SUMMARY OF OUR DATA :

Nowadays, shopping malls and Big Marts keep track of individual item sales data in order to forecast future client demand and adjust inventory management. In a data warehouse, these data stores hold a significant amount of consumer information and particular item details.with help of these informations we can find out sales for a perticular item.there are total `8523 observations` in this dataset.

Columns Descriptions of dataset :

- `1.Item_Identifier :` -> This is the column of Unique product ID with respect to each item.
- `2.Item_Weight:` -> Weight of product
- `3.Item_Fat_Content:` -> Whether the product is low fat or not
- `4.Item_Visibility:` -> The % of total display area of all products in a store allocated to the particular product
- `5.Item_Type:` -> The category to which the product belongs
- `6.Item_MRP:` -> Maximum Retail Price (list price) of the product
- `7.Outlet_Identifier:` -> Unique store ID
- `8.Outlet_Establishment_Year:` -> The year in which store was established
- `9.Outlet_Size:` -> The size of the store in terms of ground area covered
- `10.Outlet_Location_Type:` -> The type of city in which the store is located
- `11.Outlet_Type:` -> Whether the outlet is just a grocery store or some sort of supermarket
- `12.Item_Outlet_Sales:` -> Sales of the product in the particulat store. This is the outcome variable to be predicted

In [2]:

```
# importing required libraries:
import pandas as pd
import numpy as np
import plotly.express as px
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [102]:

```
train_df=pd.read_csv("D:\Project\ineuron_project\Train.csv")
test_df=pd.read_csv("D:\Project\ineuron_project\Test.csv")
```

Basic Information of Dataset :

In [103]:

```
# first 5 rows in train dataset:
train_df.head()
```

Out[103]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	O
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	

In [104]:

```
# first 5 rows in test dataset:
test_df.head()
```

Out[104]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	O
0	FDW58	20.750	Low Fat	0.007565	Snack Foods	107.8622	OUT049	
1	FDW14	8.300	reg	0.038428	Dairy	87.3198	OUT017	
2	NCN55	14.600	Low Fat	0.099575	Others	241.7538	OUT010	
3	FDQ58	7.315	Low Fat	0.015388	Snack Foods	155.0340	OUT017	
4	FDY38	NaN	Regular	0.118599	Dairy	234.2300	OUT027	

In [105]:

```
# shape of the traindataset and test dataset:
print("Shape of the train dataset is ",train_df.shape)
print("Shape of the test dataset is ",test_df.shape)
```

```
Shape of the train dataset is  (8523, 12)
Shape of the test dataset is  (5681, 11)
```

In [106]:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                7060 non-null   float64
 2   Item_Fat_Content           8523 non-null   object 
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object 
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object 
 7   Outlet_Establishment_Year  8523 non-null   int64  
 8   Outlet_Size                6113 non-null   object 
 9   Outlet_Location_Type       8523 non-null   object 
 10  Outlet_Type                8523 non-null   object 
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

In [107]:

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5681 entries, 0 to 5680
Data columns (total 11 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            5681 non-null   object 
 1   Item_Weight                4705 non-null   float64
 2   Item_Fat_Content           5681 non-null   object 
 3   Item_Visibility            5681 non-null   float64
 4   Item_Type                  5681 non-null   object 
 5   Item_MRP                   5681 non-null   float64
 6   Outlet_Identifier          5681 non-null   object 
 7   Outlet_Establishment_Year  5681 non-null   int64  
 8   Outlet_Size                4075 non-null   object 
 9   Outlet_Location_Type       5681 non-null   object 
 10  Outlet_Type                5681 non-null   object 
dtypes: float64(3), int64(1), object(7)
memory usage: 488.3+ KB
```

In [108]:

```
train_df.duplicated().sum()
```

Out[108]:

```
0
```

In [109]:

```
test_df.duplicated().sum()
```

Out[109]:

```
0
```

No duplicated rows with respect to train and test datasets.

In [110]:

```
train_df.isnull().sum()
```

Out[110]:

```
Item_Identifier                 0
Item_Weight                  1463
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  2410
Outlet_Location_Type            0
Outlet_Type                     0
Item_Outlet_Sales               0
dtype: int64
```

we can see here that in `Item_Weight` and `Outlet_Size` columns , there are missing values with respect to train and test dataset.

In [111]:

```
train_df.describe()
```

Out[111]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	7060.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.643456	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000	33.290000
25%	8.773750	0.026989	93.826500	1987.000000	834.247400
50%	12.600000	0.053931	143.012800	1999.000000	1794.331000
75%	16.850000	0.094585	185.643700	2004.000000	3101.296400
max	21.350000	0.328391	266.888400	2009.000000	13086.964800

In [112]:

```
test_df.describe()
```

Out[112]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year
count	4705.000000	5681.000000	5681.000000	5681.000000
mean	12.695633	0.065684	141.023273	1997.828903
std	4.664849	0.051252	61.809091	8.372256
min	4.555000	0.000000	31.990000	1985.000000
25%	8.645000	0.027047	94.412000	1987.000000
50%	12.500000	0.054154	141.415400	1999.000000
75%	16.700000	0.093463	186.026600	2004.000000
max	21.350000	0.323637	266.588400	2009.000000

DATA ASSESSMENT :

- **DIRTY-DATA:**
  - `Item_Identifier` -there is no quality issues.
  - `Item_Weight` -there are missing values. `completeness problem`
  - `Item_Fat_Content` -In some cell Low fat and regular are written as LF,low fat and reg respectively. `consistency problem`
  - `Item_Visibility` -there is no quality issues.
  - `Item_Type` -All good
  - `Item_MRP` -all good
  - `Outlet_Identifier` -all good
  - `Outlet_Establishment_Year` -Datatype is int64.That's not right.
  - `Outlet_Size` -there are missing values. `completeness problem`
  - `Outlet_Location_Type` - all good
  - `Outlet_Type` - all good
  - `Item_Outlet_Sales` -all good
- **MESSY DATA :**
  - `There is no messy data here`
- **EXTRA INFORMATION :**
  - `There is no duplicate row in this dataset.`

DATA CLEANING :

1.completeness problem :

- there are two columns having missing values.
  - one is `Item_Weight`
  - another is `Outlet_Size`

Experiments,coding and testing :

1.For `Item_Weight` column :

In [113]:

```
train_df['Item_Identifier']
```

Out[113]:

```
0       FDA15
1       DRC01
2       FDN15
3       FDX07
4       NCD19
        ...
8518    FDF22
8519    FDS36
8520    NCJ29
8521    FDN46
8522    DRG01
Name: Item_Identifier, Length: 8523, dtype: object
```

In [114]:

```
train_df[train_df['Item_Identifier']=='FDN15']
```

Out[114]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
2	FDN15	17.5	Low Fat	0.016760	Meat	141.618	OUT049
759	FDN15	17.5	Low Fat	0.028009	Meat	141.718	OUT010
4817	FDN15	17.5	Low Fat	0.016720	Meat	139.918	OUT013
5074	FDN15	17.5	Low Fat	0.016802	Meat	138.518	OUT018
6163	FDN15	17.5	Low Fat	0.016768	Meat	141.418	OUT045
6952	FDN15	NaN	Low Fat	0.029299	Meat	140.318	OUT019
8349	FDN15	NaN	Low Fat	0.016653	Meat	139.518	OUT027

In [ ]:

In [ ]:

In [ ]:

In [ ]:

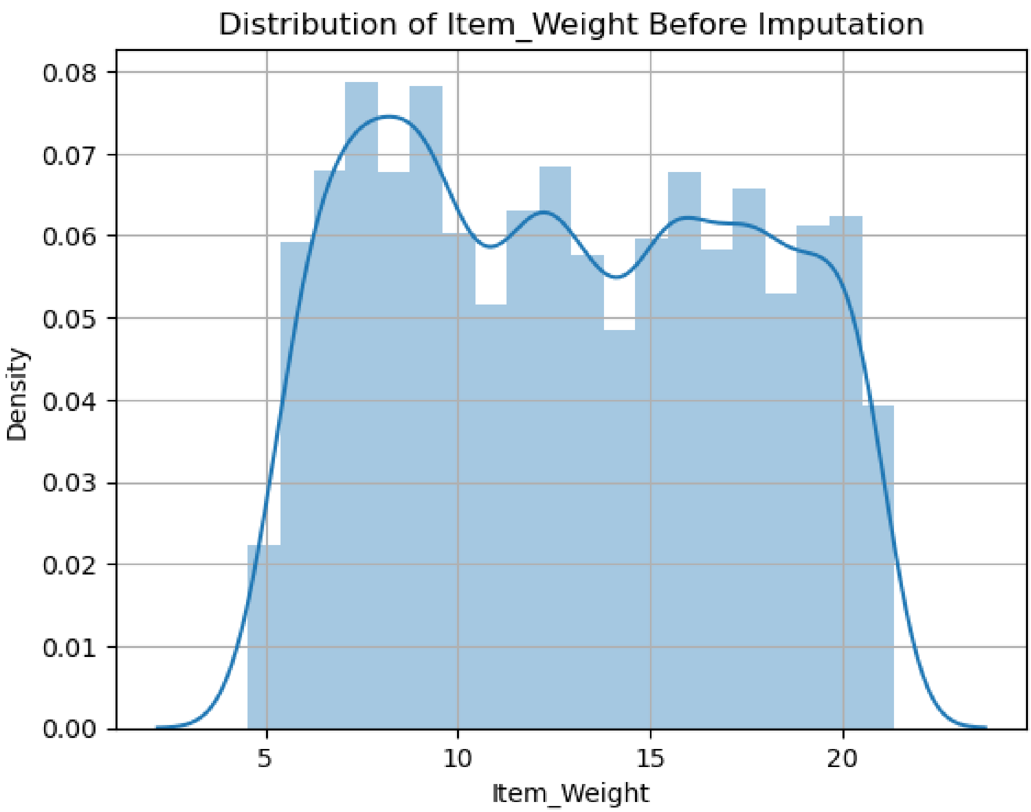
```

```

In [ ]:

```

```

In [115]:

```
# before imputing distribution of the Item_Weight column :
plt.title("Distribution of Item_Weight Before Imputation")
sns.distplot(train_df['Item_Weight'])
plt.grid()
plt.show()
```



In [116]:

```
item_dic={}
for i in list(train_df['Item_Identifier'].unique()):
    item_dic[i]=round(train_df[train_df['Item_Identifier']==i]['Item_Weight'].mean(),2)
```

In [117]:

```
train_df['Item_Weight']=train_df['Item_Weight'].fillna('missing')
```

In [118]:

```
# coding
weight=[]
for i in range(len(train_df)):
    if train_df['Item_Weight'][i]=='missing':
        val=round(item_dic[train_df['Item_Identifier'][i]],2)
        weight.append(val)
    else:
        weight.append(train_df['Item_Weight'][i])
```

In [ ]:

```

```

In [119]:

```
train_df.drop(columns=['Item_Weight'],inplace=True)
```

In [120]:

```
train_df.insert(1,"Item_Weight",weight)
```

In [121]:

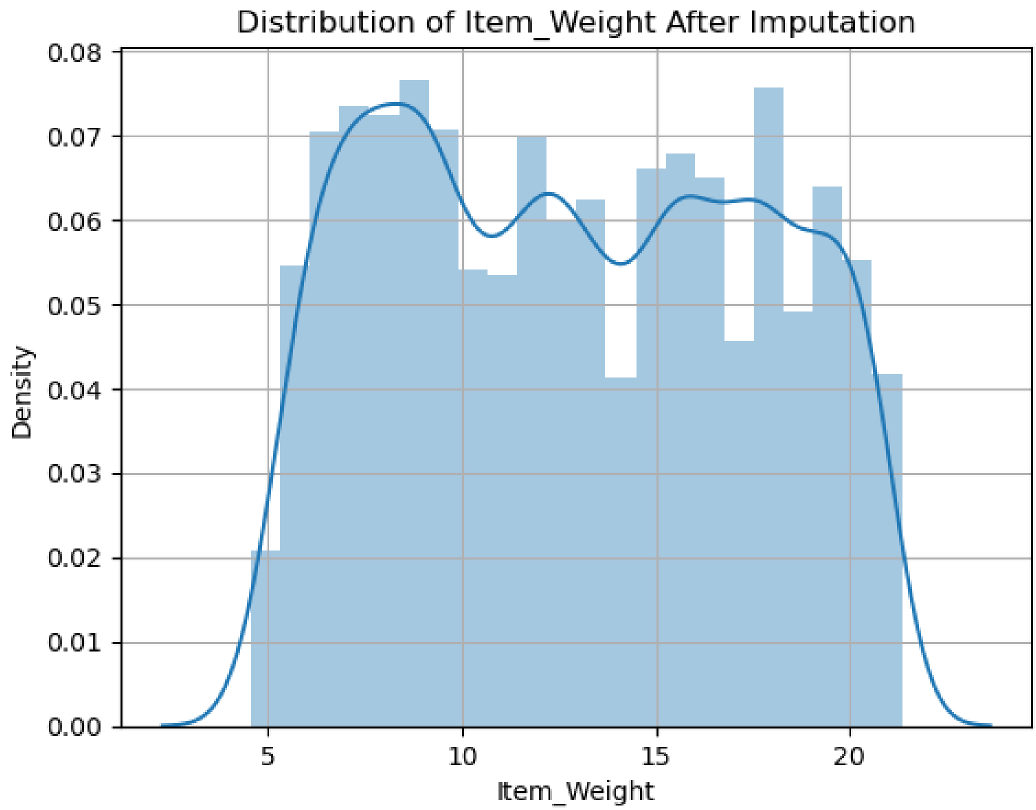
```
# testing:
train_df[train_df['Item_Identifier']=='FDN15']
```

Out[121]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
2	FDN15	17.5	Low Fat	0.016760	Meat	141.618	OUT049
759	FDN15	17.5	Low Fat	0.028009	Meat	141.718	OUT010
4817	FDN15	17.5	Low Fat	0.016720	Meat	139.918	OUT013
5074	FDN15	17.5	Low Fat	0.016802	Meat	138.518	OUT018
6163	FDN15	17.5	Low Fat	0.016768	Meat	141.418	OUT045
6952	FDN15	17.5	Low Fat	0.029299	Meat	140.318	OUT019
8349	FDN15	17.5	Low Fat	0.016653	Meat	139.518	OUT027

In [122]:

```
# After imputing distribution of the Item_Weight column :
plt.title("Distribution of Item_Weight After Imputation")
sns.distplot(train_df['Item_Weight'])
plt.grid()
plt.show()
```



In [ ]:

```

```

For test dataset:

In [126]:

```
test_df[test_df['Item_Identifier']=='FDL58']
```

Out[126]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
58	FDL58	NaN	Regular	0.129825	Snack Foods	263.2568	OUT019
3619	FDL58	NaN	Regular	0.073790	Snack Foods	265.0568	OUT027

```

```

In [127]:

```
item_dic={}
for i in list(test_df['Item_Identifier'].unique()):
    item_dic[i]=round(test_df[test_df['Item_Identifier']==i]['Item_Weight'].mean(),2)
```

In [128]:

```
test_df['Item_Weight']=test_df['Item_Weight'].fillna('missing')
```

In [129]:

```
test_df[test_df['Item_Identifier']=='FDY38']
```

Out[129]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
4	FDY38	missing	Regular	0.118599	Dairy	234.23	OUT027
1327	FDY38	13.6	Regular	0.119176	Dairy	233.93	OUT046
3622	FDY38	13.6	reg	0.119154	Dairy	231.23	OUT035
4504	FDY38	13.6	Regular	0.119662	Dairy	233.63	OUT018

In [130]:

```
weight=[]
for i in range(len(test_df)):
    if test_df['Item_Weight'][i]=='missing':
        val=round(item_dic[test_df['Item_Identifier'][i]],2)
        weight.append(val)
    else:
        weight.append(test_df['Item_Weight'][i])
```

In [131]:

```
test_df.drop(columns=['Item_Weight'],inplace=True)
```

In [132]:

```
test_df.insert(1,"Item_Weight",weight)
```

In [133]:

```
test_df[test_df['Item_Identifier']=='FDY38']
```

Out[133]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
4	FDY38	13.6	Regular	0.118599	Dairy	234.23	OUT027
1327	FDY38	13.6	Regular	0.119176	Dairy	233.93	OUT046
3622	FDY38	13.6	reg	0.119154	Dairy	231.23	OUT035
4504	FDY38	13.6	Regular	0.119662	Dairy	233.63	OUT018

In [ ]:

```

```

2.For `Outlet_Size` column :

In [134]:

```
missing_no=train_df['Outlet_Size'].isnull().sum()
percentage=missing_no/len(train_df)
print(f"There is almost {round((percentage*100),2)}% missing value in our 'Outlet_Size'column.")
```

```
There is almost 28.28% missing value in our 'Outlet_Size'column.
```

We can't fill those missing values with most frquent values(mediumn) as there are more than 28% missing values in this columns.

In [135]:

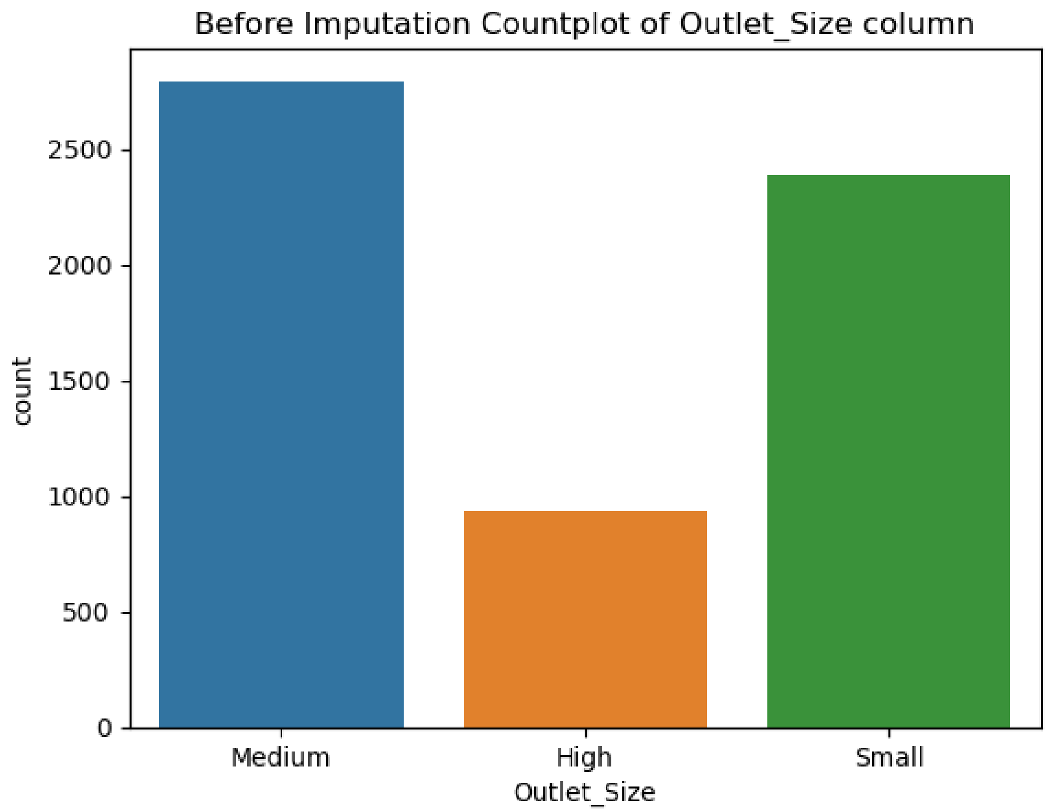
```
train_df['Outlet_Size'].value_counts()
```

Out[135]:

```
Medium    2793
Small     2388
High       932
Name: Outlet_Size, dtype: int64
```

In [136]:

```
plt.title('Before Imputation Countplot of Outlet_Size column')
sns.countplot(train_df['Outlet_Size'])
plt.show()
```



In [137]:

```
# coding:
train_df['Outlet_Size']=train_df['Outlet_Size'].fillna('not_mentioned')
```

In [138]:

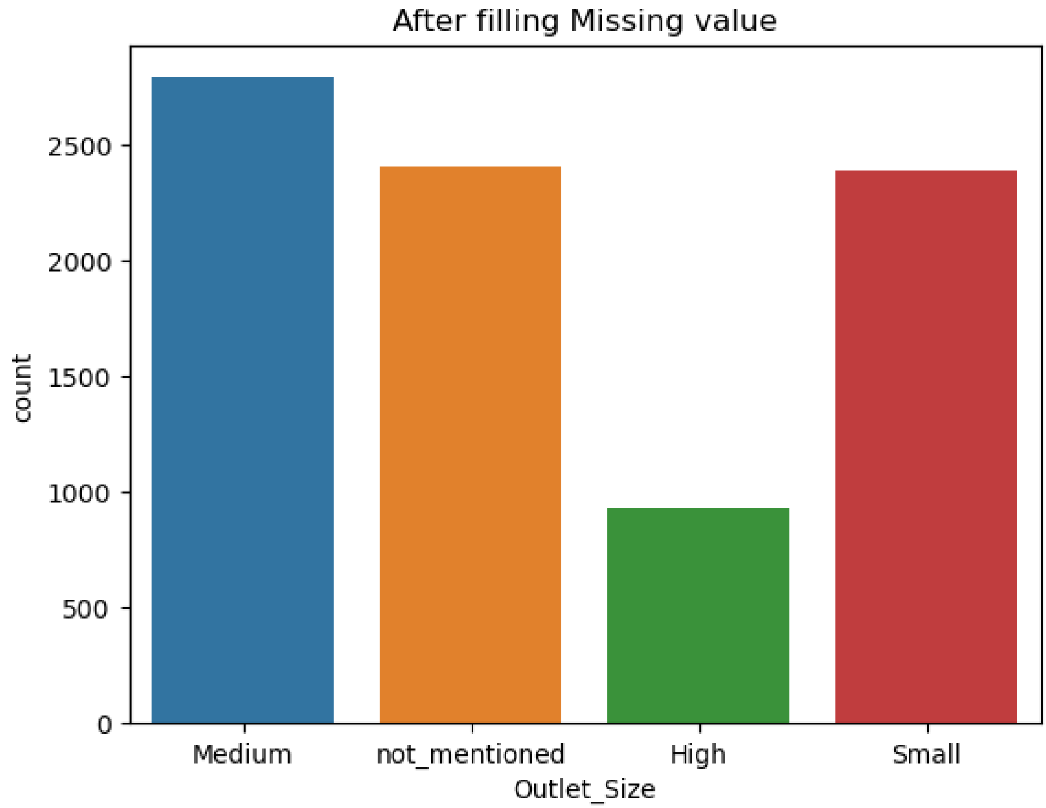
```
train_df['Outlet_Size'].value_counts()
```

