Refrigerate the Risk: Optimizing Inventory and Operations for Profit Enhancement in Dairy Retail

A Final Report for the BDM capstone Project

Submitted by

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1 Executive Summary and Title

This project focuses on optimizing the operations for ‘Kribhco Karmachari Sahkari Dhiran Purvarsh Society’, a small-scale dairy and ice cream outlet located in Kribhco Township, Surat. Operating since 2000, the business serves over 420 customers with the help of a small delivery team but faces persistent challenges such as overstocking, stockouts, spoilage during power outages and delivery inefficiencies that directly impact profitability and customer satisfaction.

To address these issues, data from April 2024 to March 2025 was collected from sales/purchase registers, supplier invoices, and environmental logs. The data was cleaned, structured, and analyzed using tools like Excel and Python (pandas, matplotlib). Analytical methods including ABC and RFM analysis, demand trend visualization, EOQ modeling, and regression-based forecasting were applied to understand demand patterns, product criticality, and potential areas of loss.

Descriptive statistics revealed product-level contributions to revenue and identified seasonal demand fluctuations for milk and ice cream.Key findings showed that milk demand rises in monsoon and ice cream in summer along with patterns of spoilage correlating with high temperature and power outages. A few high-performing products like Amul Gold Milk and chocolate-flavored ice creams were identified that contribute disproportionately to revenue. Delivery patterns also showed concentration around certain days, indicating inefficiencies.

Based on these findings, the project proposed actionable, low-cost solutions such as optimized ordering cycles using EOQ, priority stock management, basic temperature tracking, and delivery schedule adjustments.These insights have the potential to reduce spoilage and shortages, leading to smoother operations and improved revenue, even with minimal financial investment and limited manpower.

2 Detailed Explanation of Analysis Process/Method

2.1 Data Cleaning and Preprocessing

Explanation:

The initial raw datasets collected for this project included: Milk Sales, Milk Purchases, Ice Cream Sales, Ice Cream Purchases. However, these datasets had several critical inconsistencies, data gaps, ambiguities that required systematic cleaning and restructuring before analysis could begin.

- While milk purchases and deliveries occur daily, they are billed monthly.
- Customer data had minor inconsistencies in names with variations in spelling, case sensitivity, and formatting were standardized using string manipulation.
- No customer data was maintained for ice creams. Ice cream sales were recorded by quality codes only (e.g., V-240, A-300), with no direct mapping to product names. To resolve this ambiguity, a manual mapping sheet was created linking each quality code to one or multiple ice cream products using supplier bill registers. Product attributes such as flavour, pack type etc were added through web research and supplier records.
- To organize and structure the cleaned data, a star schema was designed with fact tables (milk_sales, milk_purchases, icecream_sales and icecream_purchases) and dimension tables (customer data, dates, quality code, icecream_product, mlk_product)
- External environmental data was collected from [Visual Crossing Weather Data](#).
- Other irregularities such as duplicate entries were dropped, different date formats were unified and uniformity was performed on column names.

  Importance:
- Ensure accuracy in time series forecasting and demand pattern recognition.
- Minimize the risk of incorrect business decisions due to erroneous or incomplete data.
- Enable cross-referencing between sales, purchases, and inventory across both milk and ice cream categories.
- Prepare data for visualizations, machine learning models and reporting.

2.2 Comprehensive Explanation for each Method/Analysis Used:

A solid foundation for analysis is established by addressing data discrepancies and developing a robust relational model, enabling accurate insights from data covering April 2024 to March 2025. The analysis process for the cleaned data is presented in a problem-driven approach, where each problem statement is addressed through a structured methodology.

2.2.1 Demand Trend Analysis

The objective of demand trend analysis is to identify recurring patterns in sales volume across months and products, particularly for milk and ice cream, to enable season-sensitive stock planning. Recognizing peak and off-peak periods allows the business to align procurement and storage with actual demand cycles—thereby reducing both overstocking and stockouts. Thus, understanding how demand varies by time and product forms a critical foundation for inventory decisions.

Methodology:

The approach involved aggregating and visualizing sales data across time (months) and product types to detect seasonal trends.

Let:

- $i=1,2,...,12$ represent the months of the year
- $j=1,2,...,$ represent product categories (e.g., milk names or ice cream brands)

Then,

Q_{ij}=Total quantity sold in month i for product j

Where Q_{ij} represents the monthly sales quantity matrix.

This matrix was constructed using grouped aggregation of transaction-level data from the milk and ice cream sales dataset.

Justification: Demand Trend Analysis technique directly supports critical inventory decisions in a context where product perishability and storage costs are high. It enables diminishing overstocking as off-peaks (low Q_{ij}) are identified in advance so purchase quantities are reduced accordingly thereby minimizing waste due to unsold inventory. Early ordering can be planned due to recognition of historical high-demand periods (high Q_{ij}) resulting in the prevention of stockouts. It supports capacity planning for storage and delivery staff in peak months.

2.2.2 RFM Analysis (Customer & Product Segmentation)

RFM (Recency, Frequency, Monetary) analysis is a powerful segmentation technique used to identify: High-value, repeat customers who can be retained through loyalty programs, high-performing products (SKUs) that drive revenue and should be prioritized in procurement, and low-value or inactive customers/products where resources and stocking can be reduced. In the context of this capstone project, RFM analysis was applied to both milk and ice cream data to support inventory optimization.

