In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
pd.set_option('display.max_columns', None)
```

In [2]:
```
df = pd.read_csv('dairy_dataset.csv')
df.head()
```

Out[2]:

Quantity (liters/kg)	Price per Unit	Total Value	Shelf Life (days)	Storage Condition	Production Date	Expiration Date	Quantity Sold (liters/kg)	Price per Unit (sold)	Approx. Total Revenue(INR)	Customer Location	S Cha
222.40	85.72	19064.1280	25	Frozen	2021-12-27	2022-01-21	7	82.24	575.68	Madhya Pradesh	Whole
687.48	42.61	29293.5228	22	Tetra Pack	2021-10-03	2021-10-25	558	39.24	21895.92	Kerala	Whole
503.48	36.50	18377.0200	30	Refrigerated	2022-01-14	2022-02-13	256	33.81	8655.36	Madhya Pradesh	O
823.36	26.52	21835.5072	72	Frozen	2019-05-15	2019-07-26	601	28.92	17380.92	Rajasthan	O
147.77	83.85	12390.5145	11	Refrigerated	2020-10-17	2020-10-28	145	83.07	12045.15	Jharkhand	F

Data Preprocessing Part 1

In [3]:
```
#Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

Out[3]:
```
Location               15
Farm Size               3
Date                 1278
Product Name           10
Brand                  11
Storage Condition       5
Production Date      1405
Expiration Date      1441
Customer Location      15
Sales Channel           3
dtype: int64
```

In [4]:
```
# Remove Date and Expiration Date, but keep Production Date for Exploratory Data Analysis
df.drop(columns=['Date', 'Expiration Date'], inplace=True)
df.head()
```

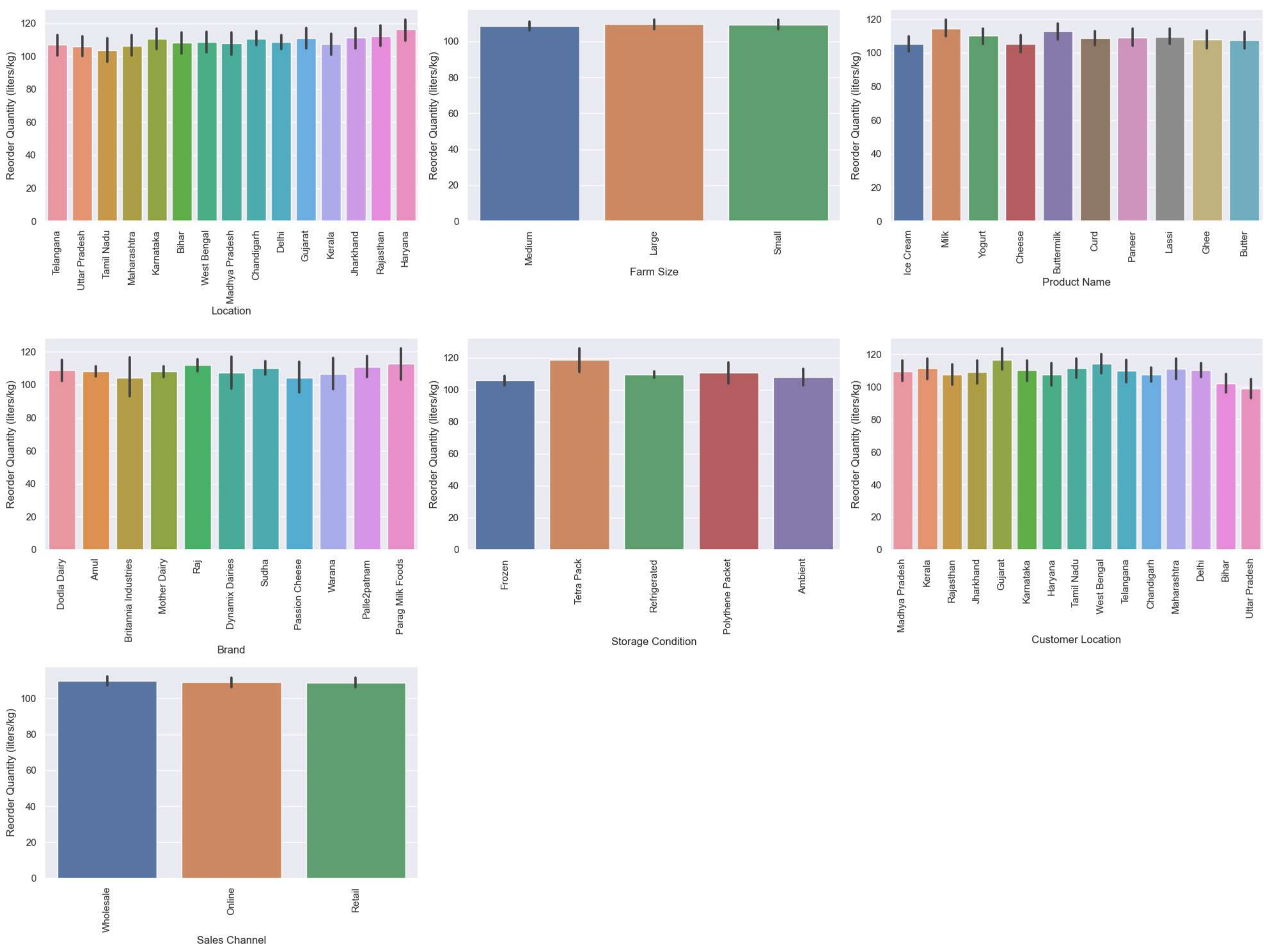
Out[4]:

	Location	Total Land Area (acres)	Number of Cows	Farm Size	Product ID	Product Name	Brand	Quantity (liters/kg)	Price per Unit	Total Value	Shelf Life (days)	Storage Condition
0	Telangana	310.84	96	Medium	5	Ice Cream	Dodla Dairy	222.40	85.72	19064.1280	25	Frozen
1	Uttar Pradesh	19.19	44	Large	1	Milk	Amul	687.48	42.61	29293.5228	22	Tetra Pack
2	Tamil Nadu	581.69	24	Medium	4	Yogurt	Dodla Dairy	503.48	36.50	18377.0200	30	Refrigerated
3	Telangana	908.00	89	Small	3	Cheese	Britannia Industries	823.36	26.52	21835.5072	72	Frozen
4	Maharashtra	861.95	21	Medium	8	Buttermilk	Mother Dairy	147.77	83.85	12390.5145	11	Refrigerated