Out[138]:

```
Medium           2793
not_mentioned    2410
Small            2388
High              932
Name: Outlet_Size, dtype: int64
```

In [139]:

```
#after filling the missing values with a constant 'not_mentioned',our columns looks like :
plt.title("After filling Missing value")
sns.countplot(train_df['Outlet_Size'])
plt.show()
```



In [140]:

```
# testing:
train_df['Outlet_Size'].isnull().sum()
```

Out[140]:

```
0
```

In [141]:

```
train_df.isnull().sum()
```

Out[141]:

```
Item_Identifier              0
Item_Weight                  4
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Identifier            0
Outlet_Establishment_Year    0
Outlet_Size                  0
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

In [142]:

```
train_df.head()
```

Out[142]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	O
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	

Solutions:

- for `Item_Weight` column ,an interesting thing has been spotted.Actually this column totally depends on `Item_Identifier` and `Item_Type` columns.So in this case , I have done column transformation.
- for `Outlet_Size` column , we see that there is 28.3% data is missing.So we have created a new category `not_mentioned` in place of missing values.Basically we have done 'Missing-Category imputation'.

2.Consistency problem :

we have a column `Item_Fat_Content` where In some cell Low fat and regular are written as LF,low fat and reg respectively.

In [143]:

```
# Experiments:
train_df['Item_Fat_Content'].unique()
```

Out[143]:

```
array(['Low Fat', 'Regular', 'low fat', 'LF', 'reg'], dtype=object)
```

In [144]:

```
#coding:
train_df['Item_Fat_Content']=train_df['Item_Fat_Content'].map({'Low Fat':'Low Fat','Regular':'Regul
                                                     'LF':'Low Fat','reg':'Regular'})
```

In [145]:

```
# testing
train_df['Item_Fat_Content'].unique()
```

Out[145]:

```
array(['Low Fat', 'Regular'], dtype=object)
```

For test dataset:

In [146]:

```
# Experiments:
test_df['Item_Fat_Content'].unique()
```

Out[146]:

```
array(['Low Fat', 'reg', 'Regular', 'LF', 'low fat'], dtype=object)
```

In [147]:

```
#coding:
test_df['Item_Fat_Content']=test_df['Item_Fat_Content'].map({'Low Fat':'Low Fat','Regular':'Regular
                                                      'LF':'Low Fat','reg':'Regular'})
```

In [148]:

```
# testing
train_df['Item_Fat_Content'].unique()
```

Out[148]:

```
array(['Low Fat', 'Regular'], dtype=object)
```

SOLUTION :

- We have replaced with `Low Fat` and `Regular` respectively.

In [149]:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                8519 non-null   float64
 2   Item_Fat_Content           8523 non-null   object 
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object 
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object 
 7   Outlet_Establishment_Year  8523 non-null   int64  
 8   Outlet_Size                8523 non-null   object 
 9   Outlet_Location_Type       8523 non-null   object 
 10  Outlet_Type                8523 non-null   object 
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

As we have 4 rows with `nan` values , we simply drop them from dataset.

In [150]:

```
train_df=train_df.dropna()
```

In [151]:

```
train_df
```

Out[151]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
0	FDA15	9.300	Low Fat	0.016047	Dairy	249.8092	OUT049
1	DRC01	5.920	Regular	0.019278	Soft Drinks	48.2692	OUT018
2	FDN15	17.500	Low Fat	0.016760	Meat	141.6180	OUT049
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010
4	NCD19	8.930	Low Fat	0.000000	Household	53.8614	OUT013
...	...	...	...	...	...	...	...
8518	FDF22	6.865	Low Fat	0.056783	Snack Foods	214.5218	OUT013
8519	FDS36	8.380	Regular	0.046982	Baking Goods	108.1570	OUT045
8520	NCJ29	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	OUT035
8521	FDN46	7.210	Regular	0.145221	Snack Foods	103.1332	OUT018
8522	DRG01	14.800	Low Fat	0.044878	Soft Drinks	75.4670	OUT046

8519 rows × 12 columns

In [152]:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8519 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8519 non-null   object 
 1   Item_Weight                8519 non-null   float64
 2   Item_Fat_Content           8519 non-null   object 
 3   Item_Visibility            8519 non-null   float64
 4   Item_Type                  8519 non-null   object 
 5   Item_MRP                   8519 non-null   float64
 6   Outlet_Identifier          8519 non-null   object 
 7   Outlet_Establishment_Year  8519 non-null   int64  
 8   Outlet_Size                8519 non-null   object 
 9   Outlet_Location_Type       8519 non-null   object 
 10  Outlet_Type                8519 non-null   object 
 11  Item_Outlet_Sales          8519 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 865.2+ KB
```

In [4]:

```
train_df.isnull().sum()
```

Out[4]:

```
Item_Identifier              0
Item_Weight                  0
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Identifier            0
Outlet_Establishment_Year    0
Outlet_Size                  0
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

In [154]:

```
## saving the dataset in folder:
#train_df.to_csv('cleantrain.csv',index=False)
#test_df.to_csv('cleantest.csv',index=False)
```

In [54]:

```
train_df=pd.read_csv(r"D:\Project\ineuron_project\process_dataset\cleantrain.csv")
train_df
```

Out[54]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier
0	FDA15	9.300	Low Fat	0.016047	Dairy	249.8092	OUT049
1	DRC01	5.920	Regular	0.019278	Soft Drinks	48.2692	OUT018
2	FDN15	17.500	Low Fat	0.016760	Meat	141.6180	OUT049
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010
4	NCD19	8.930	Low Fat	0.000000	Household	53.8614	OUT013
...	...	...	...	...	...	...	...
8514	FDF22	6.865	Low Fat	0.056783	Snack Foods	214.5218	OUT013
8515	FDS36	8.380	Regular	0.046982	Baking Goods	108.1570	OUT045
8516	NCJ29	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	OUT035
8517	FDN46	7.210	Regular	0.145221	Snack Foods	103.1332	OUT018
8518	DRG01	14.800	Low Fat	0.044878	Soft Drinks	75.4670	OUT046

8519 rows × 12 columns

Data cleaning part is done . Now we are ready for EDA on top of train dataset.

EXPLORATORY DATA ANALYSIS and FEATURE ENGINEERING:

We are going to devide colummns as numerical and categorical.

In [55]:

```
#for numerical columns:
num_cols=[col for col in train_df.columns if train_df[col].dtypes!='O']
num_cols
```

Out[55]:

```
['Item_Weight',
 'Item_Visibility',
 'Item_MRP',
 'Outlet_Establishment_Year',
 'Item_Outlet_Sales']
```

In [56]:

```
# for categorical columns:
cat_cols=[col for col in train_df.columns if train_df[col].dtypes=='O']
cat_cols
```

Out[56]:

```
['Item_Identifier',
 'Item_Fat_Content',
 'Item_Type',
 'Outlet_Identifier',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

FOR NUMERICAL COLUMNS:

In [57]:

```
num_cols
```

Out[57]:

```
['Item_Weight',
 'Item_Visibility',
 'Item_MRP',
 'Outlet_Establishment_Year',
 'Item_Outlet_Sales']
```

In [9]:

```
```

In [47]:

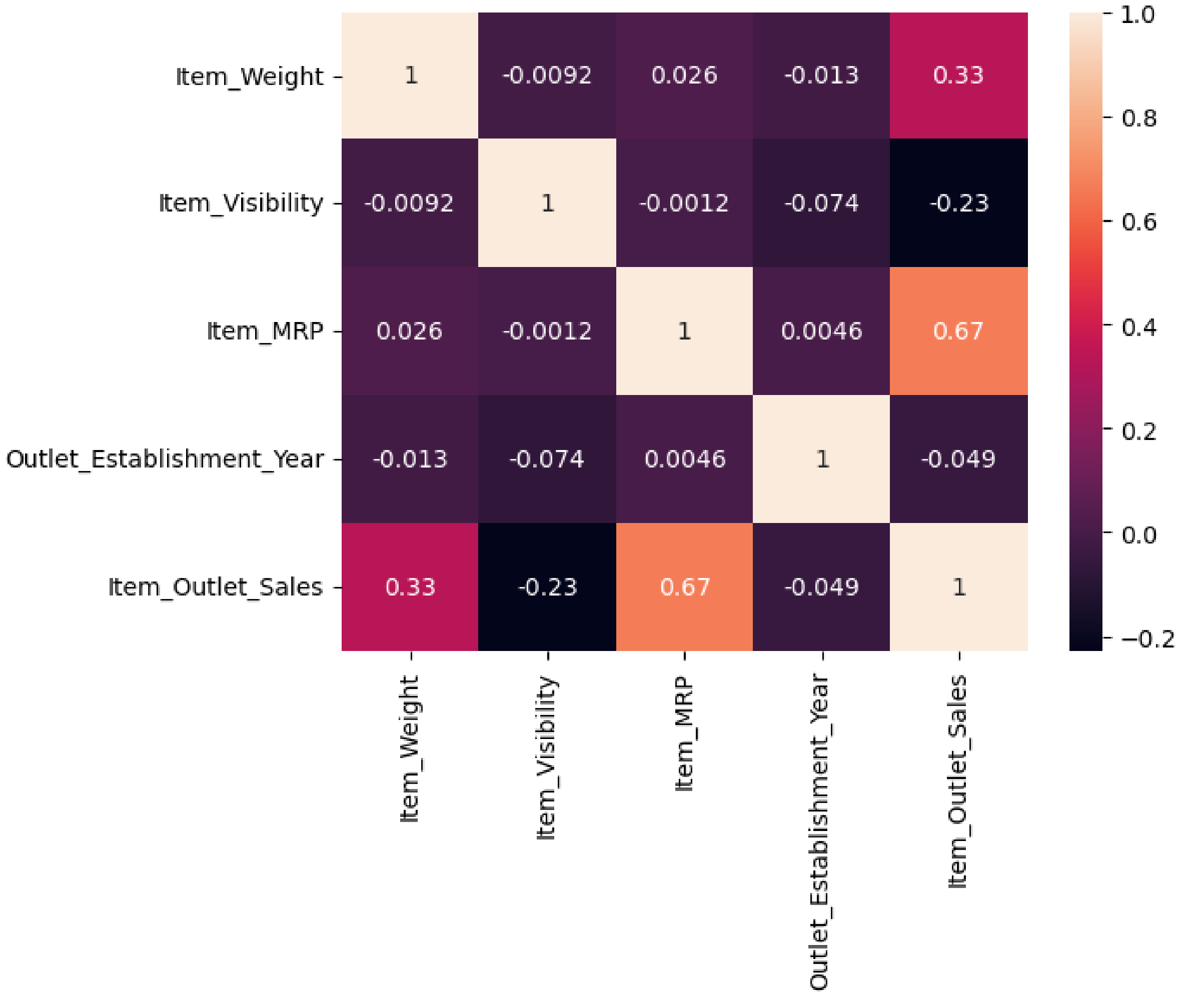
```
train_df.corr()
```

Out[47]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_S
Item_Weight	1.000000	-0.009168	0.025978	-0.013430	0.33
Item_Visibility	-0.009168	1.000000	-0.001155	-0.074325	-0.22
Item_MRP	0.025978	-0.001155	1.000000	0.004599	0.66
Outlet_Establishment_Year	-0.013430	-0.074325	0.004599	1.000000	-0.04
Item_Outlet_Sales	0.331650	-0.228297	0.667803	-0.049083	1.00