Methodology:

The RFM model evaluates each customer or product based on three dimensions:

1. Recency (R) - Time since the most recent purchase

Formula: R = Today's date - Date of last purchase

2. Frequency (F) - Total number of purchases

Formula: F = Count of transactions per customer or product

3. Monetary (M) - Total spend (by customer) or total revenue generated (by SKU)

Formula: $M = \sum(\text{Bill Amount})$

To standardize across different scales and compare relative performance, each R, F, and M value is converted into quantiles (typically into 5 bins, labeled 1- 5):

- For Recency, lower recency means higher score (inverse scale)
- For Frequency and Monetary, higher values means higher score

Let Rq, Fq, Mq be the quantile scores for Recency, Frequency, and Monetary respectively.

Then the overall RFM score is computed asRFM Score = Rq+Fq+Mq (score ranging from **3 to 15**)

Justification: Traditional sales analysis treats all customers or products equally. However, not all buyers are equally valuable, and not all products contribute equally to revenue. RFM enables data-driven prioritization by ranking based on recent transactions by a customer or a recently sold product, rate of transactions made and amount of revenue generated. By applying this technique, businesses can pinpoint their most loyal customers, streamline inventory by focusing on high-demand SKUs, and eliminate inefficiencies in storage, ultimately improving overall operational efficiency.

2.2.3 Demand Forecasting

- **Using Prophet (Milk)**

  In businesses dealing with perishables such as milk, it is critical to predict how much demand will occur in the near future.The goal of demand forecasting is to transform historical sales data into future estimates, allowing inventory decisions to be proactive and data-driven. Prophet is an additive time series forecasting model developed by Meta (Facebook), capable of modeling complex, real-world sales trends with minimal tuning. It helps to align stock levels with actual demand and anticipate seasonal changes.

  Methodology:

  It models the quantity sold at a given time t as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t$$

- g(t): Trend – the long-term growth or decline in sales
- s(t): Seasonality – weekly, monthly, or yearly recurring patterns
- h(t): Holiday effects – special spikes or dips during known events
- εt: Error term – unexplained random noise

  Performance was evaluated using the Root Mean Square Error (RMSE):

$$RMSE = sqrt((1/n) * \Sigma (\hat{y}_i - y_i)^2)$$

  $\hat{y}_i$: forecast demand, y_i: actual demand, n: number of forecast points

- **Using Gradient Booster Regressor**

  To forecast future ice cream sales more accurately by capturing non-linear dependencies and feature interactions that affect demand due to external and product-specific variables like flavor, temperature, packaging type, and storage environment. While Prophet handles trend and seasonality well, it does not consider categorical or environmental factors. GBR complements this by learning from feature-rich data.

  Methodology:

- Import Gradient Boosting Regressor (GBR) from scikit-learn due to its robustness and handling of categorical variables (via preprocessing), interactions among features, outliers and noise
- Split data into training and testing sets (e.g., 80:20 ratio).
- Train the model
- Calculate the RMSE score and plot Actual vs Predicted sales.

Justification: By aligning future purchasing decisions with the expected demand, the shop can:

- Ensure products are available when needed
- Prevent excess stock from going to waste
- Make inventory planning more strategic than reactive

2.2.4 EOQ (Economic Order Quantity) and ROP (Reorder Point)

While demand forecasting provides insight into expected demand, the next two logical things need to be put into consideration are: the amount of quantity to be ordered at a time and the time when this order should be placed. This is where EOQ and ROP come into play.

Methodology:

- **EOQ Formula:** $EOQ = sqrt((2 * D * S)/H$

  S: Ordering cost per order (fixed cost — delivery, handling, labour)
  H: Holding cost per unit per year (cost of refrigeration, spoilage risk, etc)
  D: Annual demand (in litres or units)

- **ROP Formula:** $ROP = d * L$

  Where, D: Average daily demand, L: Lead time in days (time between placing and receiving the order)

Justification:EOQ minimizes the total inventory cost by balancing high ordering cost due to ordering very frequently and high holding cost due to ordering in bulk. ROP ensures new stock arrives before current runs out. Both improve supplier coordination by enabling scheduled and predictable orders.

2.2.5 Overstock Risk Classification (Binary Classification)

Overstock Risk refers to the likelihood that a product (SKU) will accumulate in inventory beyond demand, leading to spoilage, wastage, locked capital (money tied in unsold goods) and storage pressure (cold chain or freezer space). It is a machine learning classification model that allows the shop to predict and prevent overstocking in advance.

Methodology:

- Build a Binary Classification model (Random Forest) using features like historical purchase quantity, sale trends etc
- Label the data as 1=Overstock Risk, 0=Normal Risk
- Evaluate using classification metrics such as confusion matrix, precision, recall, ROC AUC.

Justification: This technique helps the business owner to Flag SKUs that are risky and optimizes purchasing as items are actually required to be ordered. Henceforth, stocks and discounts should be adjusted accordingly.

2.2.6 Correlation Analysis

A statistical method used to determine the strength and direction of the relationship between two or more variables. It helps to uncover hidden dependencies or patterns in operational variables such as if spoilage increases with temperature, or sales decrease during rainy days.

Methodology: Visualize relationships using heatmaps by applying to variables, Temperature vs. Spoilage.

Justification: Correlation analysis helps identifying key factors impacting sales and spoilage. It enables prioritizing actions, like investing in cold storage if temperature has a strong negative impact.

2.2.7 SKU-level Spoilage Analysis

SKU (Stock Keeping Unit) spoilage analysis looks at which specific milk or ice cream products (by brand, flavour, or pack type) are spoiling more frequently or going unsold. It is necessary to identify slow-moving or vulnerable products and adjust ordering and storage strategies accordingly.

Justification: Analyzing spoilage at the SKU level ensures more accurate stocking and reduces financial loss due to expired goods as not all products spoil equally.

2.2.8 Cold Chain Performance Score

A composite metric to evaluate how well the cold storage and delivery systems maintain temperature-sensitive conditions across the supply chain. Ice cream and milk are perishable and require refrigeration. Breaks in the cold chain can cause spoilage even before reaching customers.