In [5]:
```
# Convert 'date' column to datetime
df['Production Date'] = pd.to_datetime(df['Production Date'])
```

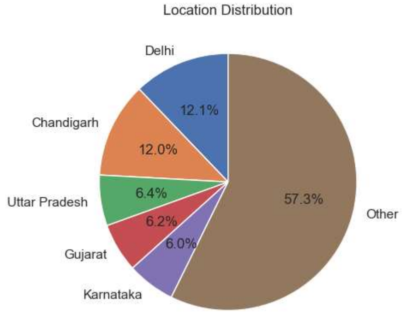
Exploratory Data Analysis

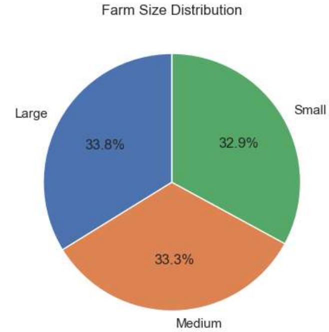
In [8]:
```
# list of categorical variables to plot
cat_vars = ['Location', 'Farm Size', 'Product Name',
            'Brand', 'Storage Condition', 'Customer Location',
            'Sales Channel']

# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(20, 15))
axs = axs.flatten()

# create barplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.barplot(x=var, y='Reorder Quantity (liters/kg)', data=df, ax=axs[i], estimator=np.mean)
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# remove the eigth subplot
fig.delaxes(axs[7])

# remove the ninth subplot
fig.delaxes(axs[8])

# adjust spacing between subplots
fig.tight_layout()

# show plot
plt.show()
```

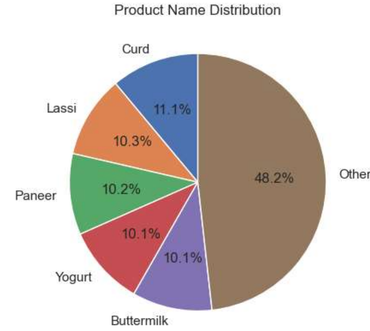


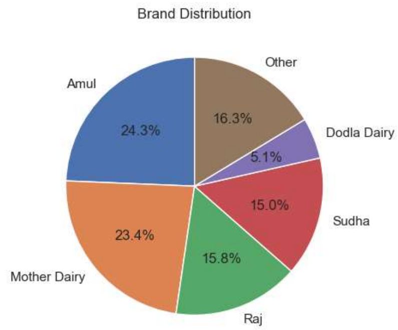
In [9]:
```
# Specify the maximum number of categories to show individually
max_categories = 5

cat_vars = ['Location', 'Farm Size', 'Product Name',
            'Brand', 'Storage Condition', 'Customer Location',
            'Sales Channel']

# Create a figure and axes
fig, axs = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))

# Create a pie chart for each categorical variable
for i, var in enumerate(cat_vars):
    if i < len(axs.flat):
        # Count the number of occurrences for each category
        cat_counts = df[var].value_counts()

        # Group categories beyond the top max_categories as 'Other'
        if len(cat_counts) > max_categories:
            cat_counts_top = cat_counts[:max_categories]
            cat_counts_other = pd.Series(cat_counts[max_categories:].sum(), index=['Other'])
            cat_counts = cat_counts_top.append(cat_counts_other)

        # Create a pie chart
        axs.flat[i].pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)

        # Set a title for each subplot
        axs.flat[i].set_title(f'{var} Distribution')

# Adjust spacing between subplots
fig.tight_layout()

# remove eigth plot
fig.delaxes(axs[2][1])

# remove ninth plot
fig.delaxes(axs[2][2])

# Show the plot
plt.show()
```

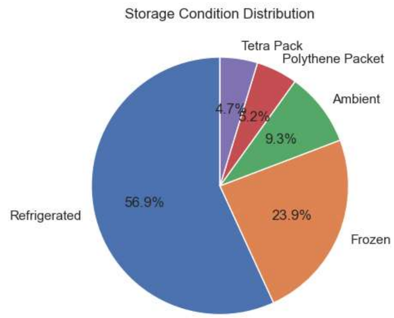
```
C:\Users\Michael\AppData\Local\Temp\ipykernel_14992\2486016364.py:21: FutureWarning: The series.a
ppend method is deprecated and will be removed from pandas in a future version. Use pandas.concat
instead.
  cat_counts = cat_counts_top.append(cat_counts_other)
C:\Users\Michael\AppData\Local\Temp\ipykernel_14992\2486016364.py:21: FutureWarning: The series.a
ppend method is deprecated and will be removed from pandas in a future version. Use pandas.concat
instead.
  cat_counts = cat_counts_top.append(cat_counts_other)
C:\Users\Michael\AppData\Local\Temp\ipykernel_14992\2486016364.py:21: FutureWarning: The series.a
ppend method is deprecated and will be removed from pandas in a future version. Use pandas.concat
instead.
  cat_counts = cat_counts_top.append(cat_counts_other)
C:\Users\Michael\AppData\Local\Temp\ipykernel_14992\2486016364.py:21: FutureWarning: The series.a
ppend method is deprecated and will be removed from pandas in a future version. Use pandas.concat
instead.
  cat_counts = cat_counts_top.append(cat_counts_other)
```

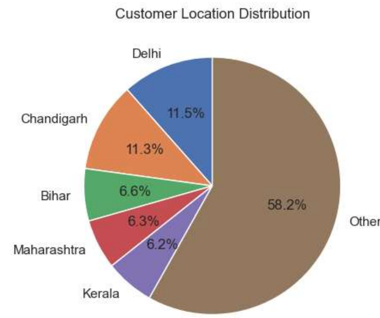

Location Distribution
Delhi
12.1%
Chandigarh
12.0%
Uttar Pradesh
6.4%
6.2%
Gujarat
6.0%
Karnataka
57.3%
Other

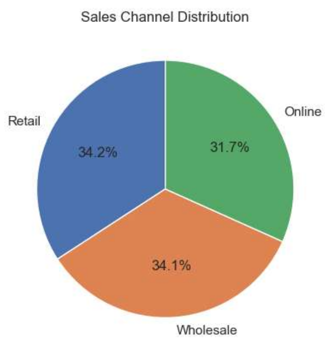

Farm Size Distribution
Large
33.8%
Small
32.9%
33.3%
Medium


Product Name Distribution
Curd
11.1%
Lassi
10.3%
Paneer
10.2%
10.1%
Yogurt
10.1%
Buttermilk
48.2%
Other