In [48]:

```
sns.heatmap(train_df.corr(),annot=True)
plt.show()
```



converting the Outlet_Establishment_Year column into outlet_Age column:

In [58]:

```
train_df['Outlet_Establishment_Year']=2023-train_df['Outlet_Establishment_Year']
```

In [59]:

```
train_df.rename(columns={'Outlet_Establishment_Year':'Outlet_Age'},inplace=True)
```

In [60]:

```
train_df.head(4)
```

Out[60]:

_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Age
FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	24
DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	14
FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	24
FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	25

After Converting correlation and heatmap :

In [63]:

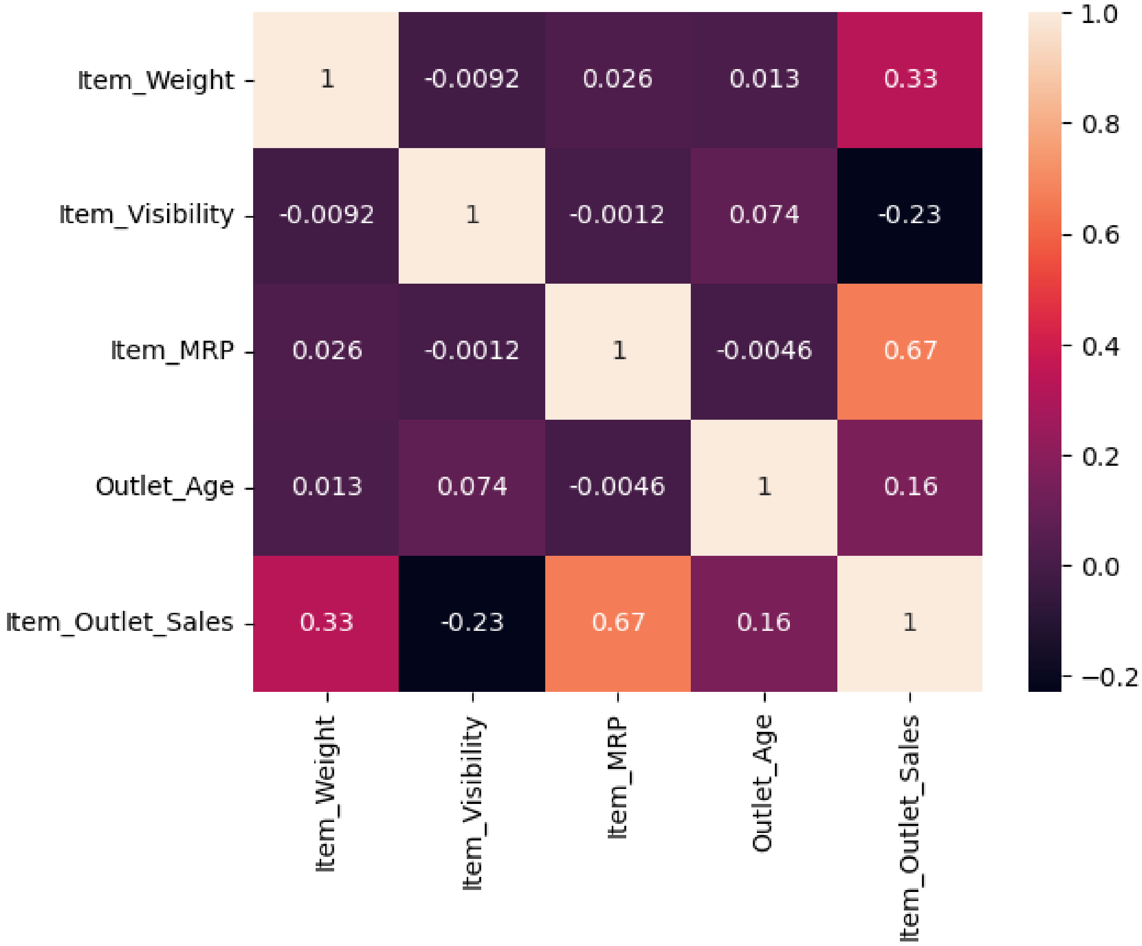
```
train_df.corr()
```

Out[63]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Age	Item_Outlet_Sales
Item_Weight	1.000000	-0.009168	0.025978	0.013430	0.331650
Item_Visibility	-0.009168	1.000000	-0.001155	0.074325	-0.228297
Item_MRP	0.025978	-0.001155	1.000000	-0.004599	0.667803
Outlet_Age	0.013430	0.074325	-0.004599	1.000000	0.159083
Item_Outlet_Sales	0.331650	-0.228297	0.667803	0.159083	1.000000

In [64]:

```
sns.heatmap(train_df.corr(),annot=True)
plt.show()
```



In [67]:

```
num_cols=[col for col in train_df.columns if train_df[col].dtypes!='O']
num_cols
```

Out[67]:

```
['Item_Weight',
 'Item_Visibility',
 'Item_MRP',
 'Outlet_Age',
 'Item_Outlet_Sales']
```

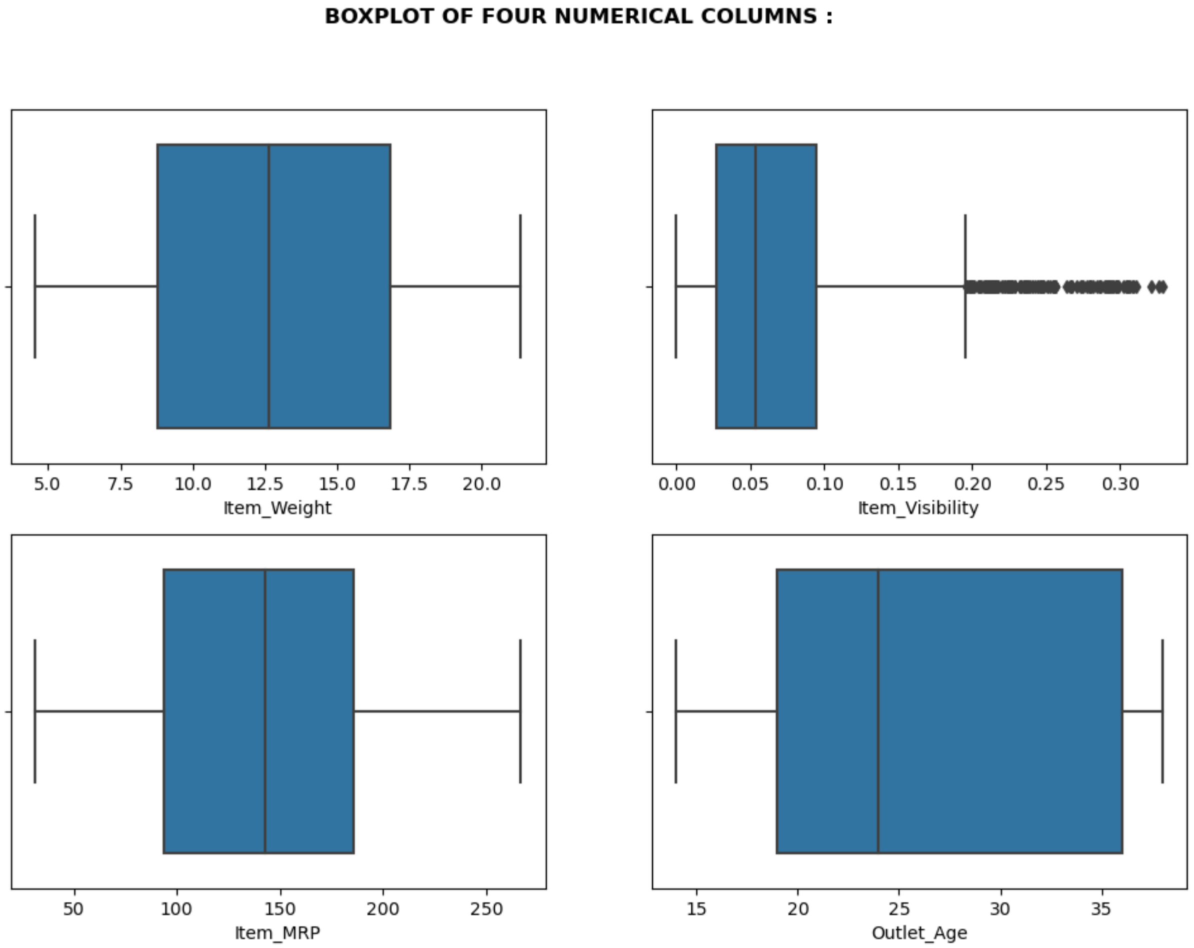
In [ ]:

In [169]:

In [ ]:

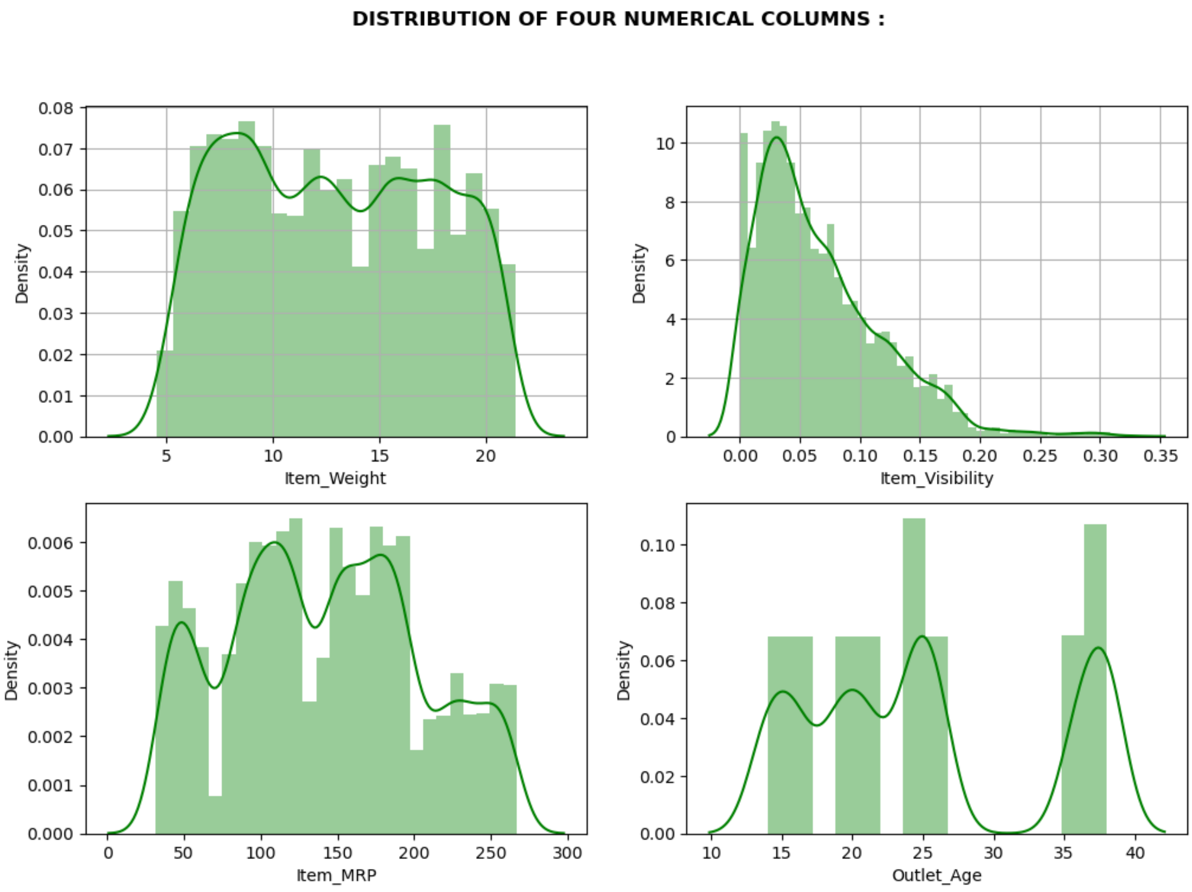
In [68]:

```
plt.figure(figsize=(12,8))
plt.suptitle('BOXPLOT OF FOUR NUMERICAL COLUMNS :',fontweight='bold')

ax1=plt.subplot(2,2,1)
sns.boxplot(train_df['Item_Weight'],ax=ax1)


ax2=plt.subplot(2,2,2)
sns.boxplot(train_df['Item_Visibility'],ax=ax2)


ax3=plt.subplot(2,2,3)
sns.boxplot(train_df['Item_MRP'],ax=ax3)

ax4=plt.subplot(2,2,4)
sns.boxplot(train_df['Outlet_Age'],ax=ax4)

plt.show()
```



