VeggieVista

May 20, 2024

1 VeggieVista- Vegetable Store Sales Analysis Project

2 Introduction

This report presents the findings of an exploratory data analysis (EDA) on the vegetable store's sales dataset over a three-month period. The analysis answers several key questions to uncover insights into the store's operations, profitability, and sales dynamics.

2.0.1 Importing libraries

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as st
import statsmodels.api as sm
import seaborn as sns
from scipy.stats import pearsonr
import warnings
warnings.filterwarnings('ignore')
```

2.0.2 Loading Dataset

[2]:
```
df = pd.read_csv('Desktop/VeggieVista.csv')
```

[3]:
```
df
```

[3]:

	DATE	PRODUCT_NAME	BUYING_RATE(per kg)	QUANTITY(kgs)	\
0	2023-01-01	Tomato	70	1000	
1	2023-01-02	Tomato	70	1000	
2	2023-01-03	Tomato	70	1000	
3	2023-01-04	Tomato	70	200	
4	2023-01-05	Tomato	70	300	
..	…	…	…	…	
568	2023-02-20	Cucumber	40	1000	
569	2023-02-21	Cucumber	50	1000	
570	2023-02-22	Cucumber	50	1000	
571	2023-02-23	Cucumber	50	1000	
572	2023-02-24	Cucumber	50	1000	

```
     SELLING_PRICE(per kg)  SOLD_QUANTITY  TOTAL_SALES(Current day)  \
0                       90            700                     63000
1                       90            900                     81000
2                       90            600                     54000
3                       90            200                     18000
4                      100            300                     30000
..                     …              …                       …
568                     60           1000                     60000
569                     60           1000                     60000
570                     60           1000                     60000
571                     70           1000                     70000
572                     70            700                     49000

    FRESHNESS_DURATION  REMAINING_QUANTITY_CURR  TOTAL_AVAILABLE_QUANTITY  \
0            2-3 days                     300                      1000
1            2-3 days                     100                      1300
2            2-3 days                     400                      1100
3            2-3 days                       0                       600
4            2-3 days                       0                       300
..                …                       …                         …
568          2-3 days                       0                      1200
569          2-3 days                       0                      1000
570          2-3 days                       0                      1000
571          2-3 days                       0                      1000
572          2-3 days                     300                      1000

     RQ_SELLING_PRICE  RQ_SOLD_QUANTITY  RQ_TOTAL_SALE(D-2)  \
0                   0                 0                   0
1                  90               300               27000
2                  90               100                9000
3                  80               400               32000
4                   0                 0                   0
..                …                 …                 …
568                50               200               10000
569                 0                 0                   0
570                 0                 0                   0
571                 0                 0                   0
572                 0                 0                   0

     REMAINING_WASTE_QUANTITY  QUANTITY_WASTE_PRICE  PROFIT_LOSS_TOTAL
0                           0                     0              63000
1                           0                     0             108000
2                           0                     0              63000
3                           0                     0              50000
4                           0                     0              30000
..                        …                     …                …
```

```
568                    0                    0                70000
569                    0                    0                60000
570                    0                    0                60000
571                    0                    0                70000
572                    0                    0                49000

[573 rows x 16 columns]
```

2.0.3 Basic Information

[15]:
```
df.info() # To gain an initial understanding of the dataset, including the␣
 ↪number of entries, column names,
          # data types, and the presence of any missing values, we use the df.
 ↪info() function.
          # This step is crucial for identifying potential issues in the␣
 ↪dataset that need
          # to be addressed during the data cleaning process.
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 360 entries, 0 to 359
Data columns (total 16 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   DATE                      360 non-null    datetime64[ns]
 1   PRODUCT_NAME              360 non-null    category
 2   BUYING_RATE(per kg)       360 non-null    int64
 3   QUANTITY(kgs)             360 non-null    int64
 4   SELLING_PRICE(per kg)     360 non-null    int64
 5   SOLD_QUANTITY             360 non-null    int64
 6   TOTAL_SALES(Current day)  360 non-null    int64
 7   FRESHNESS_DURATION        360 non-null    object
 8   REMAINING_QUANTITY_CURR   360 non-null    int64
 9   TOTAL_AVAILABLE_QUANTITY  360 non-null    int64
 10  RQ_SELLING_PRICE          360 non-null    int64
 11  RQ_SOLD_QUANTITY          360 non-null    int64
 12  RQ_TOTAL_SALE(D-2)        360 non-null    int64
 13  REMAINING_WASTE_QUANTITY  360 non-null    int64
 14  QUANTITY_WASTE_PRICE      360 non-null    int64
 15  PROFIT_LOSS_TOTAL         360 non-null    int64
dtypes: category(1), datetime64[ns](1), int64(13), object(1)
memory usage: 45.6+ KB
```

[17]:
```
df.shape # To understand the dimensions of the dataset, including the number of␣
 ↪rows and columns,
         # we use the df.shape attribute. This step is important for getting a␣
 ↪quick overview of the dataset size
```