Justification: This metric provides an objective, trackable way to measure cold chain health. It supports investment decisions like backup generators or thermal boxes.

2.2.9 Pareto Analysis (80/20 Rule)

An analysis based on the Pareto principle where 80% of results often come from 20% of inputs. In business, this could mean 80% of revenue comes from 20% of products/customers. It highlights the most impactful SKUs or customers rather than spending time managing low-impact items that aren't profitable enough.

Methodology:

- Rank SKUs or customers by sales volume or profit.
- Calculate cumulative percentage.
- Identify the top 20% contributors and visualize using a Pareto chart.

Justification: This method aids to prioritize product range, control inventory and optimize logistics.

2.2.10 Delivery Pattern Clustering

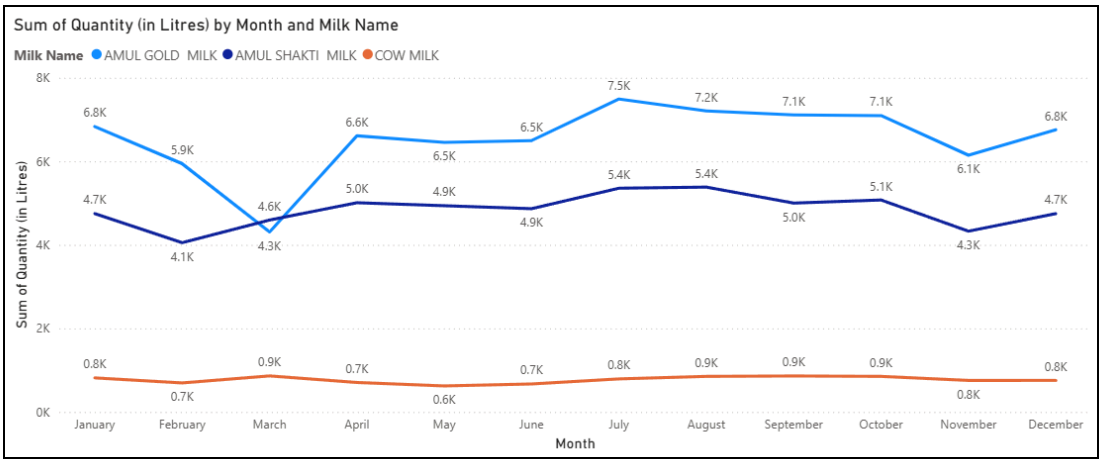
A machine learning approach like K-Means to group delivery routes or customers based on patterns such as time, frequency, location, or delays. It points out inefficiencies and customer demand clusters. In this capstone project, focus is mainly on peak and off-peak times to enhance delivery performance and streamline logistics.

Justification: Helps better in planning of daily delivery schedules and labour management.

3 Results and Findings

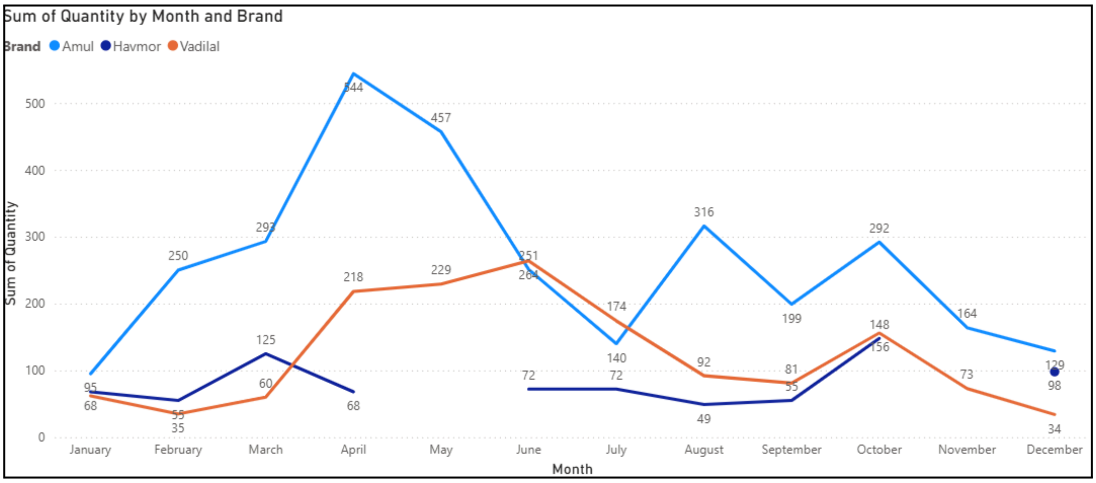
- Milk Data Analysis.ipynb
- Ice Cream Data Analysis
- BDM-Cleaned Data.xlsx

3.1 Demand Trend Analysis



Graph 1(Line Chart): Total quantity sold vs Months and Milk variety

Insights: Amul Gold dominates the market throughout the year, indicating a strong and consistent consumer preference. Both Amul Gold and Amul Shakti exhibit similar seasonal sales patterns, with noticeable peaks during the mid-year months and slight dips towards the end of the year. In contrast, Cow Milk maintains a steady but lower sales volume, suggesting it caters to a specific, niche customer segment. A dip in sales observed in November may be attributed to a temporary slowdown before the festive season, followed by a recovery in December. Overall, Amul Gold and Amul Shakti account for the majority of total milk sales, underscoring their significance in the product portfolio.