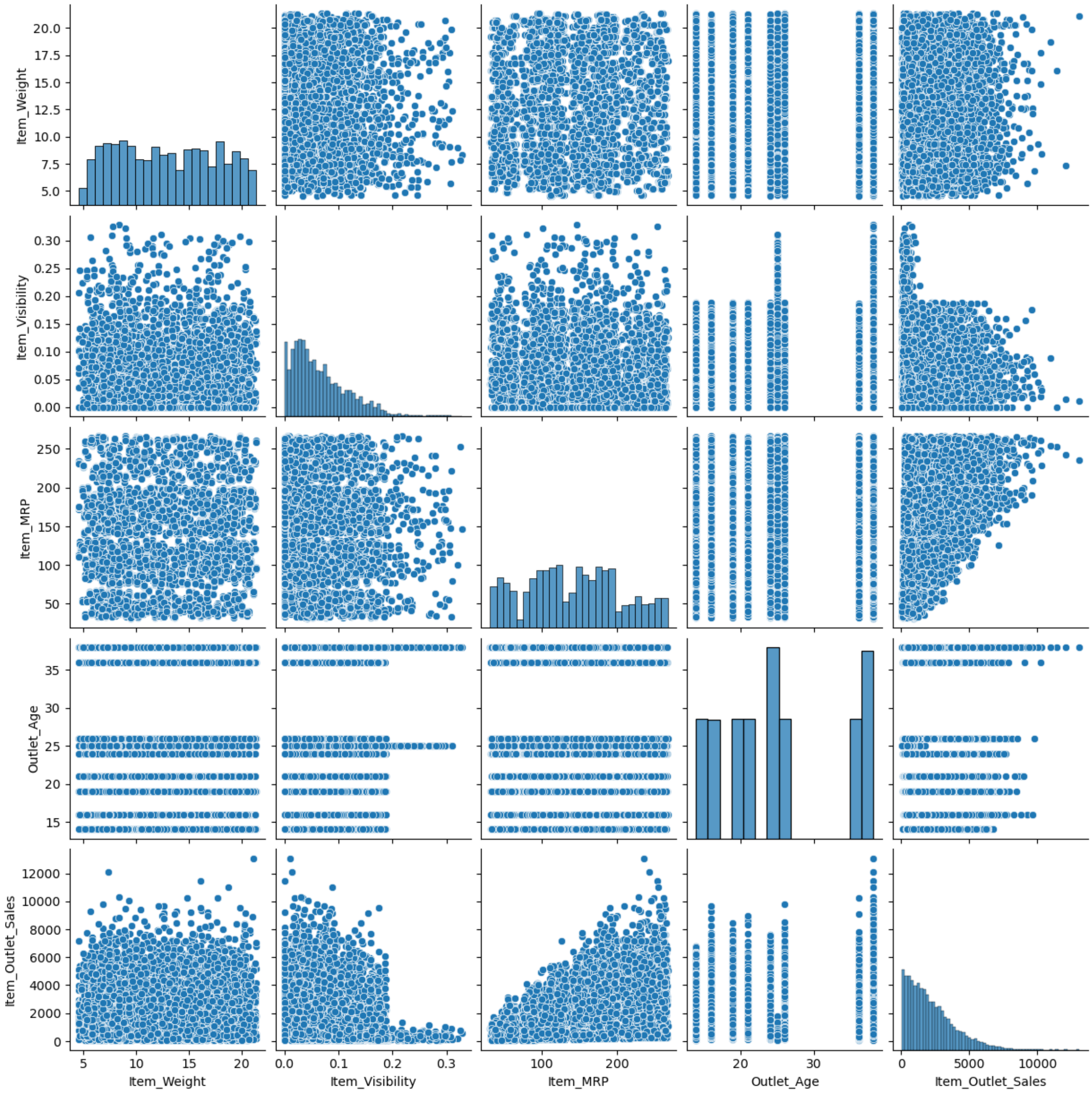
In [69]:

```
plt.figure(figsize=(12,8))
plt.suptitle('DISTRIBUTION OF FOUR NUMERICAL COLUMNS :',fontweight='bold')

ax1=plt.subplot(2,2,1)
sns.distplot(train_df['Item_Weight'],ax=ax1,color='green')
ax1.grid()


ax2=plt.subplot(2,2,2)
sns.distplot(train_df['Item_Visibility'],ax=ax2,color='green')
ax2.grid()

ax3=plt.subplot(2,2,3)
sns.distplot(train_df['Item_MRP'],ax=ax3,color='green')
ax3.grid()

ax4=plt.subplot(2,2,4)
sns.distplot(train_df['Outlet_Age'],ax=ax4,color='green')
ax3.grid()

plt.show()
```



In [70]:

```
sns.pairplot(train_df)
plt.show()
```



In [ ]:

OBSERVATION FOR NUMERICAL COLUMNS:

- 1.In `Item_Visibility` ,there are outliers.
- 2.These four columns are not normally distributed.Need to do `power transformation` .
- 3.Except `Item_MRP` column, there is no such relationship between other numerical columns and our label column.

FOR CATEGORICAL COLUMNS:

In [175]:

```
cat_cols
```

Out[175]:

```
['Item_Identifier',
 'Item_Fat_Content',
 'Item_Type',
 'Outlet_Identifier',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

In [176]:

```
train_df[cat_cols].describe().T
```

Out[176]:

	count	unique	top	freq
Item_Identifier	8519	1555	FDG33	10
Item_Fat_Content	8519	2	Low Fat	5516
Item_Type	8519	16	Fruits and Vegetables	1232
Outlet_Identifier	8519	10	OUT013	932
Outlet_Size	8519	4	Medium	2790
Outlet_Location_Type	8519	3	Tier 3	3347
Outlet_Type	8519	4	Supermarket Type1	5577

Item_Identifier -column:

In [177]:

```
train_df['Item_Identifier']
```

Out[177]:

```
0       FDA15
1       DRC01
2       FDN15
3       FDX07
4       NCD19
        ...
8514    FDF22
8515    FDS36
8516    NCJ29
8517    FDN46
8518    DRG01
Name: Item_Identifier, Length: 8519, dtype: object
```

In [178]:

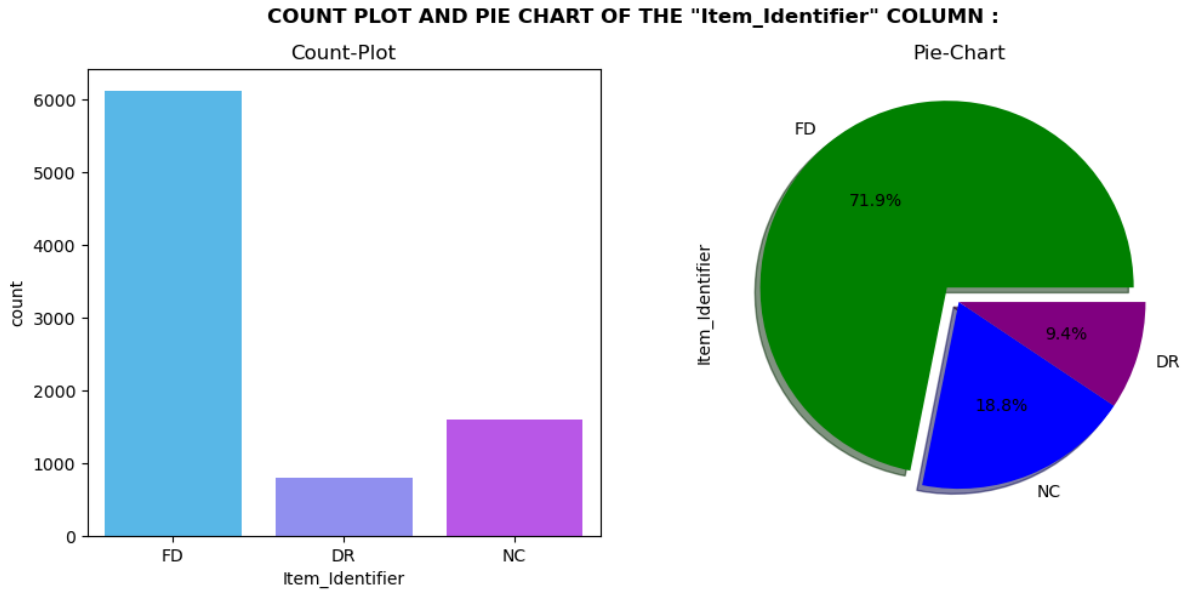
```
def code(x):
    return x[:2]
```

In [179]:

```
train_df['Item_Identifier']=train_df['Item_Identifier'].apply(code)
```

In [188]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Item_Identifier" COLUMN :',fontweight='bold')

ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')
sns.countplot(train_df['Item_Identifier'],palette='cool')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Item_Identifier'].value_counts().plot(kind='pie',autopct='%0.1f%%',explode=[0.1,0,0],
                                                shadow=True,colors=['green','blue','purple'])
plt.show()
```



Item_Fat_Content -column :

In [99]:

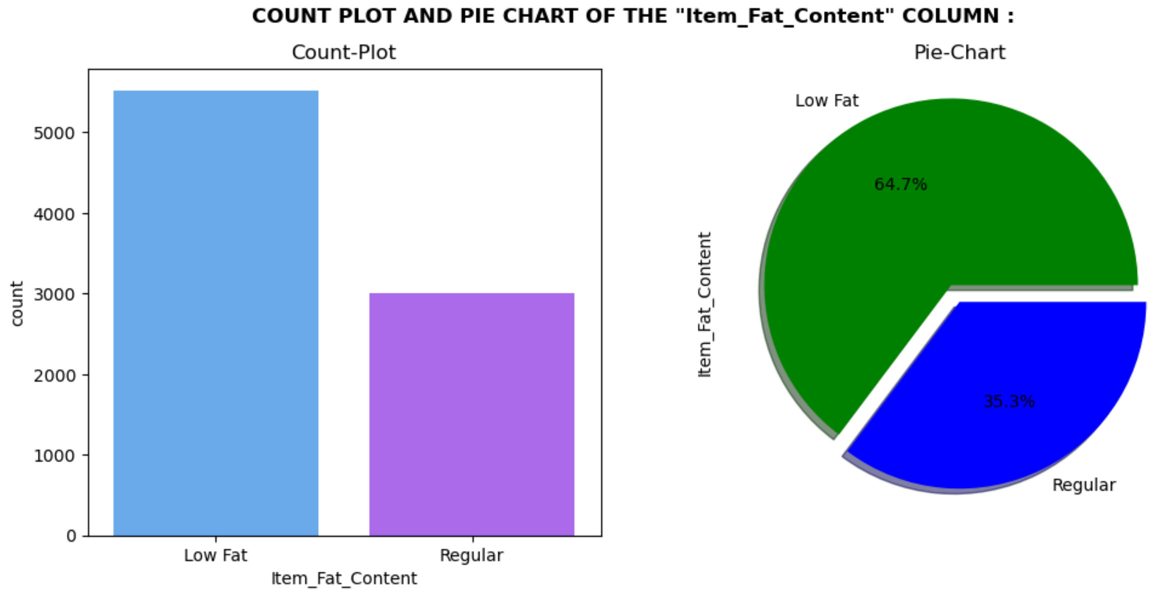
```
dfc['Item_Fat_Content'].value_counts()
```