```
        # and structure before diving deeper into the data cleaning and␣
↪analysis process.
```

[17]:
```
(360, 16)
```

[18]:
```
df.describe()  #df.describe() is a pandas DataFrame method that generates␣
↪descriptive statistics of the DataFrame's
               #numerical columns. It provides information such as count, mean,␣
↪standard deviation, minimum,
               #25th percentile, 50th percentile (median), 75th percentile, and␣
↪maximum values.
               #This function is useful for quickly understanding the␣
↪distribution and summary statistics of the data
               #in a DataFrame.
```

[18]:

	DATE	BUYING_RATE(per kg)	QUANTITY(kgs)	\
count	360	360.000000	360.000000	
mean	2023-02-14 12:00:00	84.111111	711.166667	
min	2023-01-01 00:00:00	0.000000	0.000000	
25%	2023-01-23 00:00:00	40.000000	80.000000	
50%	2023-02-14 12:00:00	50.000000	500.000000	
75%	2023-03-09 00:00:00	130.000000	1200.000000	
max	2023-03-31 00:00:00	250.000000	2200.000000	
std	NaN	63.454753	687.787843	

	SELLING_PRICE(per kg)	SOLD_QUANTITY	TOTAL_SALES(Current day)	\
count	360.000000	360.000000	360.000000	
mean	101.180556	649.138889	39414.444444	
min	0.000000	0.000000	0.000000	
25%	50.000000	80.000000	12000.000000	
50%	70.000000	400.000000	30750.000000	
75%	150.000000	1000.000000	63000.000000	
max	280.000000	2000.000000	120000.000000	
std	68.162784	645.915327	31080.314861	

	REMAINING_QUANTITY_CURR	TOTAL_AVAILABLE_QUANTITY	RQ_SELLING_PRICE	\
count	360.000000	360.000000	360.000000	
mean	62.027778	763.666667	12.625000	
min	0.000000	0.000000	0.000000	
25%	0.000000	95.000000	0.000000	
50%	0.000000	500.000000	0.000000	
75%	100.000000	1400.000000	0.000000	
max	1000.000000	2500.000000	140.000000	
std	122.163183	739.572563	26.939754	

	RQ_SOLD_QUANTITY	RQ_TOTAL_SALE(D-2)	REMAINING_WASTE_QUANTITY	\
count	360.000000	360.000000	360.000000	

```
mean          39.027778         1891.944444                23.000000
min            0.000000            0.000000                 0.000000
25%            0.000000            0.000000                 0.000000
50%            0.000000            0.000000                 0.000000
75%            0.000000            0.000000                 5.250000
max          500.000000        32000.000000               700.000000
std           86.890090         4563.635981                72.173769

       QUANTITY_WASTE_PRICE  PROFIT_LOSS_TOTAL
count            360.000000         360.000000
mean            1507.777778       39798.611111
min                0.000000      -10000.000000
25%                0.000000       10900.000000
50%                0.000000       34000.000000
75%              670.000000       68500.000000
max            70000.000000      124000.000000
std             4910.506904       33056.494939
```

2.1 Data Cleaning (Handle missing values and data types.)

2.1.1 Removing Duplicates

[6]:
```
df[df.duplicated()]  # To ensure data integrity, we need to identify and review␣
↪any duplicate rows in the dataset.
                     # Duplicate rows can lead to biased results and inaccurate␣
↪insights.
```

[6]:
```
           DATE PRODUCT_NAME  BUYING_RATE(per kg)  QUANTITY(kgs)  \
360  2023-01-12         Peas                   40              0
361  2023-01-13         Peas                   40            400
362  2023-01-14         Peas                   40            600
363  2023-01-15         Peas                   40            600
364  2023-01-16         Peas                   40            600
..          …           …                    …            …
568  2023-02-20     Cucumber                   40           1000
569  2023-02-21     Cucumber                   50           1000
570  2023-02-22     Cucumber                   50           1000
571  2023-02-23     Cucumber                   50           1000
572  2023-02-24     Cucumber                   50           1000

     SELLING_PRICE(per kg)  SOLD_QUANTITY  TOTAL_SALES(Current day)  \
360                      0              0                         0
361                     60            400                     24000
362                     60            600                     36000
363                     60            500                     30000
364                     60            600                     36000
..                     …             …                         …
```

```
568                    60           1000                    60000
569                    60           1000                    60000
570                    60           1000                    60000
571                    70           1000                    70000
572                    70            700                    49000

    FRESHNESS_DURATION  REMAINING_QUANTITY_CURR  TOTAL_AVAILABLE_QUANTITY  \
360         8-10 hours                       0                         0
361         8-10 hours                       0                       400
362         8-10 hours                       0                       600
363         8-10 hours                     100                       600
364         8-10 hours                       0                       600
..                 …                      …                         …
568           2-3 days                       0                      1200
569           2-3 days                       0                      1000
570           2-3 days                       0                      1000
571           2-3 days                       0                      1000
572           2-3 days                     300                      1000

     RQ_SELLING_PRICE  RQ_SOLD_QUANTITY  RQ_TOTAL_SALE(D-2)  \
360                 0                 0                   0
361                 0                 0                   0
362                 0                 0                   0
363                 0                 0                   0
364                 0                 0                   0
..                …                 …                   …
568                50               200               10000
569                 0                 0                   0
570                 0                 0                   0
571                 0                 0                   0
572                 0                 0                   0

     REMAINING_WASTE_QUANTITY  QUANTITY_WASTE_PRICE  PROFIT_LOSS_TOTAL
360                         0                     0                  0
361                         0                     0              24000
362                         0                     0              36000
363                       100                  4000              26000
364                         0                     0              36000
..                        …                     …                  …
568                         0                     0              70000
569                         0                     0              60000
570                         0                     0              60000
571                         0                     0              70000
572                         0                     0              49000