Graph 2(Line Chart): Total quantity sold vs Months and Ice Cream Brand variety

Insights: The chart shows clear market leadership by Amul, with major sales peaks in April and August, reflecting strong demand during the summer months. Vadilal consistently ranks second, with a peak in June and a secondary rise in October, indicating seasonally-driven sales. Havmor has the lowest and most stable sales, suggesting a niche presence. Two main peak periods are evident: April–June, where Amul dominates, and August–October, where all three brands see activity. These trends highlight Amul's broad appeal, Vadilal's steady competition, and Havmor's smaller but consistent role in the market.

3.2 RFM Analysis (Customer & Product Segmentation)

	Customer	Recency	Frequency	Monetary	R	F	M	RFM_Score
71	DINGLIWALA SANTOSH	1	13	53833	5	3	5	535
94	GOHIL S G	1	13	31046	5	3	5	535
68	DHAVAL DINESHBHAI PATEL	1	13	28317	5	3	5	535
76	DUBEY SAKSHI	1	13	40957	5	3	5	535
79	GAJJAR SANJAY N	1	13	45885	5	3	5	535
67	DHAL ASHISH KUMAR	1	13	50295	5	3	5	535
73	DOCTOR K S	1	13	38647	5	3	5	535
59	DAVE M A	1	13	36162	5	3	5	535
93	GOHIL S A	1	13	49158	5	3	5	535
69	DHIRENKUMAR P. PARMAR	1	13	23049	5	3	4	534

Image 1: List of top 10 loyal customers as per RFM analysis of Milk sales

Insight: The RFM analysis table ranks customers based on how recently (Recency), how often (Frequency), and how much (Monetary) they purchase milk. Most top customers scored 535, meaning they purchased very recently, buy frequently (13 times), and spend significantly (₹28K–₹53K). One customer scored 534 due to slightly lower spending (₹23K). These high RFM scores highlight valuable customers who should be retained through loyalty rewards or personalized offers, as they play a key role in business revenue and growth.

	Customer	Recency	Frequency	Monetary	R	F	M	RFM_Score
274	PATEL THAKORBHAI B	336	1	4080	1	1	1	111
16	BABITA NIGAM {KV}	244	5	6013	1	1	1	111
8	ANAND KUMAR JANGIR	336	1	0	1	1	1	111
299	PRIYANSHU	213	6	280	1	1	1	111
6	AMAN KATIYAR	336	1	0	1	1	1	111
308	RAJPUT PURANSINGH	336	1	34	1	1	1	111
269	PATEL S S	275	4	467	1	1	1	111
310	RAKESH RANJAN	60	8	1844	1	1	1	111
134	KASHYAP AVINASH CHANDRA	152	8	6787	1	1	1	111
419	ZALA VIMAL S	1	1	210	1	1	1	111

Image 2: List of bottom 10 inactive customers as per RFM analysis of Milk sales

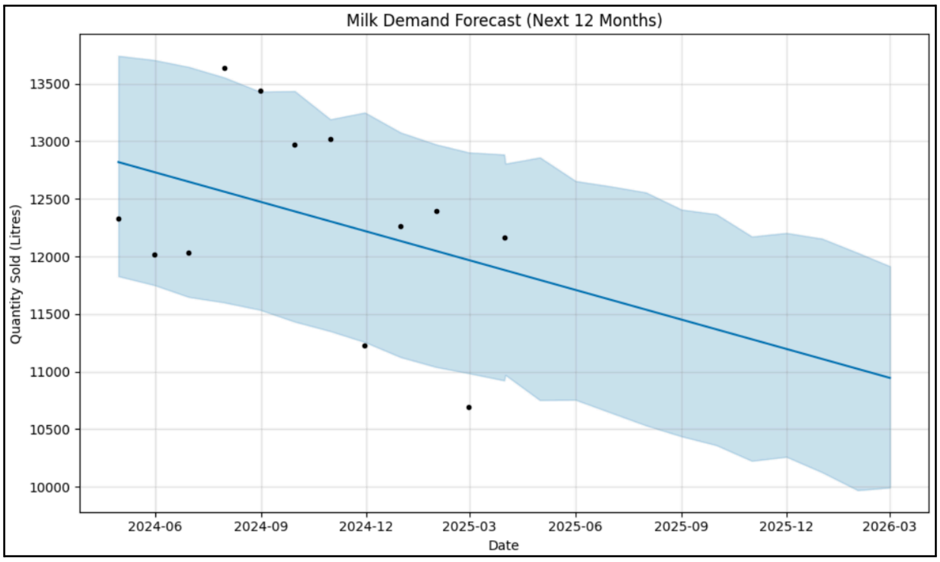
Insight: The RFM analysis highlights a segment of low-value customers, all scoring 111, the lowest possible RFM score. These customers exhibit long periods since their last purchase (e.g., 244 to 336 days), very low purchase frequency (1-8 transactions), and minimal spending (₹0 to ₹280), indicating they are inactive or disengaged. This group likely includes one-time buyers or trial users who never followed up with additional purchases. Identifying them is crucial for planning targeted win-back campaigns, sending personalized reminders, or collecting feedback to understand and address their lack of engagement. These efforts may help revive dormant customers or guide the reallocation of marketing resources more effectively.

