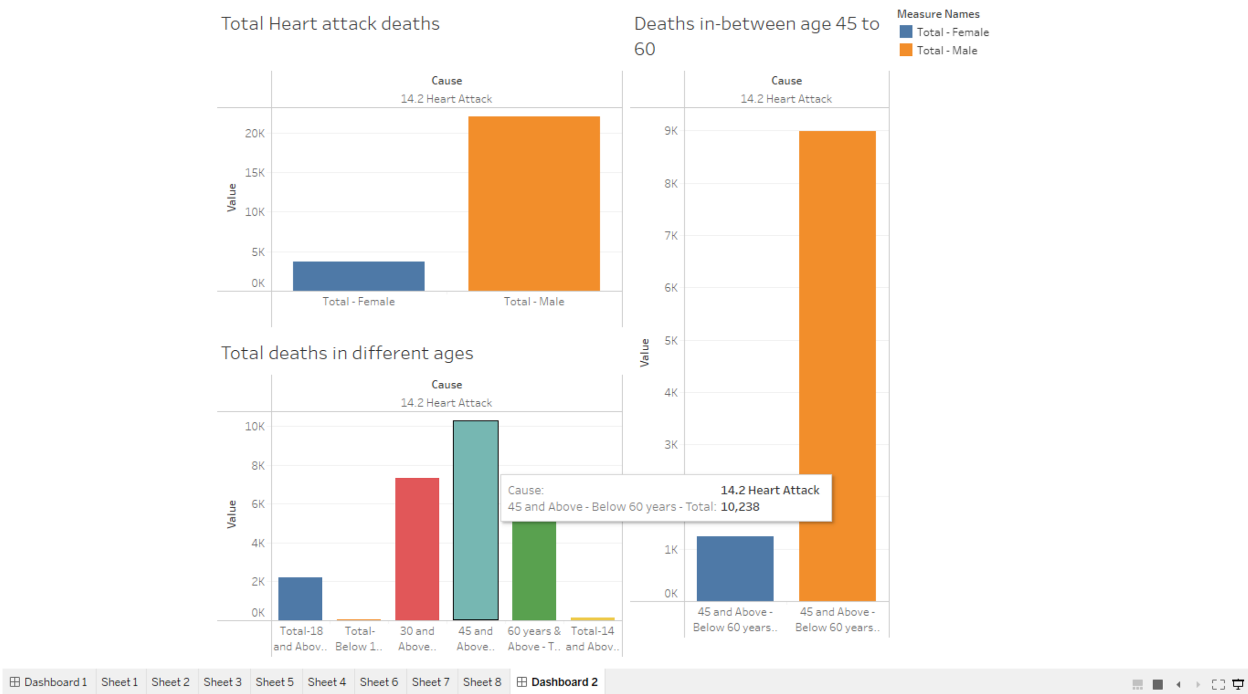
For that we have done visualization in python from the above pie chart we can say that Road accidents death has more happened in the year 2018 after that other than these causes deaths happened then the heart attack deaths percentages are more like these deaths happened in which sector we can find it with the help of the pie chart visualization.

Road accidents of different ages :



From these bar plots, we can easily visualize that most of the accidents happened between the age of 18 to 30 nearly 50,000 deaths happened due to these causes after those most accidents happened between the age of 30 to 45 which is nearly equal to the age 18-30 from that we can see we losing our young generation due to bad roads and do not take proper precautions like these so many reasons for that we have to follow traffic rules and spread the knowledge we can share information about traffic rules and regulations on social media, talk to friends and family about safe driving, or volunteer as a driver’s education instructor. We can also host educational programs in schools and other organizations, or create public service announcements about traffic safety because after some days school children are a young generation like these decisions we can take using visualization.

Heart attack deaths visualization:



In the above graphs, we can anal that most of the heart with attack deaths happened between ages 45 to 60 nearly up to 10,250 people with which most males heart attack accidental deaths had. In 2017 death because of heart attack is nearly 20,000 and in 2018 is 25,000 the patients of heart attack are increasing day by day for that we have to take precautions for this purpose visualization is important and From the above visualization, we can conclude that people should take steps to reduce their risk of heart attack, such as being physically active, eating a healthy diet, and not smoking. It also recommends making sure that people have access to medical care and treatments that can help reduce their risk of a heart attack.

Conclusion:

The accidental death that happened in 2018 was mainly due to two reason one is road accidents and another one is heart attack death in both of them most of the males died and the average dying age of any person due to the accident is between 30 to 45 different accidents in 2018 about 4,04,933 people lost their lives due to different accidents in which total males are 3,25,767 and deaths occurred in females are 79,149 as well as 17 trans genders lost their life in different accidents. 2018 saw a considerable number of accidents, both fatal and non-fatal, which resulted in the loss of life and serious injury to both drivers and passengers. The causes for these accidents were diverse, with a high number of negligent driving, speeding, and alcohol-related incidents. It is important to take greater steps to ensure safe driving, such as more stringent regulations and harsher penalties for those convicted of dangerous driving offenses. It is also essential to educate drivers on the importance of safe driving. By taking these measures, we can work to reduce the number of accidents in the future. Also for heart attack accidents, the conclusion of this study is those heart attack incidents are a serious health issue that needs to be addressed. While the causes of heart attacks vary, healthcare providers should work to identify people at risk and provide education on lifestyle changes that can reduce the risk of a heart attack. Additionally, more research into the causes and treatments of heart attacks is needed to further reduce the burden of heart attack incidents.