[213 rows x 16 columns]
```

[7]:
```
df.drop_duplicates(inplace=True)  #  step is used to remove duplicate rows from a DataFrame.
                                  #  By using drop_duplicates, you ensure that each row in your DataFrame is unique,
                                  #  which is often necessary for data analysis and modeling tasks.
```

[8]:
```
df.shape
```

[8]:
```
(360, 16)
```

[9]:
```
df['PRODUCT_NAME'].value_counts()
```

[9]:
```
PRODUCT_NAME
Tomato      90
Cucumber    90
Peas        90
Spinach     90
Name: count, dtype: int64
```

2.1.2 Convert columns to appropriate data types

[10]:
```
df['DATE']= pd.to_datetime(df['DATE'])
df['PRODUCT_NAME'] = df['PRODUCT_NAME'].astype('category')
```

2.1.3 Check for missing values

[12]:
```
df.isnull().sum()
```

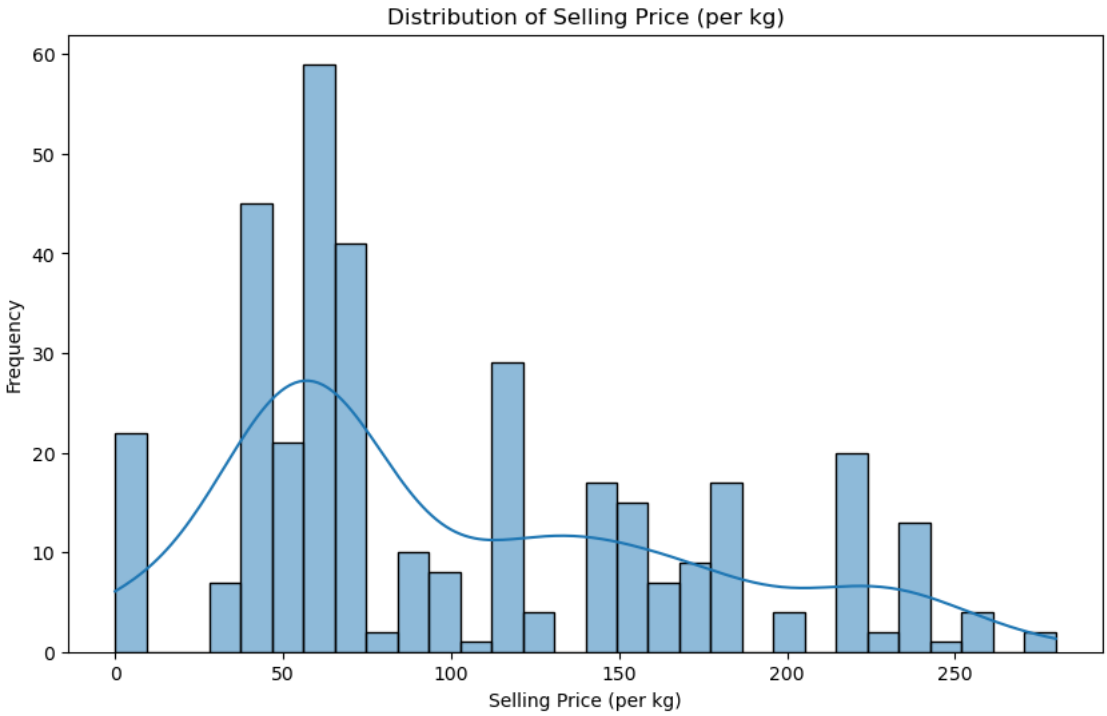
[12]:
```
DATE                        0
PRODUCT_NAME                0
BUYING_RATE(per kg)         0
QUANTITY(kgs)               0
SELLING_PRICE(per kg)       0
SOLD_QUANTITY               0
TOTAL_SALES(Current day)    0
FRESHNESS_DURATION          0
REMAINING_QUANTITY_CURR     0
TOTAL_AVAILABLE_QUANTITY    0