	Quality Name	Total Quantity	Revenue	Last Sold Date
33	A-400	1030	3334250.0	2025-03-26
40	A-700	975	3076940.0	2025-03-26
11	A-160	1492	2772108.0	2025-03-26
22	A-280	404	2709744.0	2025-03-26
27	A-300	884	2599040.0	2025-03-26
...	...	...	...	...
18	A-250	3	675.0	2024-04-13
8	A-140	5	630.0	2024-04-26
51	H-180	2	324.0	2024-04-04
59	H-290	1	261.0	2024-04-04
83	V-200	1	180.0	2024-04-03

Image 3: List of top 5 and bottom 5 ice cream products based on their performance

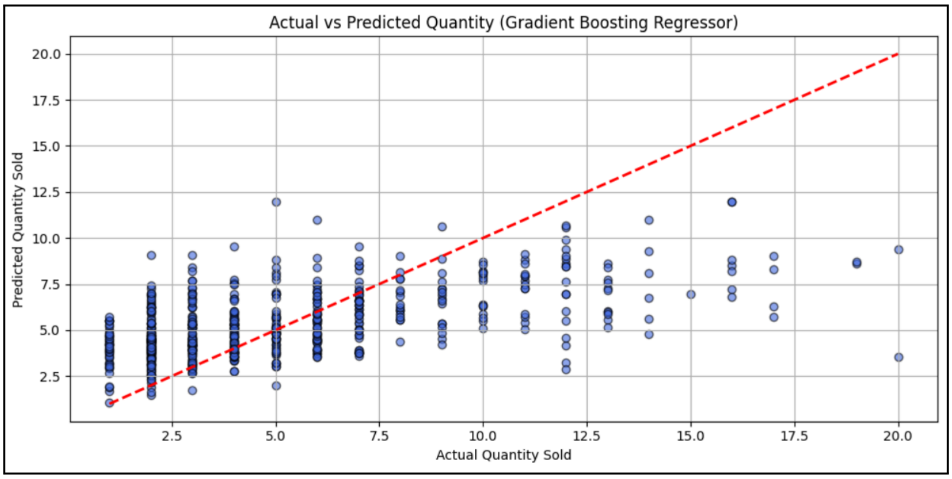
Insight: The sales analysis table reflects the top 5 and bottom 5 ice cream products based on RFM. Top performers like A-400 and A-700 have generated revenues in the millions and continue to sell actively, with the latest sales dated 2025-03-26. These products also show high quantities sold, reflecting strong market demand. In contrast, the bottom performers like A-250, H-290 show minimal sales 1- 5 units, with the last transactions over a year ago, indicating low demand or discontinued status. This sharp contrast suggests few products dominate revenue while others have become obsolete.

3.3 Demand Forecasting



Graph 3: Milk Demand Forecast for next 12 months using Prophet model

Insight: The Prophet-based forecast for milk demand shows a clear downward trend, with monthly demand expected to decline from around 12,800 litres in mid-2024 to nearly 11,000 litres by early 2026. The model's RMSE of 759 suggests moderate accuracy, and the wide confidence interval reflects uncertainty in monthly predictions. With average current demand at 12,349 litres, future demand is projected to consistently fall below this level. These insights indicate a need for strategic action such as adjusting inventory, investigating demand drop causes, strengthening marketing, and exploring product diversification to adapt to changing consumption patterns.



Graph 4: Comparison between actual and predicted quantity of ice cream packets sold using GBR

Insight: The Gradient Boosting Regressor model shows moderate accuracy in predicting ice cream sales, with an RMSE of 3.04 against an average daily demand of 14.84 units. The scatter plot indicates that while predictions align fairly well with actual sales at lower volumes, the model consistently underpredicts higher sales, failing to capture peak demand days. This could lead to stock-outs and poor planning during high-demand periods. The model performs reasonably overall but requires improvement—through better features, tuning, or alternative models—to reduce bias and enhance accuracy, especially for forecasting higher-than-average sales.

3.4 EOQ (Economic Order Quantity) and ROP (Reorder Point)

Milk:

Annual Demand (D) (litres)	148193.50
Ordering Cost (S) per order (₹)	200
Holding cost (H) per unit per year (₹)	30
EOQ (litres)	1405.67

Total Quantity for 12 Months:	148193.50 litres
Total Days in 12 Months:	365
Average Daily Demand:	406.01 litres
Lead Time (in days):	1
Reorder Point:	406 litres

Insight: The EOQ of 1,405 litres indicates the optimal order size that minimizes total inventory cost by balancing ordering and holding costs. This batch size is both operationally feasible and cost-effective for managing milk stock. With an average daily demand of 406 litres and a 1-day lead time, the Reorder Point (ROP) is calculated at 406 litres, ensuring that a new order is placed just in time to avoid stockouts.

Ice Cream:

Annual Demand (D) (packets/boxes)	5418
Ordering Cost (S) per order (₹)	100
Holding cost (H) per unit per year (₹)	25
EOQ	208

Total Quantity for 12 Months:	5418
Total Days in 12 Months:	365
Average Daily Demand:	14.84
Lead Time (in days):	2
Reorder Point:	29.6 (~30) units

Insight: The calculated EOQ of 208 units strikes an effective balance between ordering and holding costs, enabling the business to place fewer, larger, and more cost-efficient orders. With an average daily demand of 14.84 units and a 2-day lead time, the Reorder Point (ROP) is approximately 30 units, acting as a critical safeguard against stockouts. This timely replenishment is particularly important for frozen products like ice cream, where maintaining product quality depends on temperature-controlled storage and fast turnover. Additionally, the ability to order in bulk supports higher demand during seasonal peaks, reducing the risk of missed sales and enhancing overall inventory efficiency.