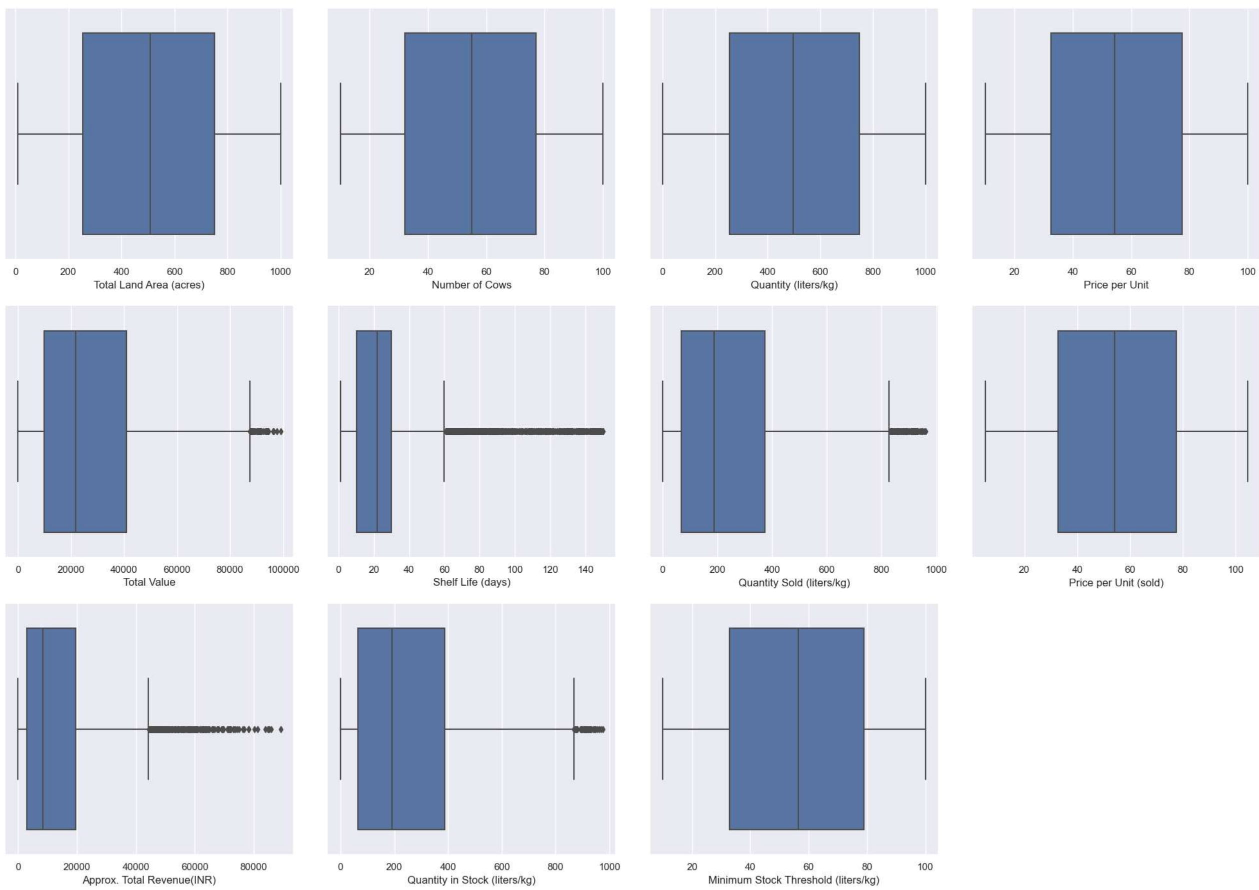

Brand Distribution
Amul
24.3%
Other
16.3%
Dodla Dairy
5.1%
15.0%
Sudha
23.4%
Mother Dairy
15.8%
Raj


Storage Condition Distribution
Tetra Pack
Polythene Packet
4.7%
5.2%
Ambient
9.3%
Refrigerated
56.9%
23.9%
Frozen