RQ_SELLING_PRICE            0
RQ_SOLD_QUANTITY            0
RQ_TOTAL_SALE(D-2)          0
REMAINING_WASTE_QUANTITY    0
QUANTITY_WASTE_PRICE        0
PROFIT_LOSS_TOTAL           0
dtype: int64
```

Exploratory Analysis

2.1.4 Univariate Analysis - Analyze individual columns to understand their distributions.

2.1.5 i. Distribution of Selling Price

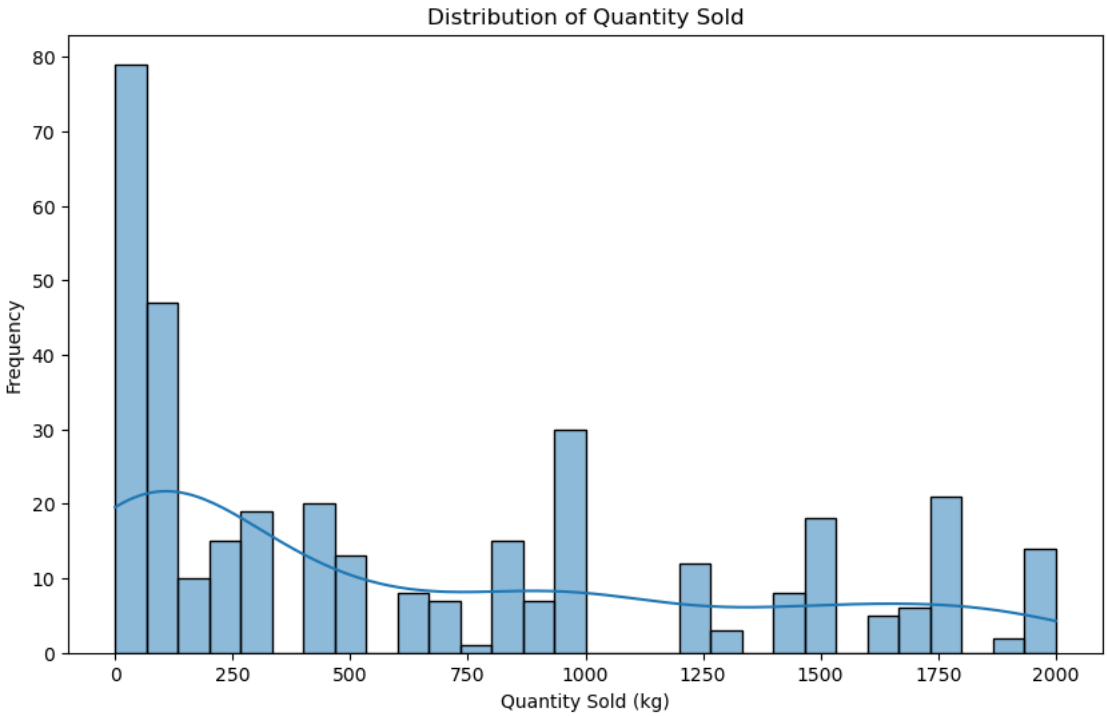
[44]:



2.1.6 ii. Distribution of Quantity Sold

[22]:

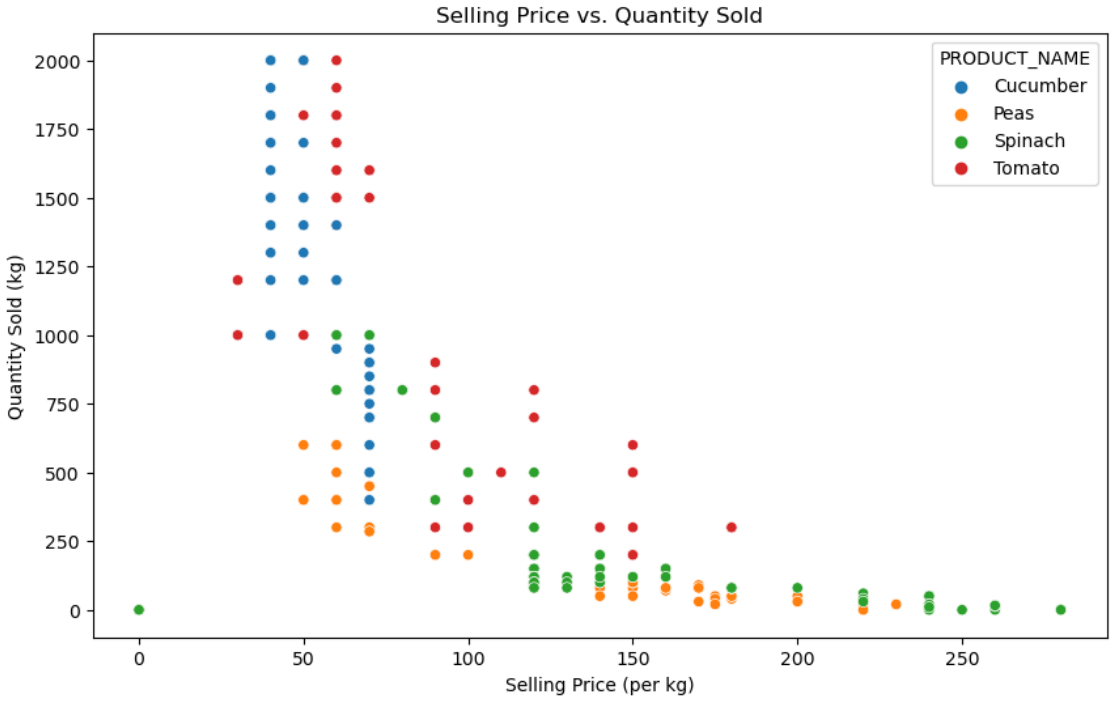
```
plt.figure(figsize=(10, 6))
sns.histplot(df['SOLD_QUANTITY'], bins=30, kde=True)
plt.title('Distribution of Quantity Sold')
plt.xlabel('Quantity Sold (kg)')
plt.ylabel('Frequency')
plt.show()
```



2.2 Bivariate Analysis - Analyze relationships between pairs of columns.

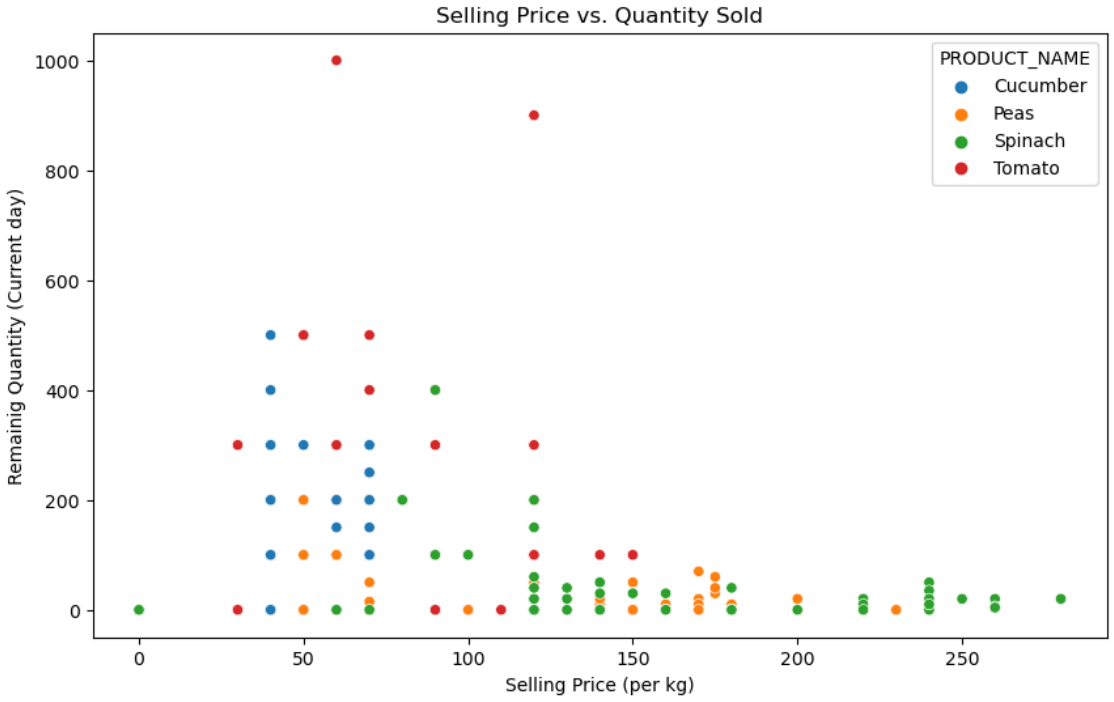
2.2.1 i. Relationship between Selling Price and Quantity Sold

[23]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='SELLING_PRICE(per kg)', y='SOLD_QUANTITY',␣
↪hue='PRODUCT_NAME', data=df)
plt.title('Selling Price vs. Quantity Sold')
plt.xlabel('Selling Price (per kg)')
plt.ylabel('Quantity Sold (kg)')
plt.show()
```