3.5 Overstock Risk Classification (Binary Classification)

Ice cream Overstock Analysis score:

	precision	recall	f1-score	support
0	0.82	0.77	0.79	272
1	0.83	0.87	0.85	348
accuracy			0.83	620
macro avg	0.83	0.82	0.82	620

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weighted avg       0.83      0.83      0.83       620
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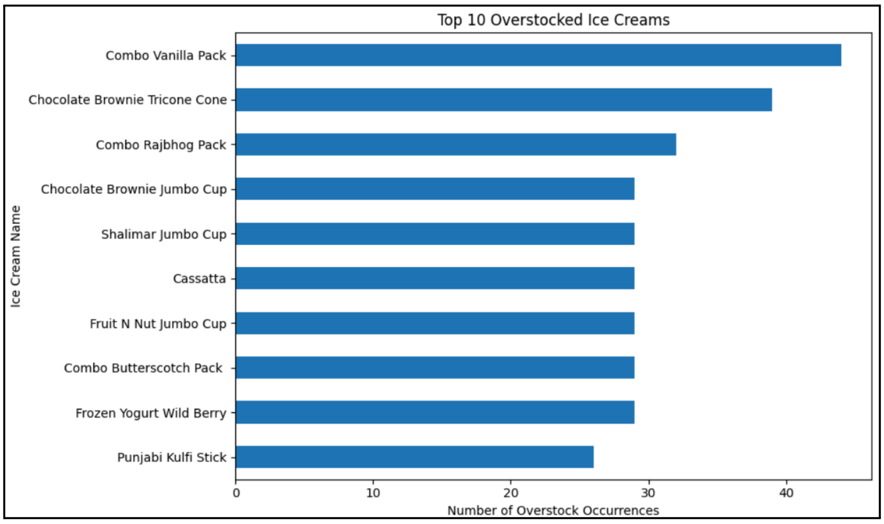
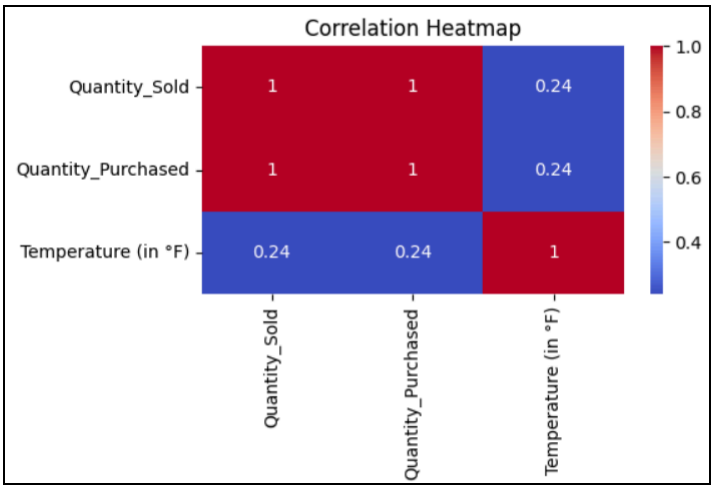


Graph 5: Bar Chart highlighting the top 10 overstocked ice creams

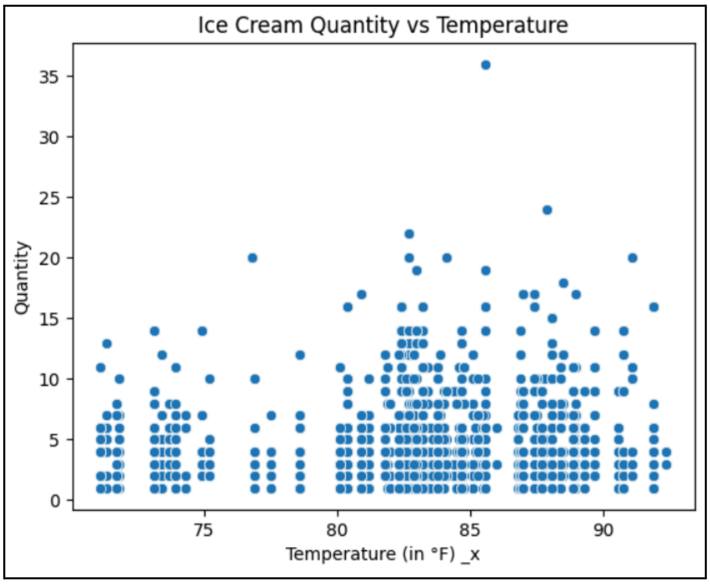
Insight: The analysis identifies the top 10 overstocked ice cream products, with "Combo Vanilla Pack" and "Chocolate Brownie Tricone Cone" showing the highest excess units. This overstocking poses financial risks due to potential spoilage and increased storage costs. A Random Forest classifier was developed to predict overstock risk, achieving an overall accuracy of 83%. The model performs particularly well in identifying overstocked items (Class 1) with high recall (87%) and precision (83%), ensuring reliable detection of inventory at risk. However, it is slightly less effective for the "not overstocked" class (Class 0), with a recall of 77%, suggesting room for refinement. The Random Forest model's strong performance, especially its high recall for the "overstocked" class, makes it a valuable tool. The business can confidently use this model to proactively flag products that are at risk of becoming overstocked in the future, allowing them to take preventative measures before the problem arises.

3.6 Correlation Analysis



Graph 6: Correlation heatmap of Milks sales and purchases and external heat

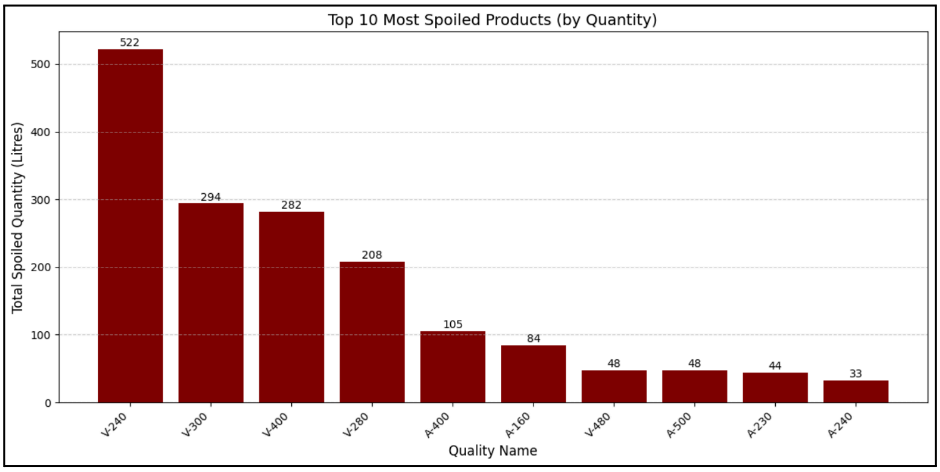
Insight: The correlation heatmap reveals that milk quantity sold and purchased have a perfect positive correlation (1.00), suggesting either a highly efficient just-in-time inventory system or a limitation in data recording where purchases mirror sales. Meanwhile, the weak positive correlation (0.24) between milk sales and temperature indicates that temperature has little influence on milk demand. This suggests that forecasting milk demand should rely more on behavioral or temporal factors (like day of the week or customer habits) rather than environmental ones.