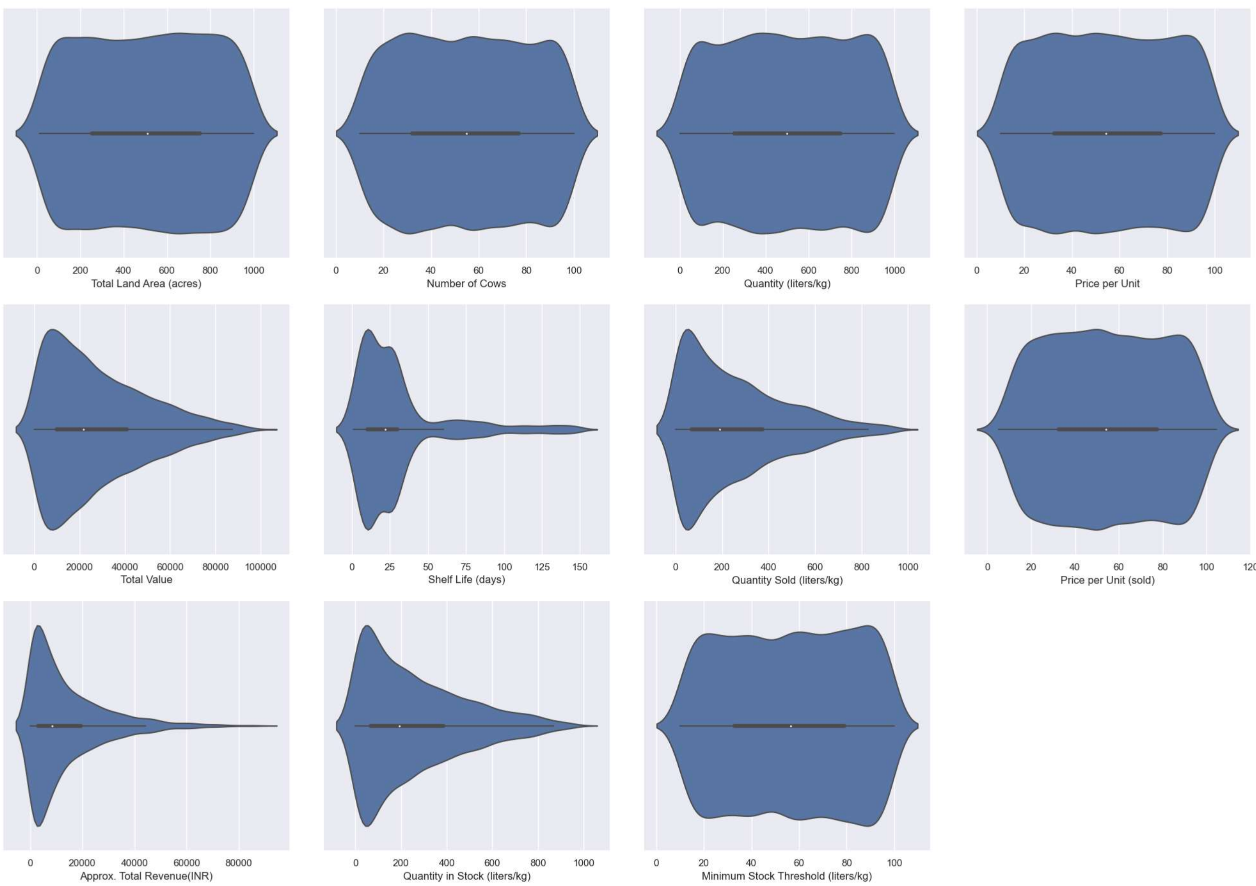

Customer Location Distribution
Delhi
11.5%
Chandigarh
11.3%
Bihar
6.6%
6.3%
Maharashtra
6.2%
Kerala
58.2%
Other


Sales Channel Distribution
Retail
34.2%
Online
31.7%
34.1%
Wholesale

In [11]:
```python
# list of numerical variables to plot
num_vars = ['Total Land Area (acres)', 'Number of Cows', 'Quantity (liters/kg)', 'Price per Unit',
            'Total Value', 'Shelf Life (days)', 'Quantity Sold (liters/kg)', 'Price per Unit (sold
            'Approx. Total Revenue(INR)', 'Quantity in Stock (liters/kg)', 'Minimum Stock Threshol

# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=4, figsize=(20, 14))
axs = axs.flatten()

# create violinplot for each numerical variable
for i, var in enumerate(num_vars):
    sns.boxplot(x=var, data=df, ax=axs[i])

# adjust spacing between subplots
fig.tight_layout()

# remove the 12th subplot
fig.delaxes(axs[11])

plt.show()
```



In [13]:
```
# list of numerical variables to plot
num_vars = ['Total Land Area (acres)', 'Number of Cows', 'Quantity (liters/kg)', 'Price per Unit',
            'Total Value', 'Shelf Life (days)', 'Quantity Sold (liters/kg)', 'Price per Unit (sold
            'Approx. Total Revenue(INR)', 'Quantity in Stock (liters/kg)', 'Minimum Stock Threshol

# create figure with subplots
fig, axs = plt.subplots(nrows=3, ncols=4, figsize=(20, 14))
axs = axs.flatten()

# create violinplot for each numerical variable
for i, var in enumerate(num_vars):
    sns.violinplot(x=var, data=df, ax=axs[i])

# adjust spacing between subplots
fig.tight_layout()

# remove the 12th subplot
fig.delaxes(axs[11])

plt.show()
```



Data Preprocessing Part 2

In [18]:
```
df.head()
```

Out[18]:

	Location	Total Land Area (acres)	Number of Cows	Farm Size	Product ID	Product Name	Brand	Quantity (liters/kg)	Price per Unit	Total Value	Shelf Life (days)	Storage Condition
0	Telangana	310.84	96	Medium	5	Ice Cream	Dodla Dairy	222.40	85.72	19064.1280	25	Frozen
1	Uttar Pradesh	19.19	44	Large	1	Milk	Amul	687.48	42.61	29293.5228	22	Tetra Pack
2	Tamil Nadu	581.69	24	Medium	4	Yogurt	Dodla Dairy	503.48	36.50	18377.0200	30	Refrigerated
3	Telangana	908.00	89	Small	3	Cheese	Britannia Industries	823.36	26.52	21835.5072	72	Frozen
4	Maharashtra	861.95	21	Medium	8	Buttermilk	Mother Dairy	147.77	83.85	12390.5145	11	Refrigerated

In [19]:
```
# Remove Unnecesary column / attribute
df.drop(columns=['Product ID', 'Production Date'], inplace=True)
```

In [20]:
```
df.shape
```

Out[20]: (4325, 19)

In [21]:
```
#Check missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

Out[21]: Series([], dtype: float64)

Label Encoding each Object datatypes

In [22]:
```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

```
Location: ['Telangana' 'Uttar Pradesh' 'Tamil Nadu' 'Maharashtra' 'Karnataka'
 'Bihar' 'West Bengal' 'Madhya Pradesh' 'Chandigarh' 'Delhi' 'Gujarat'
 'Kerala' 'Jharkhand' 'Rajasthan' 'Haryana']
Farm Size: ['Medium' 'Large' 'Small']
Product Name: ['Ice Cream' 'Milk' 'Yogurt' 'Cheese' 'Buttermilk' 'Curd' 'Paneer' 'Lassi'
 'Ghee' 'Butter']
Brand: ['Dodla Dairy' 'Amul' 'Britannia Industries' 'Mother Dairy' 'Raj'
 'Dynamix Dairies' 'Sudha' 'Passion Cheese' 'Warana' 'Palle2patnam'
 'Parag Milk Foods']
Storage Condition: ['Frozen' 'Tetra Pack' 'Refrigerated' 'Polythene Packet' 'Ambient']
Customer Location: ['Madhya Pradesh' 'Kerala' 'Rajasthan' 'Jharkhand' 'Gujarat' 'Karnataka'
 'Haryana' 'Tamil Nadu' 'West Bengal' 'Telangana' 'Chandigarh'
 'Maharashtra' 'Delhi' 'Bihar' 'Uttar Pradesh']
Sales Channel: ['Wholesale' 'Online' 'Retail']
```