Out[99]:

```
Low Fat    5516
Regular    3003
Name: Item_Fat_Content, dtype: int64
```

In [189]:

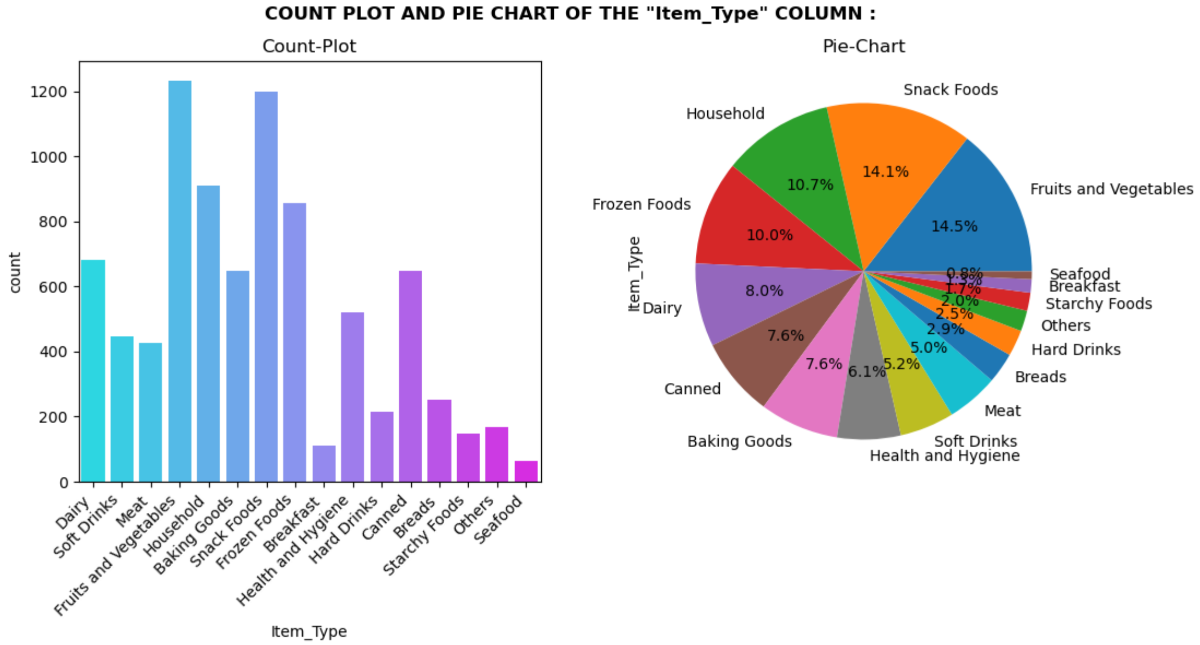
```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Item_Fat_Content" COLUMN :',fontweight='bold')

ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')
sns.countplot(train_df['Item_Fat_Content'],palette='cool')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Item_Fat_Content'].value_counts().plot(kind='pie',autopct='%0.1f%%',
                                                  explode=[0.1,0],shadow=True,colors=['green','blue'
plt.show()
```



Item_Type -column :

In [71]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Item_Type" COLUMN :',fontweight='bold')

categories=train_df['Item_Type'].unique()
ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')
ax1.set_xticklabels(categories,rotation=45, ha='right')

sns.countplot(train_df['Item_Type'],palette='cool')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Item_Type'].value_counts().plot(kind='pie',autopct='%0.1f%%')
plt.show()
```



In [196]:

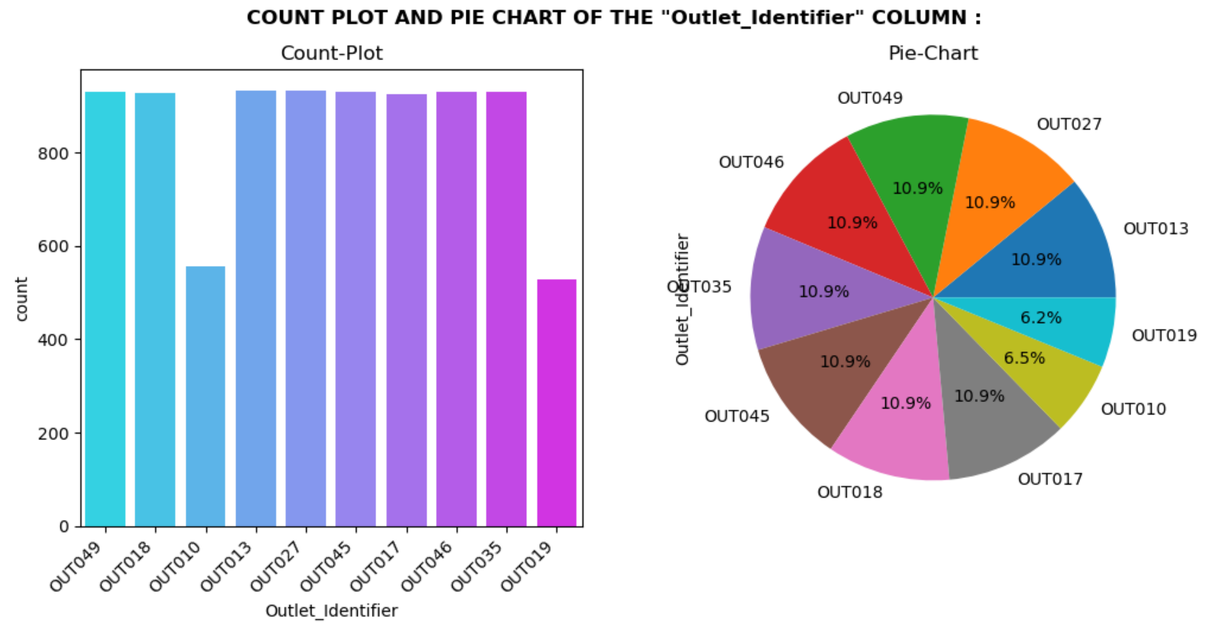
```
cat_cols
```

Out[196]:

```
['Item_Identifier',
 'Item_Fat_Content',
 'Item_Type',
 'Outlet_Identifier',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

In [72]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Outlet_Identifier" COLUMN :',fontweight='bold')

categories=train_df['Outlet_Identifier'].unique()
ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')
sns.countplot(train_df['Outlet_Identifier'],palette='cool')
ax1.set_xticklabels(categories,rotation=45, ha='right')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Outlet_Identifier'].value_counts().plot(kind='pie',autopct='%0.1f%%')
plt.show()
```



In [73]:

```
train_df['Outlet_Identifier'].value_counts()
```

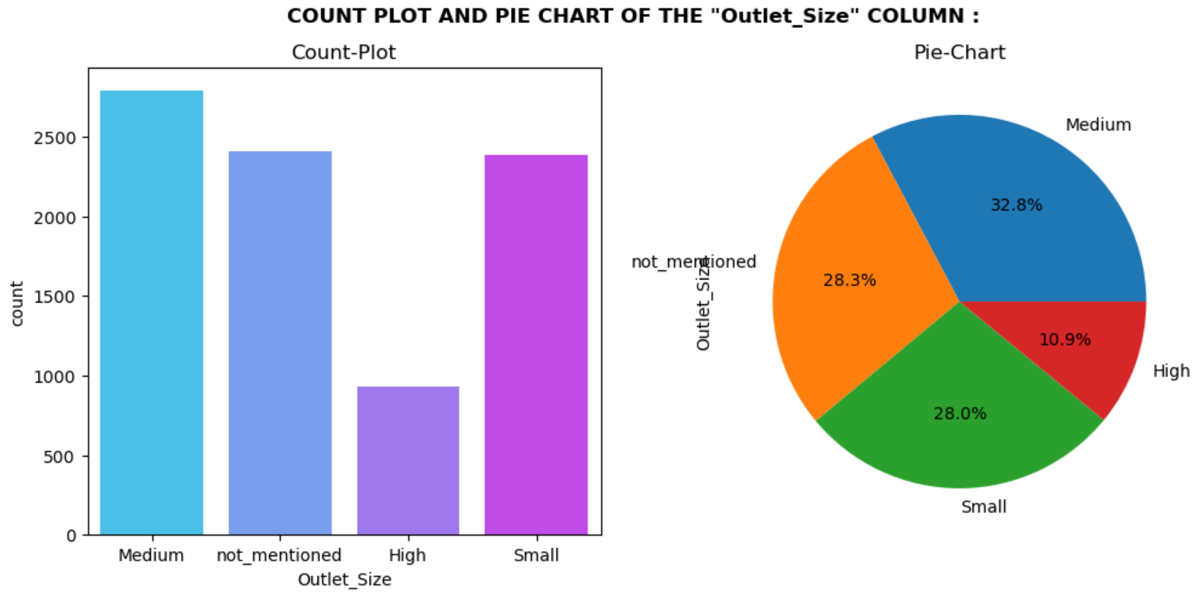
Out[73]:

```
OUT013    932
OUT027    932
OUT049    930
OUT046    930
OUT035    930
OUT045    929
OUT018    928
OUT017    926
OUT010    555
OUT019    527
Name: Outlet_Identifier, dtype: int64
```

In [ ]:

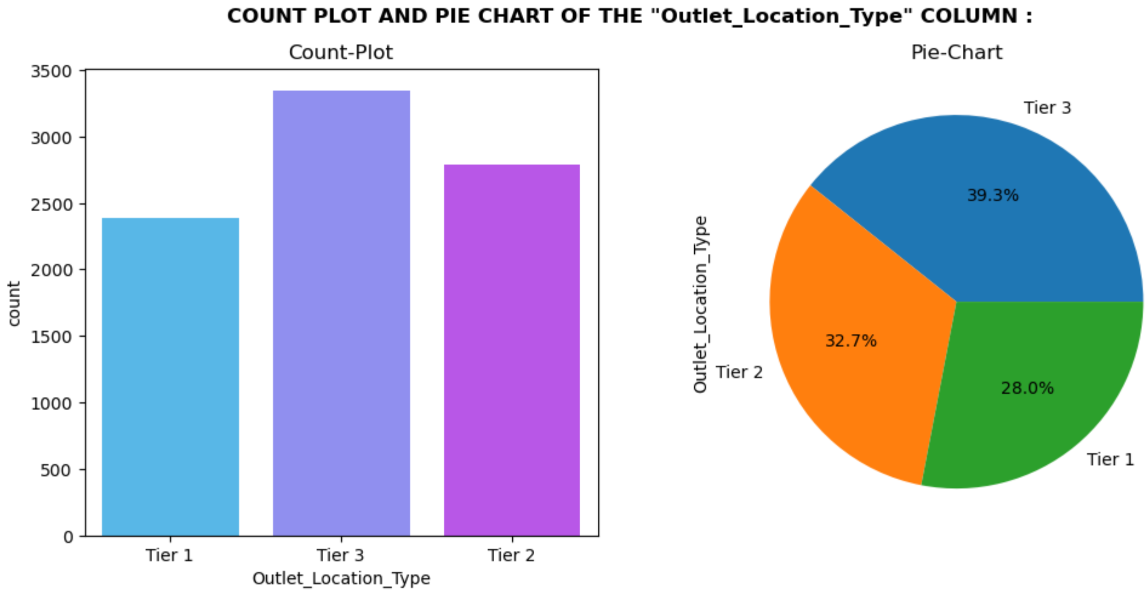
In [202]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Outlet_Size" COLUMN :',fontweight='bold')

ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')

sns.countplot(train_df['Outlet_Size'],palette='cool')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Outlet_Size'].value_counts().plot(kind='pie',autopct='%0.1f%%')
plt.show()
```