Graph 7: Scatter plot ice cream quantity sold vs Temperature

Insight: The "Ice Cream Quantity vs Temperature" scatter plot shows a clear positive correlation. As the temperature increases from 70°F to over 85°F, there is a noticeable increase in both the average and maximum quantity of ice cream sold. The highest sales volumes (above 20 units) are almost exclusively observed at temperatures above 80°F. However, it somewhat declines around 90°F. This finding confirms that temperature is a significant driver of ice cream sales that are highly volatile and exhibit strong seasonal patterns.

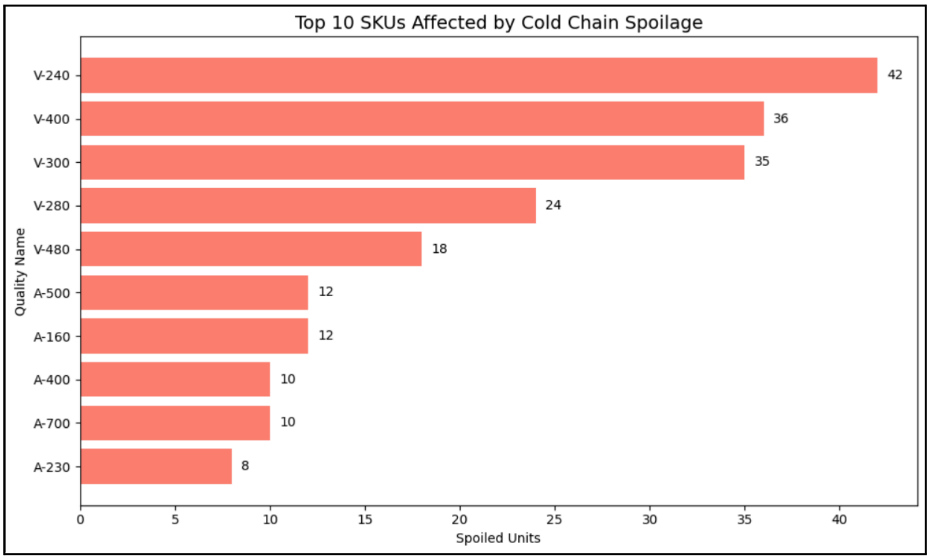
3.7 SKU-level Spoilage Analysis



Graph 8: Top 10 most spoiled ice cream quality codes

Insight: The "Top 10 Most Spoiled Products" chart reveals a major operational challenge, with high spoilage numbers for items like "V-240" (522 units) and "V-300" (294 units). This horizontal bar chart underscores significant weaknesses in cold chain logistics, inventory management, or demand forecasting. The spoilage represents a direct revenue loss and suggests inefficiencies that may be contributing to the poor performance of certain products. Addressing these issues is critical to improving overall product handling and reducing waste.

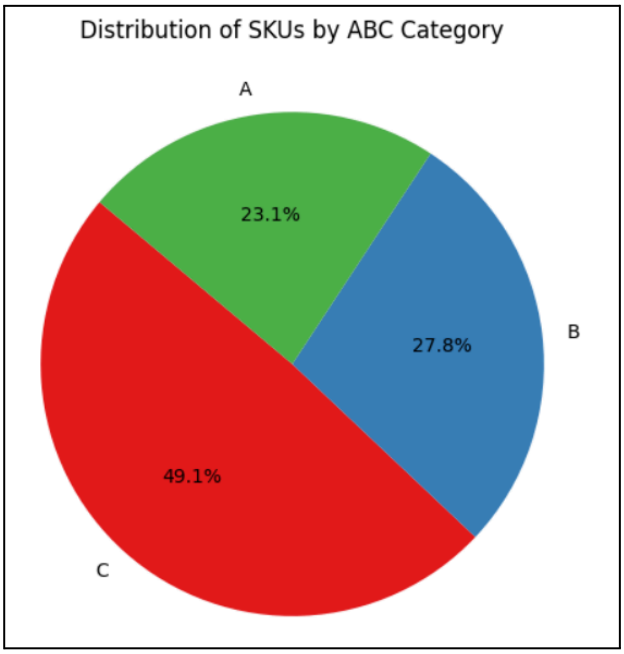
3.8 Cold Chain Performance Score



Graph 9: Top 10 SKUs affected by cold chain spoilage

Insight: This horizontal bar chart highlights the top 10 ice cream products that have been most affected by spoilage. "V-240" is the most spoiled product with 42 units, followed by "V-400" with 36 units. This list points to a critical issue with inventory management and cold chain logistics.