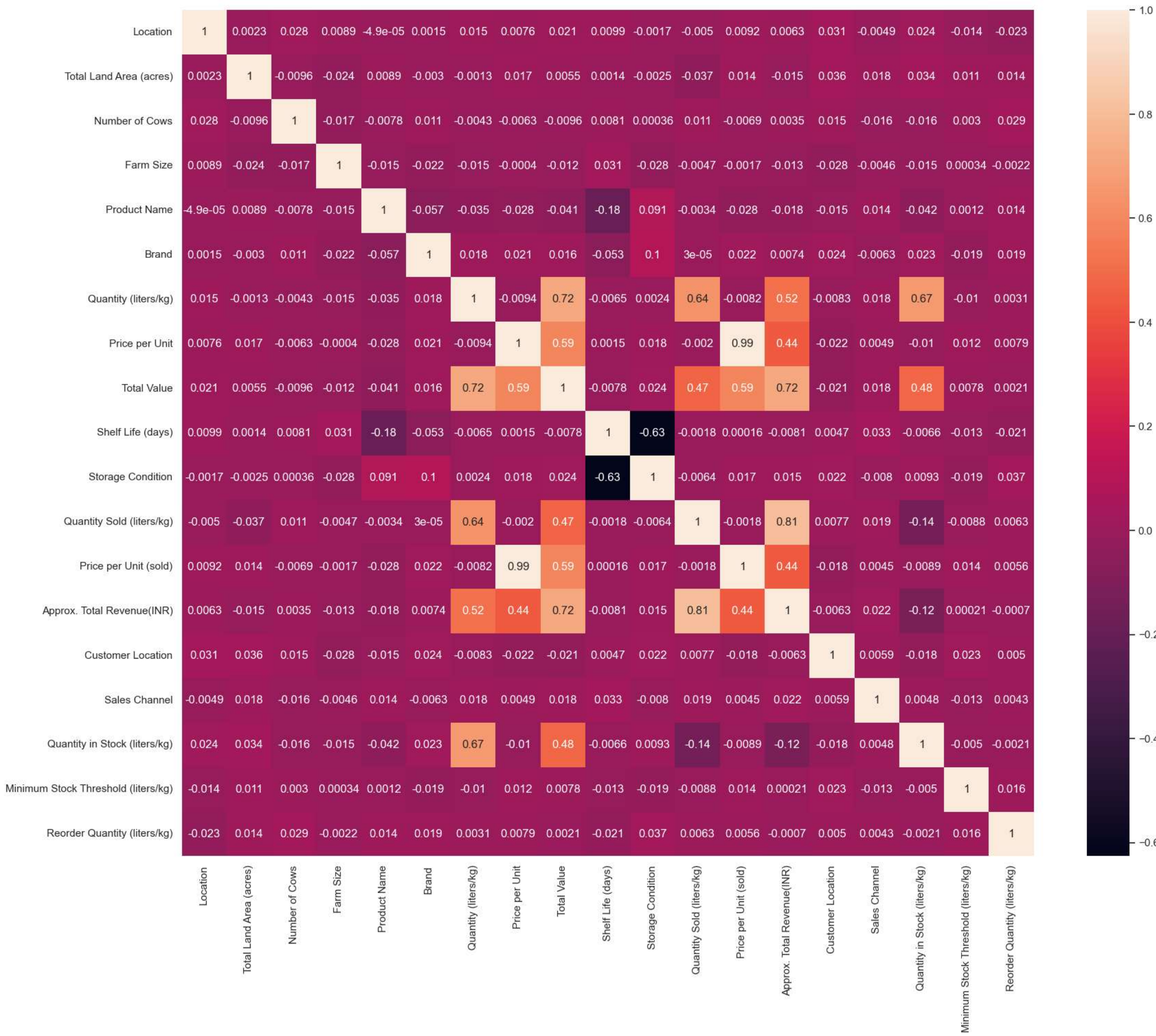
In [23]:
```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
Location: [12 13 11  9  6  0 14  8  1  2  3  7  5 10  4]
Farm Size: [1 0 2]
Product Name: [5 7 9 2 1 3 8 6 4 0]
Brand: [ 2  0  1  4  8  3  9  7 10  5  6]
Storage Condition: [1 4 3 2 0]
Customer Location: [ 8  7 10  5  3  6  4 11 14 12  1  9  2  0 13]
Sales Channel: [2 0 1]
```

Correlation Heatmap

In [24]:
```
#Correlation Heatmap
plt.figure(figsize=(20, 16))
sns.heatmap(df.corr(), fmt='.2g', annot=True)
```

Out[24]: <AxesSubplot:>



Train Test Split

In [25]:
```
from sklearn.model_selection import train_test_split

# Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(df.drop('Reorder Quantity (liters/kg)', axis=1
```

Remove Train Data Outlier Using IQR

In [27]:
```
# Concatenate X_train and y_train for outlier removal
train_df = pd.concat([X_train, y_train], axis=1)

# Calculate the IQR values for each column
Q1 = train_df.quantile(0.25)
Q3 = train_df.quantile(0.75)
IQR = Q3 - Q1

# Remove outliers from X_train
train_df = train_df[~((train_df < (Q1 - 1.5 * IQR)) | (train_df > (Q3 + 1.5 * IQR))).any(axis=1)]

# Separate X_train and y_train after outlier removal
X_train = train_df.drop('Reorder Quantity (liters/kg)', axis=1)
y_train = train_df['Reorder Quantity (liters/kg)']
```

