[5]:	# first 5 rows of the dataframe super_mart_data.head()    tem_Identifier   tem_Weight   tem_Fat_Content   tem_Visibility   tem_Type   tem_MRP   Outlet_Identifier   Outlet_Establishment_Year   Outlet_Size   Outlet_Location_Type   Outlet_Type   tem_Outlet_Sate
[6]: [6]: [7]:	4 FDY38 NaN Regular 0.118599 Dairy 234.2300 OUT027 1985 Medium Tier 3 Supermarket Type3 5857.916.  # number of data points and number of features super_mart_data.shape  (5681, 12)
	<pre>super_mart_data.info()  <class 'pandas.core.frame.dataframe'=""> RangeIndex: 5681 entries, 0 to 5680  Data columns (total 12 columns):  # Column</class></pre>
[8]:	6 Outlet_Identifier 5681 non-null object 7 Outlet_Establishment_Year 5681 non-null int64 8 Outlet_Size 5681 non-null object 9 Outlet_Location_Type 5681 non-null object 10 Outlet_Type 5681 non-null object 11 Item_Outlet_Sales 5681 non-null float64 dtypes: float64(4), int64(1), object(7) memory usage: 532.7+ KB  Categorical Features  # checking for missing values
	super_mart_data.isnull().sum()  Item_Identifier
	Item_Outlet_Sales 0 dtype: int64  Handling missing values  # mean value of "Item_Weight" column super_mart_data['Item_Weight'].mean()  12.695633368756374
11]: 11]:	<pre>super_mart_data['Item_Weight'].fillna(super_mart_data['Item_Weight'].mean(), inplace = True)</pre>
12]:	Outlet_Identifier 0 Outlet_Establishment_Year 0 Outlet_Size 0 Outlet_Location_Type 0 Outlet_Type 0 Item_Outlet_Sales 0 dtype: int64  Data Analysis  # statistical measures about the data super_mart_data.describe()
12]:	Item_Weight         Item_Visibility         Item_MRP         Outlet_Establishment_Year         Item_Outlet_Sales           count         5681.000000         5681.000000         5681.000000         5681.000000           mean         12.695633         0.065684         141.023273         1997.828903         2255.144238           std         4.245189         0.051252         61.809091         8.372256         1525.001339           min         4.555000         0.00000         31.990000         1985.000000         -100.129007           25%         9.195000         0.027047         94.412000         1987.000000         1175.989070           50%         12.695633         0.054154         141.415400         1999.000000         2008.295734           75%         15.850000         0.093463         186.026600         2004.000000         3208.434636
13]: 14]:	<pre>max 21.350000 0.323637 266.588400 2009.000000 46524.870000  Numerical Features  sns.set()  # Item_Weight distribution plt.figure(figsize=(7,7)) sns.distplot(super_mart_data['Item_Weight'])</pre>
	C:\Users\Windows 10\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a ure version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for historians).  warnings.warn(msg, FutureWarning)  0.30  0.25
	0.20 Example 0.15 0.10
15]:	plt.figure(figsize=(7,7)) sns.distplot(super_mart_data['Item_Visibility'])
	C:\Users\Windows 10\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a ure version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for historians).  warnings.warn(msg, FutureWarning)
	8 6 4 4 4
16]:	plt.figure(figsize=(7,7)) sns.distplot(super_mart_data['Item_MRP'])
	C:\Users\Windows 10\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a ure version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for historians).  warnings.warn(msg, FutureWarning)
	0.005 0.003 0.002
17]:	# Item_Outlet_Sales distribution plt.figure(figsize=(7,7)) sns.distplot(super_mart_data['Item_Outlet_Sales']) plt.show()
	C:\Users\Windows 10\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a ure version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for historians).  warnings.warn(msg, FutureWarning)  0.00030
	0.00020 
18]:	0.00000  # Outlet_Establishment_Year column plt.figure(figsize=(7,7)) sns.countplot(x='Outlet_Establishment_Year', data=super_mart_data) plt.show()
	1000 800 600
	200
19]:	1985 1987 1997 1998 1999 2002 2004 2007 2009  # Item_Fat_Content column plt.figure(figsize=(6,6)) sns.countplot(x='Item_Fat_Content', data=super_mart_data) plt.show()  3500
	3000 - 2500 - 2000 - 2500 - 2000 - 2500 - 2000 - 2500 - 2000 - 2500 - 2000 - 2500 - 2000 - 2500 - 2000 - 2500 - 20
20]:	# Item_Type column plt.figure(figsize=(25,10)) sns.countplot(x='Item_Type', data=super_mart_data)
	plt.show()  800  600
	500 8 400 200
21]:	# Outlet_Size column plt.figure(figsize=(6,6)) sns.countplot(x='Outlet_Size', data=super_mart_data) plt.show()
	1750 1500 1250
	750 500 250 Medium small Small High Outlet_Size
22]: 22]:	Item_Weight
	Item_MRP
23]: 23]:	super_mart_data.head()
24]:	1       FDW14       8.300000       reg       0.038428       Dairy       87.3198       OUT017       2007       small       Tier 2       Supermarket Type1       1409.355         2       NCN55       14.600000       Low Fat       0.099575       Others       241.7538       OUT010       1998       small       Tier 3       Grocery Store       710.594         3       FDQ58       7.315000       Low Fat       0.015388       Snack Foods       155.0340       OUT017       2007       small       Tier 2       Supermarket Type1       2355.184         4       FDY38       12.695633       Regular       0.118599       Dairy       234.2300       OUT027       1985       Medium       Tier 3       Supermarket Type3       5857.916