2.2.2 ii Relationship between Selling Price and Remaining Quantity

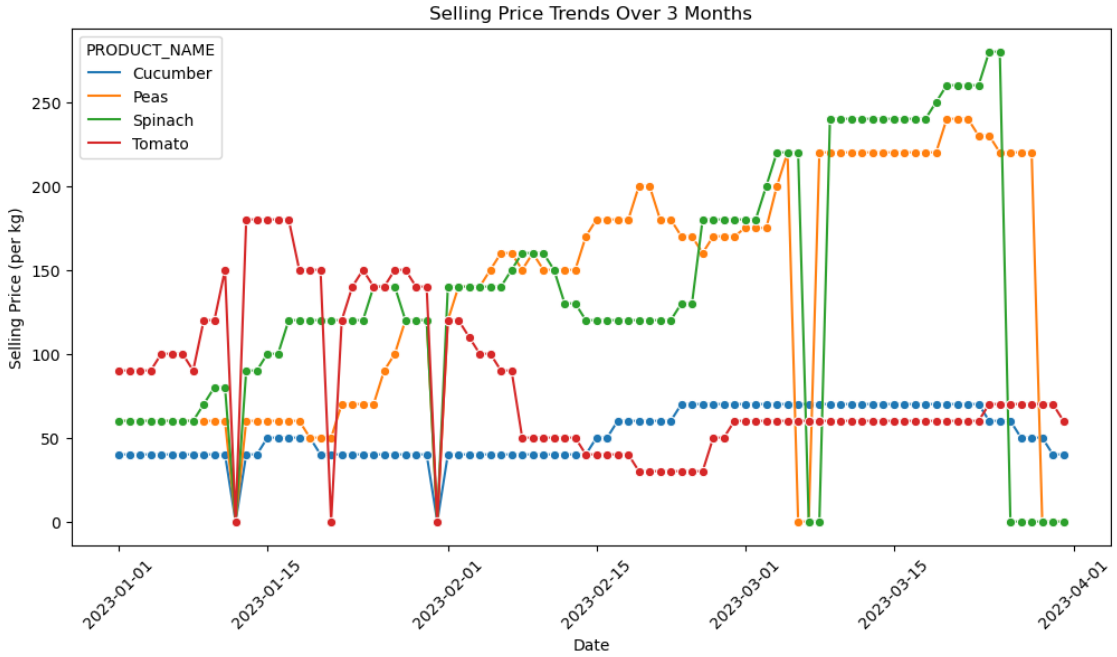
[46]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='SELLING_PRICE(per kg)', y='REMAINING_QUANTITY_CURR',␣
↪hue='PRODUCT_NAME', data=df)
plt.title('Selling Price vs. Quantity Sold')
plt.xlabel('Selling Price (per kg)')
plt.ylabel('Remainig Quantity (Current day)')
plt.show()
```



3 Time Series Analysis - Analyze trends over time.

3.1 i) Selling Price Trends Over 3 Months for each vegetables

[47]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(data=df, x='DATE', y='SELLING_PRICE(per kg)', hue='PRODUCT_NAME',␣
 ↪marker='o')
plt.title('Selling Price Trends Over 3 Months')
plt.xlabel('Date')
plt.ylabel('Selling Price (per kg)')
plt.xticks(rotation=45)
plt.show()
```



3.2 Avegrage selling price for each vegetable in months

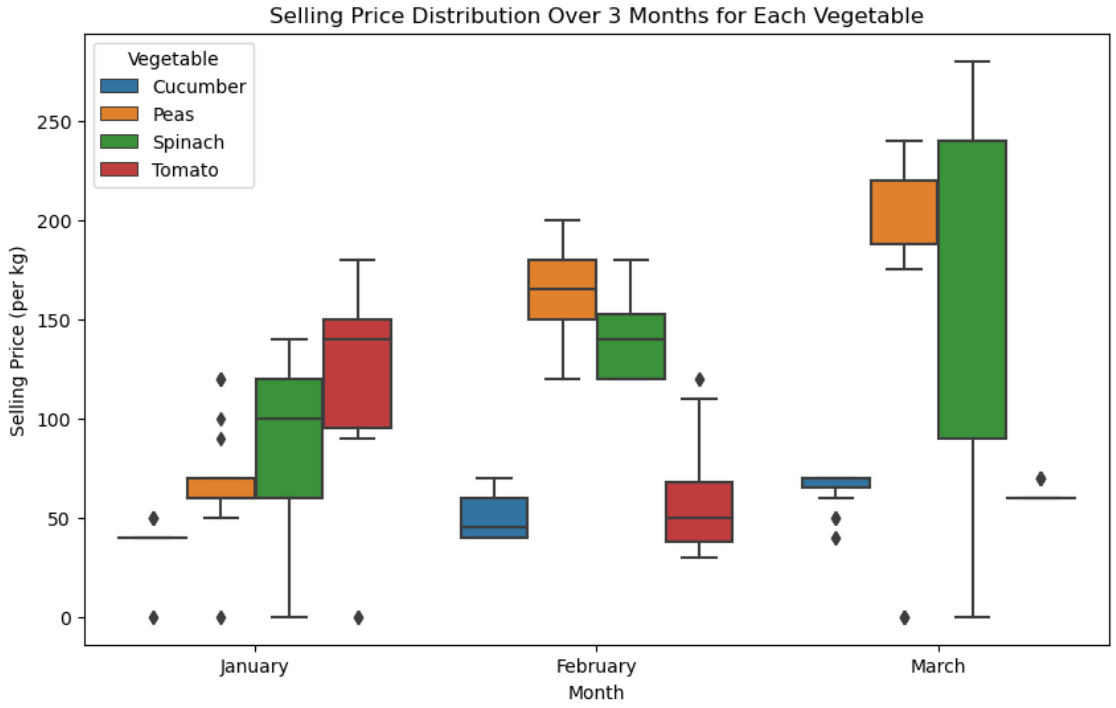
3.2.1 Create a new column 'month' to extract the month from the 'date' column