Decision Tree Regressor

In [29]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import load_boston


# Create a DecisionTreeRegressor object
dtree = DecisionTreeRegressor()

# Define the hyperparameters to tune and their values
param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state': [0,42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring='neg_mean_squared_error')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 2, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_s
tate': 42}
```

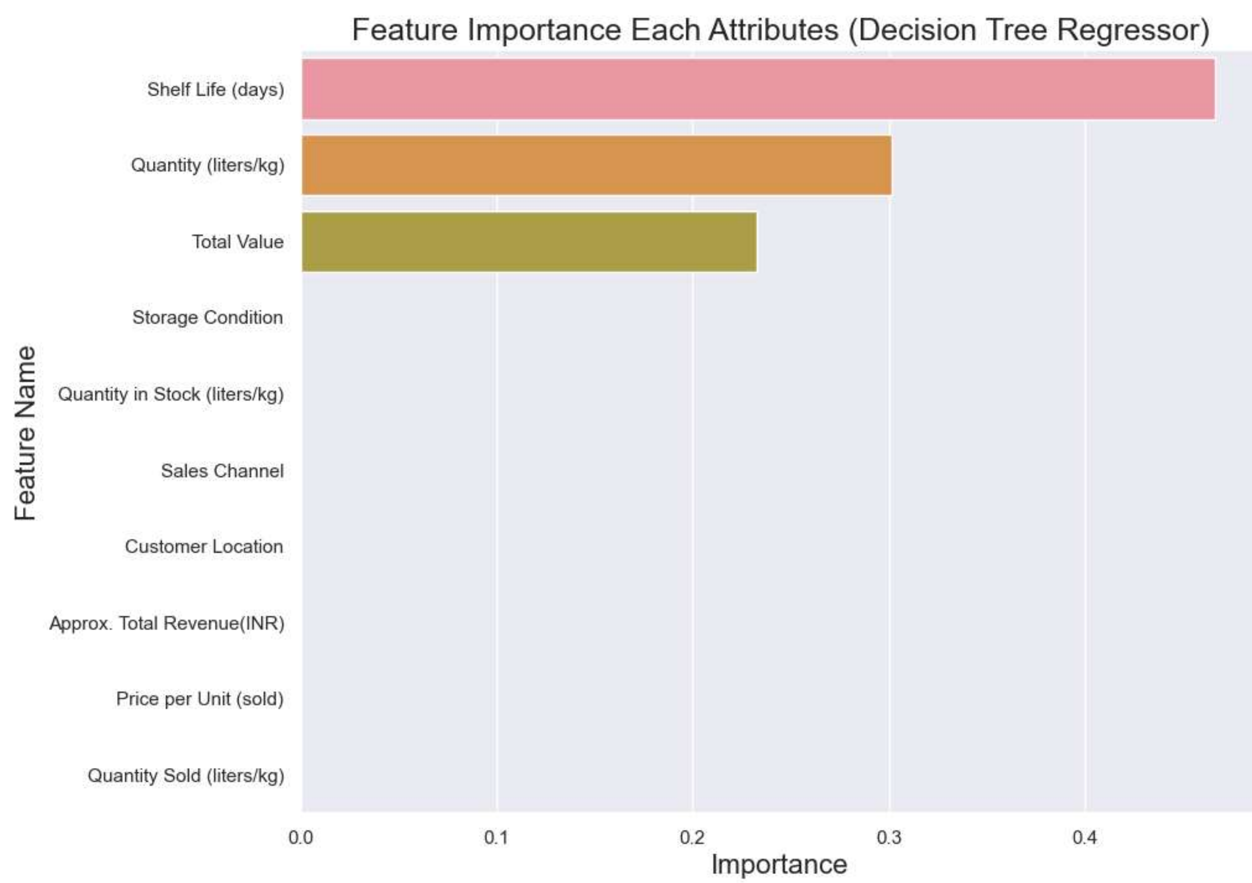
In [30]:
```
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor(random_state=42, max_depth=2, max_features='sqrt', min_samples_leaf=
dtree.fit(X_train, y_train)
```

Out[30]:
```
DecisionTreeRegressor(max_depth=2, max_features='sqrt', random_state=42)
```

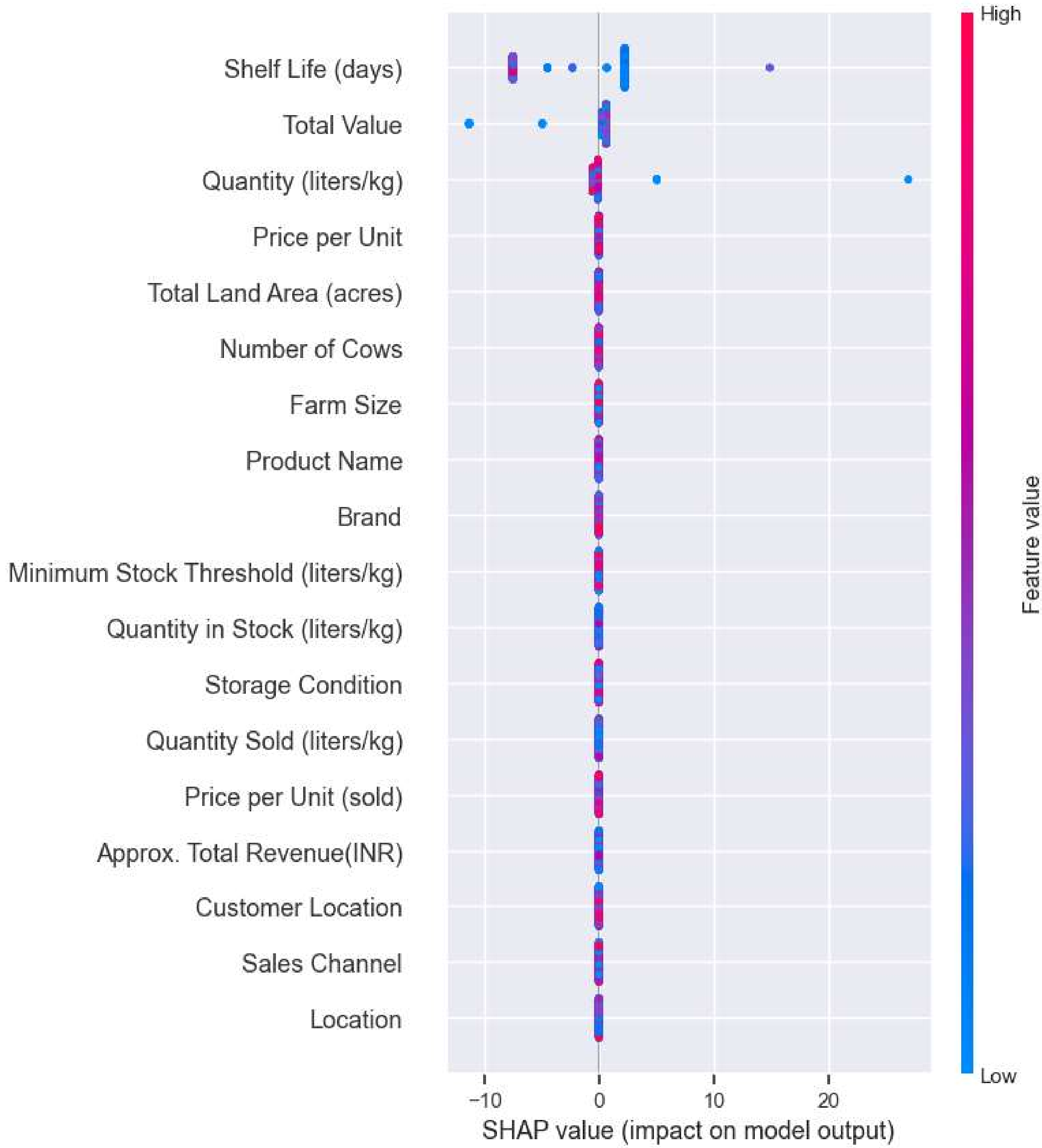
In [31]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = dtree.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 44.96403721244464
MAPE is 0.6818198463108295
MSE is 2714.630434875525
R2 score is -0.010652761493847862
RMSE score is 52.10211545489804
```