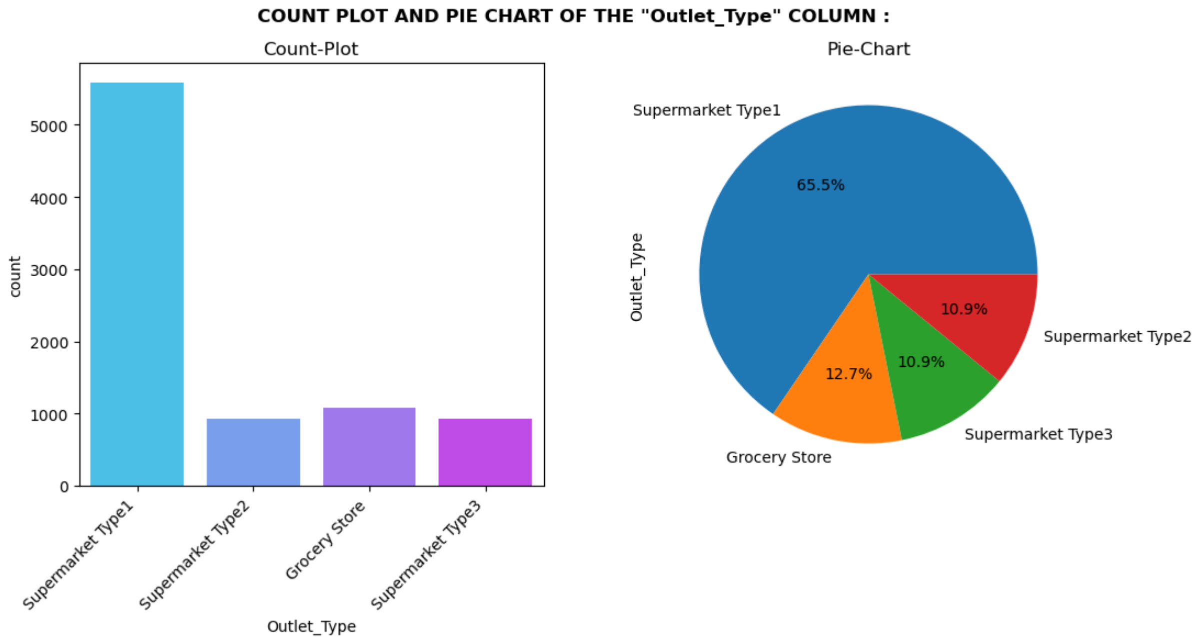
In [203]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Outlet_Location_Type" COLUMN :',fontweight='bold')

ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')

sns.countplot(train_df['Outlet_Location_Type'],palette='cool')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Outlet_Location_Type'].value_counts().plot(kind='pie',autopct='%0.1f%%')
plt.show()
```



In [74]:

```
plt.figure(figsize=(12,5))
plt.suptitle('COUNT PLOT AND PIE CHART OF THE "Outlet_Type" COLUMN :',fontweight='bold')

categories=train_df['Outlet_Type'].unique()
ax1=plt.subplot(1,2,1)
ax1.set_title('Count-Plot')
sns.countplot(train_df['Outlet_Type'],palette='cool')
ax1.set_xticklabels(categories,rotation=45, ha='right')

ax2=plt.subplot(1,2,2)
ax2.set_title('Pie-Chart')
train_df['Outlet_Type'].value_counts().plot(kind='pie',autopct='%0.1f%%')
plt.show()
```



In [ ]:

In [75]:

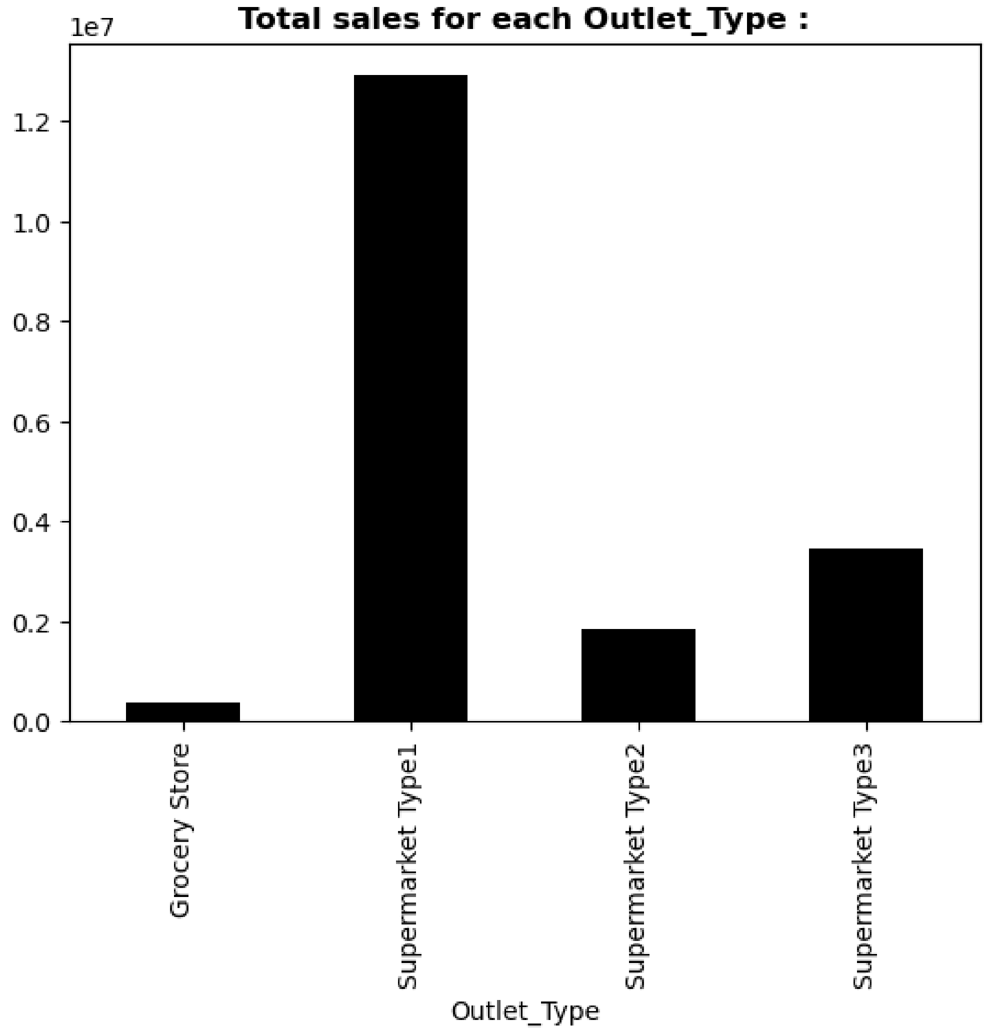
```
train_df.head(3)
```

Out[75]:

n_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Age	Outlet_Size
9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	24	Medium
5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	14	Medium
17.50	Low Fat	0.016760	Meat	141.6180	OUT049	24	Medium

In [103]:

```
plt.title("Total sales for each Outlet_Type :",fontweight='bold')
train_df.groupby(['Outlet_Type']).sum()['Item_Outlet_Sales'].plot(kind='bar',color='black')
plt.show()
```



In [85]:

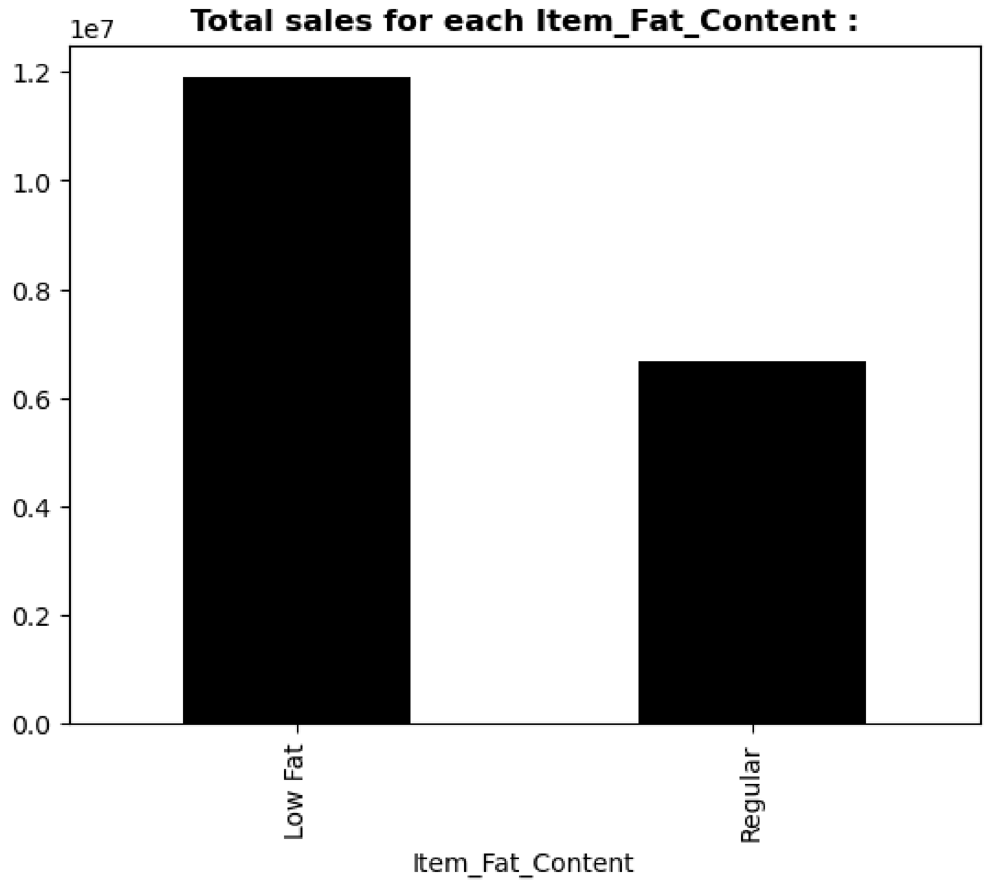
```
train_df.groupby(['Outlet_Type']).sum()['Item_Outlet_Sales'].round(2)
```

Out[85]:

```
Outlet_Type
Grocery Store           367913.76
Supermarket Type1     12917342.26
Supermarket Type2      1851822.83
Supermarket Type3      3444468.36
Name: Item_Outlet_Sales, dtype: float64
```

In [102]:

```
plt.title("Total sales for each Item_Fat_Content :",fontweight='bold')
train_df.groupby(['Item_Fat_Content']).sum()['Item_Outlet_Sales'].plot(kind='bar',color='black')
plt.show()
```



In [88]:

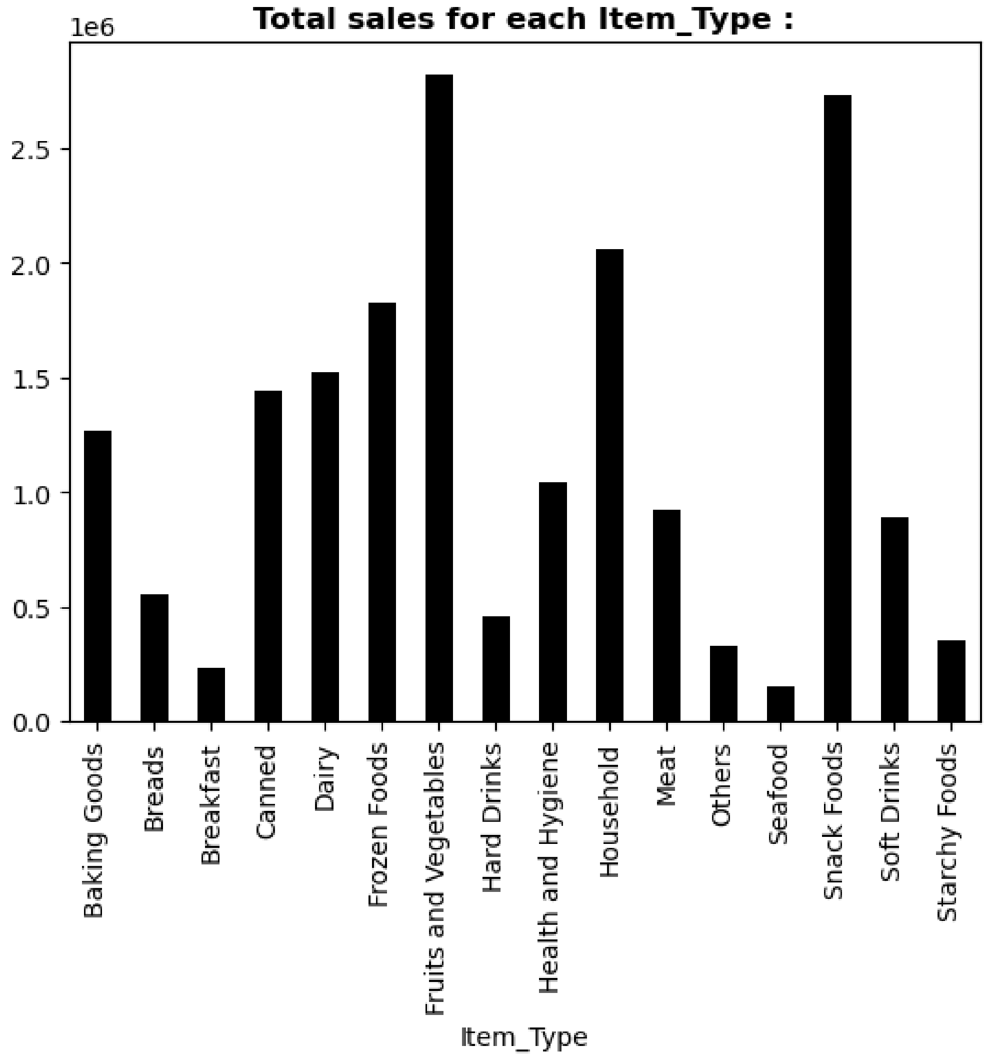
```
train_df.groupby(['Item_Fat_Content']).sum()['Item_Outlet_Sales'].round(2)
```

Out[88]:

```
Item_Fat_Content
Low Fat     11899660.30
Regular      6681886.91
Name: Item_Outlet_Sales, dtype: float64
```

In [101]:

```
plt.title("Total sales for each Item_Type :",fontweight='bold')
train_df.groupby(['Item_Type']).sum()['Item_Outlet_Sales'].plot(kind='bar',color='black')
plt.show()
```



In [93]:

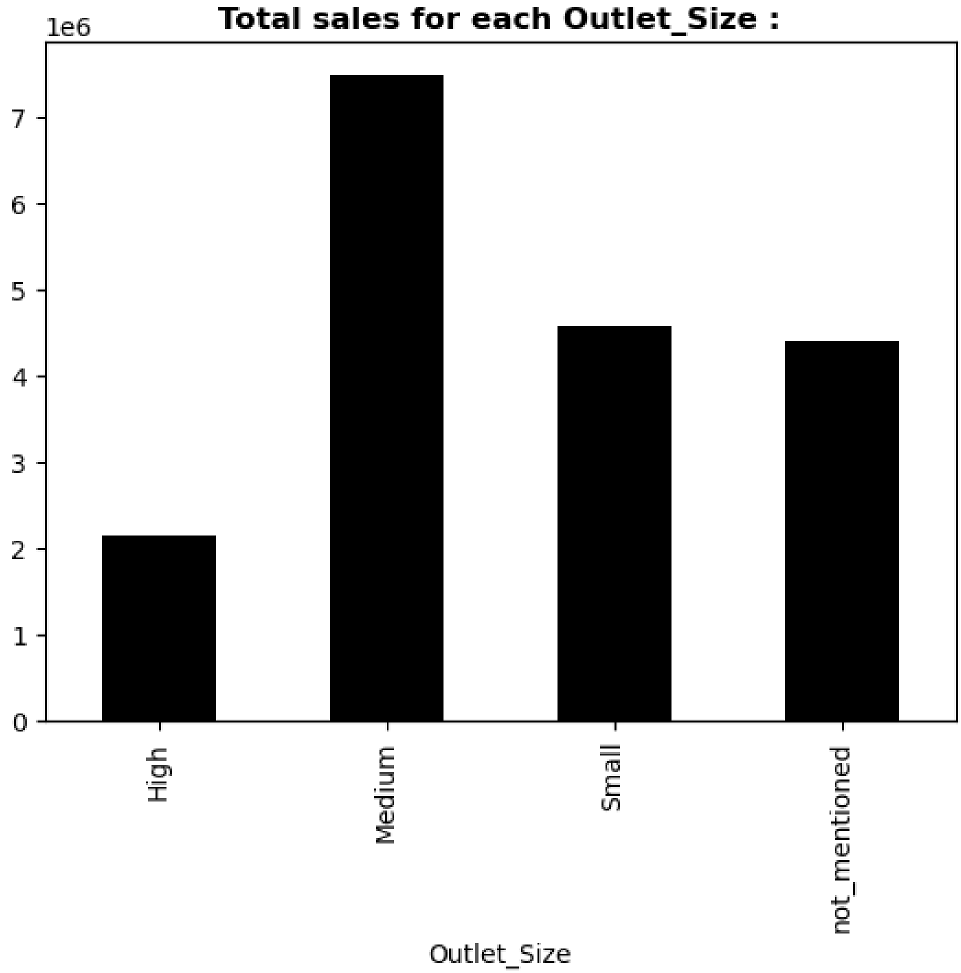
```
train_df.groupby(['Item_Type']).sum()['Item_Outlet_Sales'].round(2)
```

Out[93]:

```
Item_Type
Baking Goods             1265404.83
Breads                    553237.19
Breakfast                 232298.95
Canned                   1444151.49
Dairy                    1519140.55
Frozen Foods             1824164.83
Fruits and Vegetables    2820059.82
Hard Drinks               457793.43
Health and Hygiene       1045200.14
Household                2055493.71
Meat                      917565.61
Others                    325517.61
Seafood                   148868.22
Snack Foods              2728351.86
Soft Drinks               892897.72
Starchy Foods             351401.25
Name: Item_Outlet_Sales, dtype: float64
```

In [100]:

```
plt.title("Total sales for each Outlet_Size :",fontweight='bold')
train_df.groupby(['Outlet_Size']).sum()['Item_Outlet_Sales'].plot(kind='bar',color='black')
plt.show()
```



In [96]:

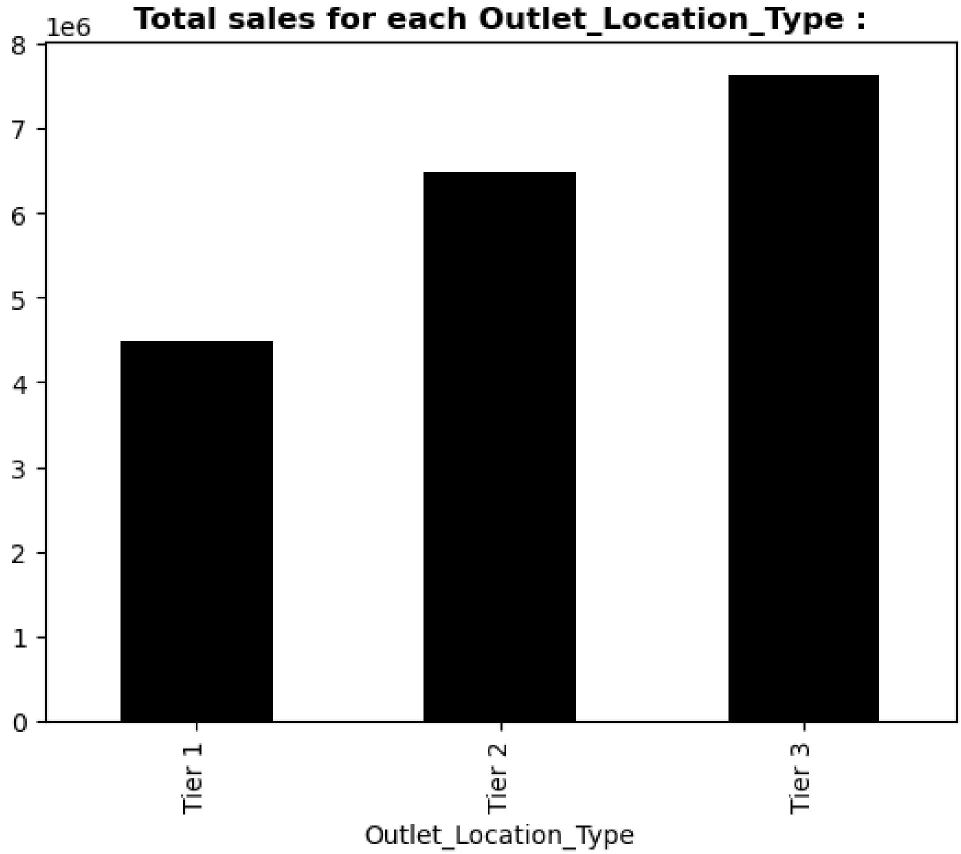
```
train_df.groupby(['Outlet_Size']).sum()['Item_Outlet_Sales'].round(2)
```

Out[96]:

```
Outlet_Size
High             2142663.58
Medium           7480261.00
Small            4566091.69
not_mentioned    4392530.94
Name: Item_Outlet_Sales, dtype: float64
```

In [99]:

```
plt.title("Total sales for each Outlet_Location_Type :",fontweight='bold')
train_df.groupby(['Outlet_Location_Type']).sum()['Item_Outlet_Sales'].plot(kind='bar',color='black'
plt.show()
```



In [98]:

```
train_df.groupby(['Outlet_Location_Type']).sum()['Item_Outlet_Sales'].round(2)
```

Out[98]:

```
Outlet_Location_Type
Tier 1    4481938.56
Tier 2    6472313.71
Tier 3    7627294.94
Name: Item_Outlet_Sales, dtype: float64
```

In [ ]:

In [208]:

```
#train_df.to_csv('train_cleaned.csv',index=False)
```