[58]:
```
df['MONTH'] = df['DATE'].dt.month
```

[61]:
```
month_map = {1:'January', 2:'February', 3:'March'}
```

[62]:
```
df['MONTH']= df['MONTH'].map(month_map)
```

[68]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df, x='MONTH', y='SELLING_PRICE(per kg)', hue='PRODUCT_NAME')
plt.title('Selling Price Distribution Over 3 Months for Each Vegetable')
plt.xlabel('Month')
plt.ylabel('Selling Price (per kg)')
plt.legend(title='Vegetable')
plt.show()
```



3.3 ii) Profit percentage for each vegetable

3.3.1 Create a new column 'Invested_amount' to calculate total invested_amount for each vegetable per day

[71]:
```
df['INVESTED_AMOUNT'] = df['BUYING_RATE(per kg)']*df['QUANTITY(kgs)']
```

Invested amount for each vegetable

[73]:
```
df.groupby('PRODUCT_NAME')['INVESTED_AMOUNT'].sum().reset_index()
```

[73]:

	PRODUCT_NAME	INVESTED_AMOUNT
0	Cucumber	3654000
1	Peas	962200
2	Spinach	1564200
3	Tomato	4656000

Toral amount for each vegetable after sales

[74]:
```
df.groupby('PRODUCT_NAME')['PROFIT_LOSS_TOTAL'].sum().reset_index()
```

[74]:

	PRODUCT_NAME	PROFIT_LOSS_TOTAL
0	Cucumber	5775700
1	Peas	1006800
2	Spinach	1599500
3	Tomato	5945500

Create a new column 'Profit/Loss_Per_Day' to calculate profit or loss for each vegetable per day

[76]:
```
df['PROFIT/LOSS_PER_DAY'] = df['PROFIT_LOSS_TOTAL']-df['INVESTED_AMOUNT']
```

Profit for each vegetable

[78]:
```
df.groupby('PRODUCT_NAME')['PROFIT/LOSS_PER_DAY'].sum().reset_index()
```

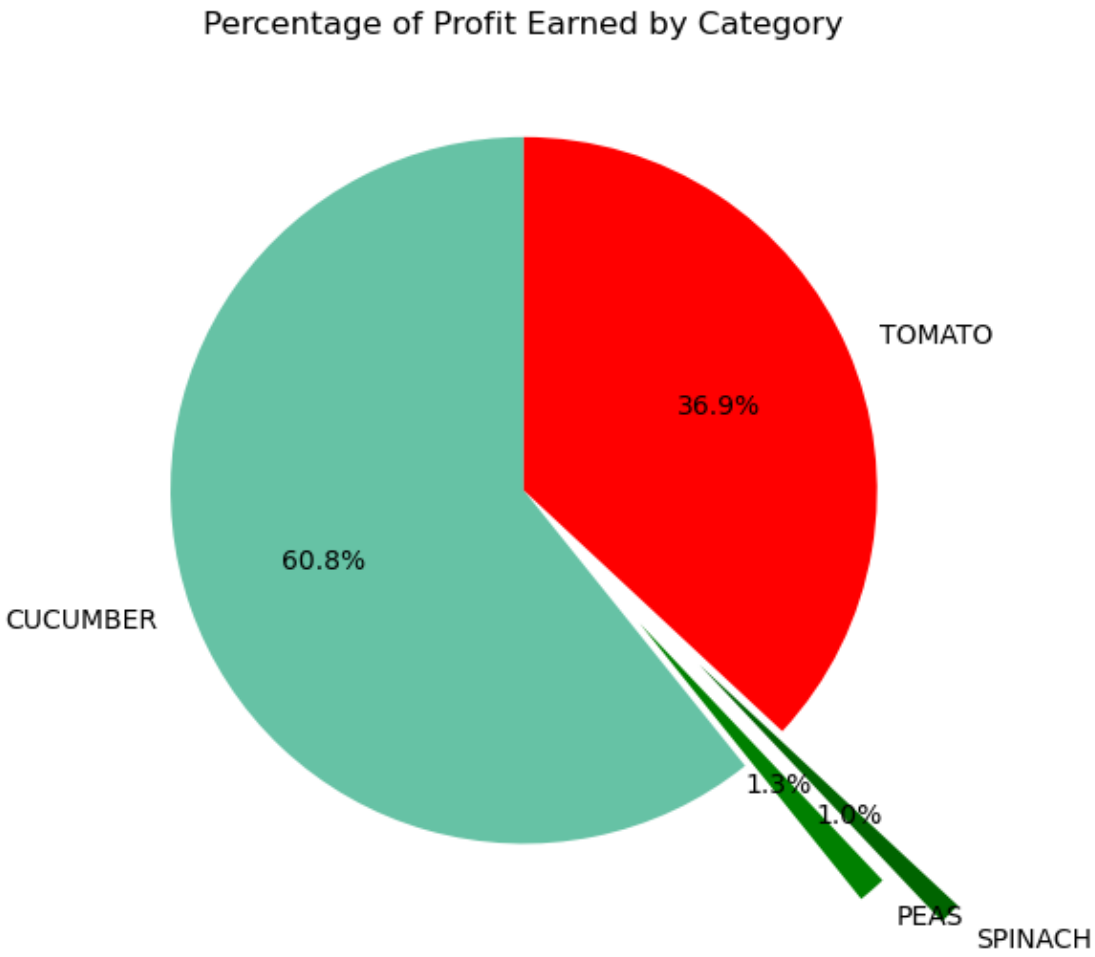
[78]:

	PRODUCT_NAME	PROFIT/LOSS_PER_DAY
0	Cucumber	2121700
1	Peas	44600
2	Spinach	35300
3	Tomato	1289500

3.3.2 Percentage of Profit Earned by each vegetable

[79]:
```
Profit_by_category = df.groupby('PRODUCT_NAME')['PROFIT/LOSS_PER_DAY'].sum()
```