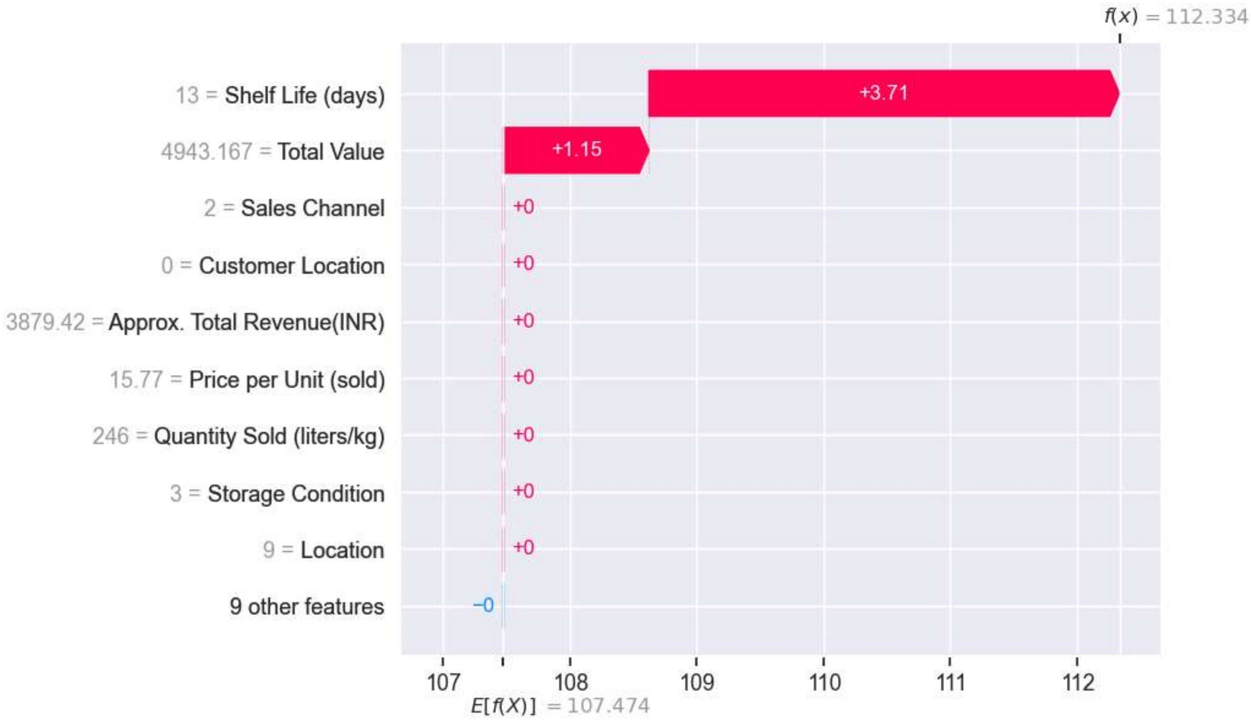
In [32]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Decision Tree Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [33]:
```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [35]:
```
explainer = shap.Explainer(dtree, X_test, check_additivity=False)
shap_values = explainer(X_test, check_additivity=False)
shap.plots.waterfall(shap_values[0])
```



Random Forest Regressor

In [36]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Create a Random Forest Regressor object
rf = RandomForestRegressor()

# Define the hyperparameter grid
param_grid = {
    'max_depth': [3, 5, 7, 9],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'random_state': [0,42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='r2')

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'max_depth': 3, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_sampl
es_split': 2, 'random_state': 0}
```