24]: 25]:	Super_mare_data replace({ Item_rac_content : { Iow rat : Low rat ; reg : Regular }}, Implace=Irac)
26]: 26]: 27]:	Low Fat 3668 Regular 2013 Name: Item_Fat_Content, dtype: int64 Label Encoding  encoder = LabelEncoder()
J:	<pre>super_mart_data['Item_Identifier'] = encoder.fit_transform(super_mart_data['Item_Identifier']) super_mart_data['Item_Fat_Content'] = encoder.fit_transform(super_mart_data['Item_Fat_Content']) super_mart_data['Item_Type'] = encoder.fit_transform(super_mart_data['Item_Type']) super_mart_data['Outlet_Identifier'] = encoder.fit_transform(super_mart_data['Outlet_Identifier']) super_mart_data['Outlet_Location_Type'] = encoder.fit_transform(super_mart_data['Outlet_Location_Type']) super_mart_data['Outlet_Type'] = encoder.fit_transform(super_mart_data['Outlet_Type']) super_mart_data['Outlet_Size'] = encoder.fit_transform(super_mart_data['Outlet_Size'])</pre>
29]: 29]:	super_mart_data.head()           Item_Identifier         Item_Weight         Item_Fat_Content         Item_Visibility         Item_MRP         Outlet_Identifier         Outlet_Establishment_Year         Outlet_Size         Outlet_Location_Type         Outlet_Type         Item_Outlet_Size           0         1103         20.750000         0         0.007565         13         107.8622         9         1999         1         0         1         1636.244           1         1067         8.300000         1         0.038428         4         87.3198         2         2007         3         1         1         1409.355           2         1406         14.600000         0         0.099575         11         241.7538         0         1998         3         2         0         710.594           3         809         7.315000         0         0.015388         13         155.0340         2         2007         3         1         1         2355.184
30]: 31]:	4 1184 12.695633 1 0.118599 4 234.2300 5 1985 1 2 3 5857.916  Splitting features and Target  X = super_mart_data.drop(columns='Item_Outlet_Sales', axis=1) Y = super_mart_data['Item_Outlet_Sales']  print(X)
	Item_Identifier       Item_Weight       Item_Fat_Content       Item_Visibility         0       1103       20.750000       0       0.007565         1       1067       8.300000       1       0.038428         2       1406       14.600000       0       0.09575         3       809       7.315000       0       0.015388         4       1184       12.695633       1       0.118599               5676       231       10.500000       1       0.013496         5677       306       7.600000       1       0.142991         5678       1412       10.000000       0       0.073529         5679       517       15.300000       1       0.000000         5680       987       9.500000       1       0.104720
	Item_Type       Item_MRP       Outlet_Identifier       Outlet_Establishment_Year       \         0       13       107.8622       9       1999         1       4       87.3198       2       2007         2       11       241.7538       0       1998         3       13       155.0340       2       2007         4       4       234.2300       5       1985                5676       13       141.3154       8       1997         5677       15       169.1448       3       2009         5678       8       118.7440       7       2002         5679       3       214.6218       2       2007         5680       3       79.7960       7       2002
	Outlet_Size         Outlet_Location_Type         Outlet_Type           0         1         0         1           1         3         1         1           2         3         2         0           3         3         1         1           4         1         2         3                 5676         2         0         1           5677         1         2         2           5678         3         1         1           5679         3         1         1           5680         3         1         1
32]:	[5681 rows x 11 columns]  print(Y)  0
33]: 34]:	5677 2602.671833 5678 1832.451358 5679 3538.685188 5680 1281.144462 Name: Item_Outlet_Sales, Length: 5681, dtype: float64  Splitting the data into Training data anad Testing data  X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
	(5681, 11) (4544, 11) (1137, 11)  XGBoost Regressor  regressor = XGBRegressor()  regressor.fit(X_train, Y_train)  XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
	<pre>colsample_bynode=1, colsample_bytree=1, enable_categorical=False,     gamma=0, gpu_id=-1, importance_type=None,     interaction_constraints='', learning_rate=0.300000012,     max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,     monotone_constraints='()', n_estimators=100, n_jobs=4,     num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,     reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',     validate_parameters=1, verbosity=None)</pre> Evaluation
40]: 41]: 42]:	<pre>training_data_Prediction = regressor.predict(X_train)  # R squared Value r2_train = metrics.r2_score(Y_train, training_data_Prediction)  print('R Squared value = ',r2_train)  R Squared value = 0.9932069865155904  # Prediction on test data</pre>
44]: 45]:	<pre>test_data_Prediction = regressor.predict(X_test)  # R Squared value r2_test = metrics.r2_score(Y_test, test_data_Prediction)  print('R Squared value = ',r2_test)  R Squared value = 0.5848150919749066</pre>
[]:	