[83]:
```
plt.figure(figsize=(10, 6))
plt.pie(Profit_by_category,␣
 ↪labels=['CUCUMBER','PEAS','SPINACH','TOMATO'],autopct='%1.1f%%',
       startangle=90,explode=(0,0.5,0.7,0),colors = ['#66c2a5', 'Green',␣
 ↪'darkgreen', 'red'])
plt.title('Percentage of Profit Earned by Category')
plt.show()
```



3.4 iii) Monthly Profit/Loss for each vegetable

Calculating monthly profit/loss for each vegetable per month

[84]:
```
monthly_profit = df.groupby(['PRODUCT_NAME','MONTH'])['PROFIT/LOSS_PER_DAY'].
↪sum().reset_index()
```

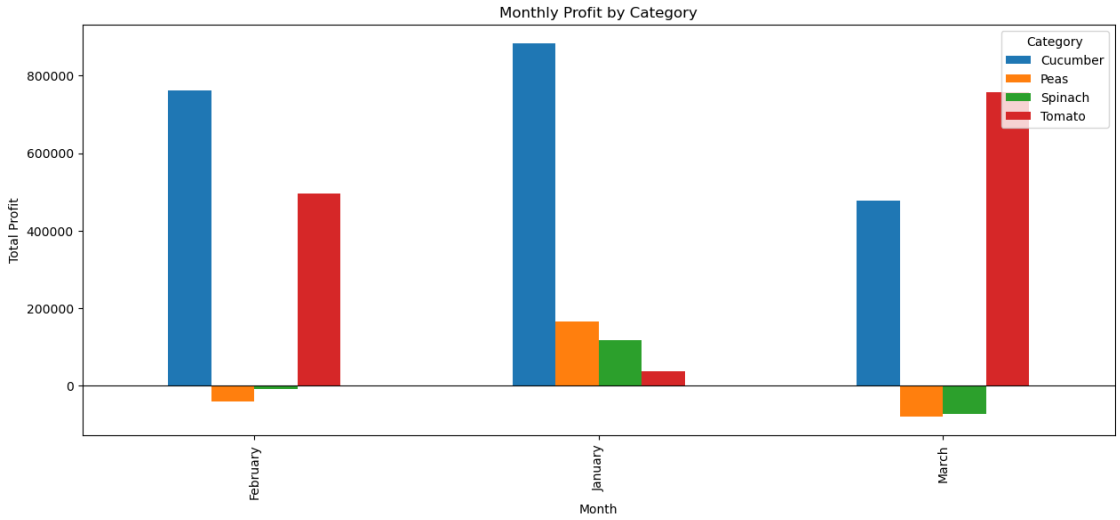
[86]:
```
pivot_table = monthly_profit.pivot(index='MONTH', columns='PRODUCT_NAME',␣
↪values='PROFIT/LOSS_PER_DAY')
pivot_table
```

[86]:

PRODUCT_NAME	Cucumber	Peas	Spinach	Tomato
MONTH				
February	761200	-41000	-9400	496000
January	883350	165050	116800	37000
March	477150	-79450	-72100	756500

3.4.1 Monthly Profit/Loss for each vegetable per month

[93]:
```
pivot_table.plot(kind='bar', figsize=(15 ,6))
plt.title('Monthly Profit by Category')
plt.xlabel('Month')
plt.ylabel('Total Profit')
plt.legend(title='Category')
plt.axhline(0, color='black', linewidth=0.8)  # Add a horizontal line at y=0
plt.show()
```



3.4.2 Calculating Average Remaining quantity of vegetable per month

[94]:
```
avg_remaining = df.groupby(['PRODUCT_NAME','MONTH'])['REMAINING_QUANTITY_CURR'].
↪mean().reset_index()
```

[95]:
```
avg_remaining
```

[95]:

	PRODUCT_NAME	MONTH	REMAINING_QUANTITY_CURR
0	Cucumber	February	117.857143
1	Cucumber	January	54.838710
2	Cucumber	March	109.677419
3	Peas	February	10.714286
4	Peas	January	23.064516
5	Peas	March	8.548387
6	Spinach	February	12.500000
7	Spinach	January	50.322581
8	Spinach	March	7.741935
9	Tomato	February	100.000000
10	Tomato	January	93.548387