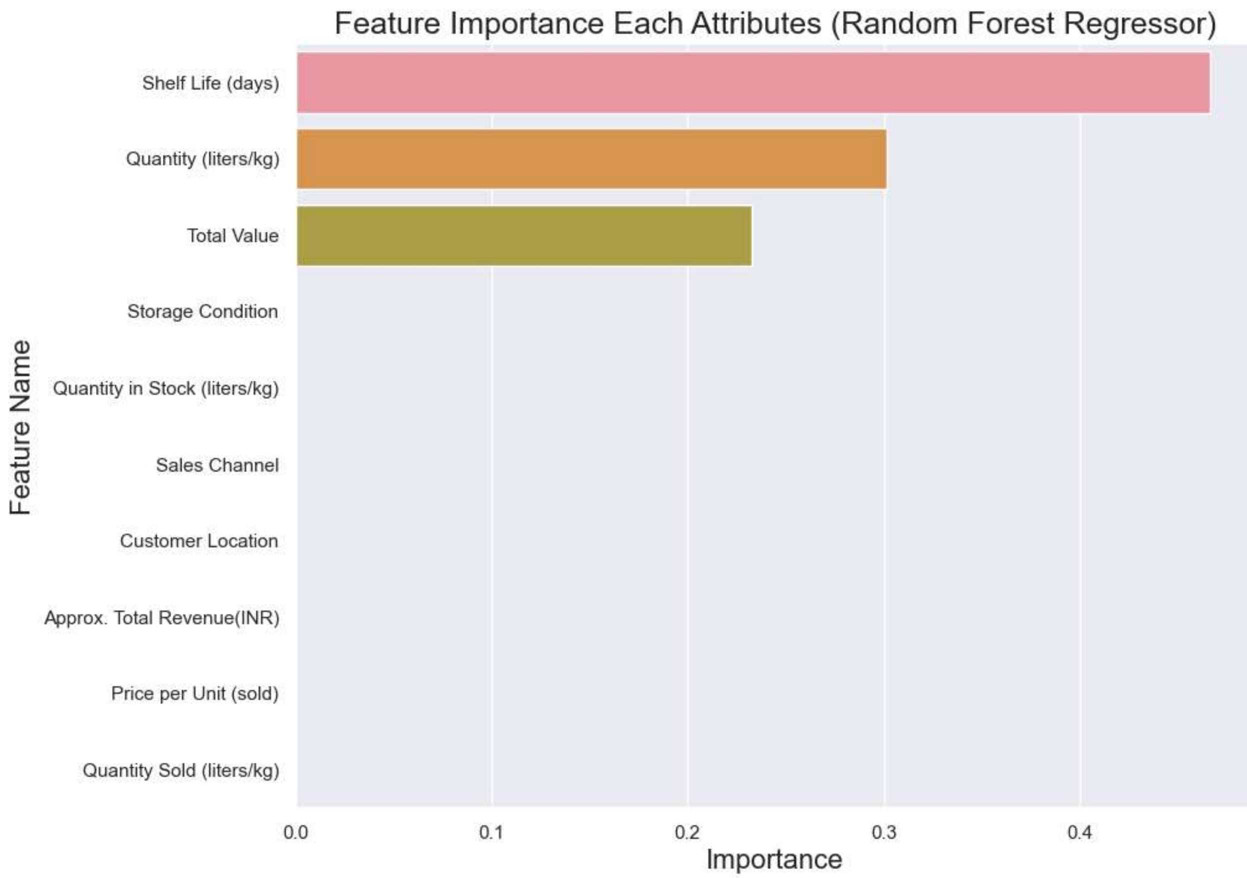
In [37]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state=0, max_depth=3, min_samples_split=2, min_samples_leaf=2,
                           max_features='sqrt')
rf.fit(X_train, y_train)
```

Out[37]:
```
RandomForestRegressor(max_depth=3, max_features='sqrt', min_samples_leaf=2,
                      random_state=0)
```

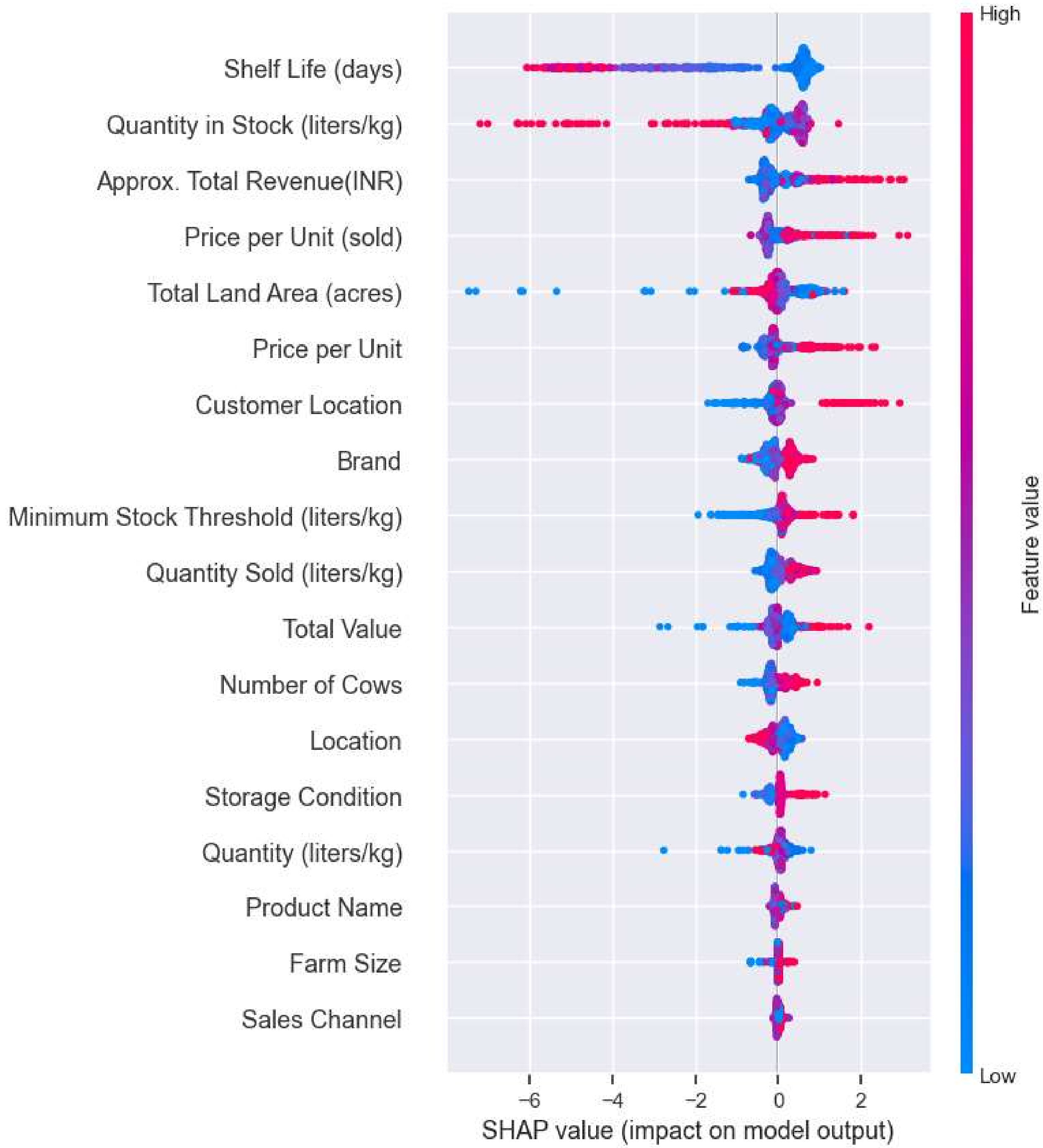
In [38]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = rf.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 44.81831149698112
MAPE is 0.6843108868886055
MSE is 2687.1962997387245
R2 score is -0.0004390749164797647
RMSE score is 51.83817415514096
```

In [39]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Random Forest Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [40]:
```
import shap
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [41]:
```
explainer = shap.Explainer(rf, X_test, check_additivity=False)
shap_values = explainer(X_test, check_additivity=False)
shap.plots.waterfall(shap_values[0])
```