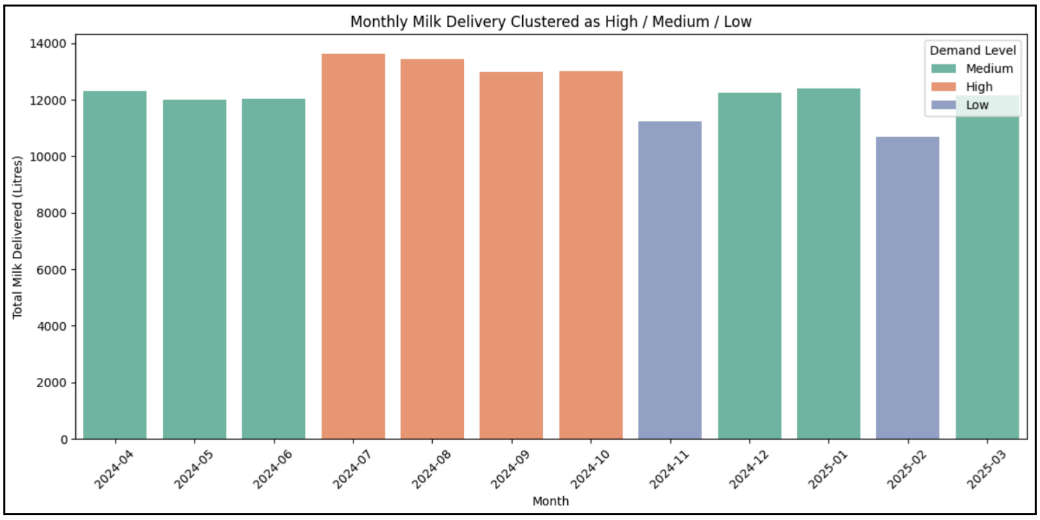
3.9 Pareto Analysis (80/20 Rule)



Graph 10: ABC classification of ice cream SKUs

Insight: The ABC (Pareto) analysis chart categorizes SKUs based on their contribution to revenue, highlighting key inventory priorities. Category A, comprising just 23.1% of products, generates the highest revenue share, while Category B (27.8%) represents medium-value items. Nearly half the SKUs (49.1%) fall under Category C, contributing the least despite their quantity. This underscores the Pareto principle which says that the most revenue comes from a small fraction of products. For effective inventory management and items to be best taken care of during logistics, the business should prioritize Category A items for optimization and closely review Category C items for potential consolidation or phase-out.

3.10 Delivery Pattern Clustering



Graph 11: Monthly Milk Delivery Clustered as High / Medium / Low (Bar Chart)

Insight: This bar chart visualizes the total monthly milk delivered, categorized into three demand levels: "High," "Medium," and "Low." The chart shows a strong seasonal pattern, with demand peaking in the summer months (July-October) and dipping in the fall/winter months. It aids in planning delivery schedules and labour management.

4 Interpretation of Results and Recommendations

- **Inventory Management Issues**

Interpretation:

According to the EOQ and ROP analysis for both milk and ice cream provides a strategic framework for optimizing inventory levels. Overstocking was identified as a critical issue as per overstock risk analysis, especially for ice cream products like "Combo Vanilla Pack", while other insights such as pareto and RFM analysis show that only a small number of products contribute to the majority of revenue.

Simultaneously, many low-performing SKUs (Category C) and spoiled items as per spoilage and overstocked analysis, are consuming valuable storage space and resources without returns. This indicates inefficiencies in SKU prioritization, purchasing frequency, and spoilage control**.** With limited manpower and budget, frequent reordering or wastage is not sustainable.

Recommendations:

1. Immediate implementation of EOQ and ROP-driven ordering cycles to reduce both excess inventory and stockouts.
2. Focus on Category A products for availability and service levels and review C-category SKUs for phase-out or demand-boosting tactics such as small discounts or combos.
3. Regularly restock fast moving SKUs whereas slow moving ones should be restocked only when requested by customers

- **Cold Storage Issues**

Interpretation:

According to insights, severe spoilage of frozen items can be pointed out due to cold chain failures. High-value items like "V-240" are repeatedly wasted due to improper temperature monitoring and power backup issues. Seasonal peaks further strain storage infrastructure. Frozen inventory also suffers more from overstock, increasing the spoilage risk.

Recommendations:

1. To prevent spoilage, it's crucial to buy just enough ice cream stock to meet demand within a 7-10 day period.
2. Consider using low-cost insulated ice boxes or a basic inverter paired with a cooler to maintain product temperatures and extend shelf life during power outages.
3. Label the stocks with purchase date using a marker to follow FIFO (first in, first out) usage.

- **Delivery Issues**

Interpretation:

Seasonal spikes and high-demand milk place pressure on last-mile delivery systems. RFM insights show that while there is a loyal high-value customer base, many users become inactive, possibly due to issues like delays or damaged products. Packet damage during delivery could also be attributed to packaging issues and over-bundling in high-volume scenarios.

Recommendations:

1. Split large deliveries into smaller ones and stagger timings on weekends or festival days.
2. Streamline deliveries by clustering orders by area, designing daily routes, and assigning delivery staff to minimize travel time and fuel usage.
3. Protect packets in transit by utilizing thick cloth bags or repurposed cardboard boxes, ensuring safe and secure delivery.

5 Implementation Impact

Implementing these recommendations is expected to significantly enhance the overall operational efficiency and profitability of the business. By aligning inventory with actual demand patterns and phasing out underperforming products, the shop can reduce overstocking, minimize spoilage, and free up storage space. Strategic marketing focused on top-performing products and loyal customers will improve sales conversion and customer retention, while targeted discounts for irregular buyers can boost repeat purchases. Improved cold-chain handling and planning around temperature variations will reduce wastage, especially of ice cream during peak summer months. Delivery process improvements will minimize product damage and ensure timely service, enhancing customer satisfaction. Overall, these actions will create a more resilient, customer-focused, and data-driven business model.