```
11        Tomato      March                154.838710
```

Inventory Trends:

Cucumber: The remaining quantity increased from January to February but decreased slightly in March.

Peas: The remaining quantity decreased from January to February and then decreased further in March.

Spinach: The remaining quantity decreased from January to February and decreased again in March.

Tomato: The remaining quantity increased from January to February and increased further in March, showing a positive trend.¶

3.4.3 Calculating Sold quantity of vegetable per month

[106]:
```
avg_sold = df.groupby(['PRODUCT_NAME','MONTH'])['SOLD_QUANTITY'].sum().
↪reset_index()
```

[107]:
```
avg_sold
```

[107]:

	PRODUCT_NAME	MONTH	SOLD_QUANTITY
0	Cucumber	February	38000
1	Cucumber	January	45600
2	Cucumber	March	29300
3	Peas	February	1920
4	Peas	January	11085
5	Peas	March	545
6	Spinach	February	3220
7	Spinach	January	14940
8	Spinach	March	680
9	Tomato	February	32700
10	Tomato	January	10100
11	Tomato	March	45600

Sales Trends by Month:

Cucumber: Highest sales in January, followed by February and then March.

Peas: Highest sales in January, significantly lower sales in February, and the lowest sales in March.

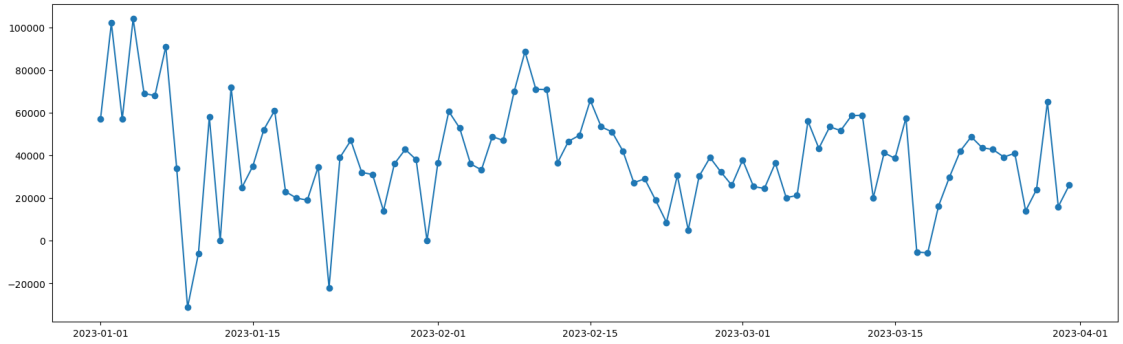
Spinach: Highest sales in January, followed by February and then March.

Tomato: Highest sales in March, followed by February and then January.

3.5 Calculating profit per day

[97]:
```
daily_profit = df.groupby('DATE')['PROFIT/LOSS_PER_DAY'].sum().reset_index()
```

[99]:
```
plt.figure(figsize=(20,6))
plt.plot(daily_profit['DATE'], daily_profit['PROFIT/LOSS_PER_DAY'], marker='o',␣
↪linestyle='-')
plt.show()
```



3.6 Correlation Between Selling Price and Remaining Quantity for Current Day

[100]:
```
corr = pearsonr(df['SELLING_PRICE(per kg)'],df['REMAINING_QUANTITY_CURR'])
corr
```

[100]:
```
PearsonRResult(statistic=-0.2064509734077289, pvalue=7.943396594275751e-05)
```

Negative Relationship: The negative sign indicates that as one variable (selling price per kilogram) increases, the other variable (remaining quantity) tends to decrease slightly.

Strength of the Relationship: The correlation coefficient of -0.206 suggests a weak relationship. This means that while there is a tendency for the remaining quantity to decrease as the selling price per kilogram increases, the relationship is not very strong or consistent.

Statistical Significance: The p-value of approximately 7.94e-05 indicates that this weak negative correlation is unlikely to be due to random chance. It suggests that there may be a true but weak relationship between the selling price per kilogram and the remaining quantity of the products.

3.7 Correlation Between Buying Price and Buying Quantity for Current Day

[101]:
```
corr_2 = pearsonr(df['BUYING_RATE(per kg)'],df['QUANTITY(kgs)'])
corr_2
```

[101]:
```
PearsonRResult(statistic=-0.6827762294722514, pvalue=9.822693847161112e-51)
```

Inverse Relationship: The negative correlation coefficient (-0.680) suggests that as the buying rate per kilogram increases, the quantity purchased tends to decrease. Conversely, as the buying rate per kilogram decreases, the quantity purchased tends to increase.

Magnitude of the Relationship: The correlation coefficient being relatively close to -1 (-1 indicates a perfect negative correlation) indicates that the relationship is strong. This suggests that changes in the buying rate per kilogram are highly associated with changes in the quantity purchased.

Statistical Significance: The very low p-value (approximately 3.46e-50) indicates that this relationship is highly unlikely to be due to random chance. This suggests that the relationship between the buying rate per kilogram and the quantity purchased is a real and significant one.

Business Implications:

Pricing Strategy: Businesses can use this information to adjust their pricing strategies. For example, if they want to sell more quantity, they might consider reducing the buying rate per kilogram. Inventory Management: Understanding this relationship can help businesses manage their inventory more effectively, as changes in buying rate per kilogram may have a predictable impact on the quantity purchased.

3.8 Correlation Between Selling Price and Sold Quantity for Current Day

[102]:
```
corr_3 = pearsonr(df['SELLING_PRICE(per kg)'],df['SOLD_QUANTITY'])
corr_3
```

[102]:
```
PearsonRResult(statistic=-0.5982402016343884, pvalue=2.5562771394474185e-36)
```

Inverse Relationship: The negative correlation coefficient (-0.598) suggests that as the selling price per kilogram increases, the quantity sold tends to decrease. Conversely, as the selling price per kilogram decreases, the quantity sold tends to increase.

Magnitude of the Relationship: The correlation coefficient being relatively close to -1 (-1 indicates a perfect negative correlation) indicates that the relationship is moderately strong. This suggests that changes in the selling price per kilogram are associated with noticeable changes in the quantity sold.

Statistical Significance: The very low p-value (approximately 2.56e-36) indicates that this relationship is highly unlikely to be due to random chance. This suggests that the relationship between the selling price per kilogram and the quantity sold is a real and significant one.

Business Implications:

Pricing Strategy: Businesses can use this information to adjust their pricing strategies. For example, if they want to increase sales volume, they might consider reducing the selling price per kilogram.

Revenue Optimization: Understanding this relationship can help businesses optimize their revenue by balancing price and quantity sold.

4 Report and Insights

The analysis of the sales data revealed several trends and insights that can help in understanding the market dynamics and optimizing business strategies. Here is a brief description of the key trends and insights gathered:

Seasonal Variation: Different vegetables exhibited distinct seasonal sales patterns. For example, Cucumber and Spinach showed peak sales in January, while Peas and Tomato had different peak months (January for Peas and March for Tomato). Understanding these seasonal variations can help businesses plan their production and inventory management accordingly.

Price-Quantity Relationship:

Selling Price vs. Remaining Quantity: A weak negative correlation was observed, indicating that as the selling price per kilogram increased, the remaining quantity tended to decrease slightly.

Buying Rate vs. Quantity: A strong negative correlation was found, suggesting that higher buying rates per kilogram were associated with lower quantities purchased.

Selling Price vs. Sold Quantity: A moderately strong negative correlation was observed, indicating that higher selling prices per kilogram were associated with lower quantities sold.

Sales Trends:

Cucumber had the highest sales in January, followed by February and then March. (Profit Percentage = 60.8%)

Peas had the highest sales in January, significantly lower sales in February, and the lowest sales in March.(Profit Percentage = 1.3)

Spinach had the highest sales in January, followed by February and then March.(Profit Percentage = 1.0%)

Tomato had the highest sales in March, followed by January and then February.(Profit Percentage =36.9%)

Business Implications:

Inventory Management: Businesses can use the sales trends to optimize their inventory management, ensuring they stock more in high-sales months and avoid overstocking in low-sales months.

Pricing Strategy: The price-quantity relationship insights can help businesses adjust their pricing strategies to maximize revenue. For example, reducing prices during peak sales months may increase quantity sold.

Marketing Strategy: Understanding the seasonal variations and sales trends can help in developing targeted marketing campaigns to capitalize on peak sales periods for each vegetable.