International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I8P115

Volume 73 Issue 8, 180-189, August 2025

Original Article

Advanced Automation for Subscription-Based Order Management on Online Grocery Platforms

Priyanka More[1], Sachin Sakhare[2], Anushka More[3]

[1,2]*Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India.*
[3]*Department of Artificial Intelligence and Data Science, Vishwakarma Institute of Technology, Pune, India.*

[1]*Corresponding Author : rpriyanka.more@viit.ac.in*

Received: 10 April 2025 Revised: 19 June 2025 Accepted: 29 July 2025 Published: 30 August 2025

Abstract - *This work proposes a statistical averaging with a machine learning-based system to automate subscription-based grocery ordering on e-commerce websites. This new system uses dynamic rate analysis of consumption, forecasted ordering, and intelligent feedback systems to maximize the availability of products and minimize wastage. The system determines the most efficient reorder levels and frequencies by evaluating past purchase history and real-time consumption rates and levels. The implementation results demonstrate the improvement in customer satisfaction and accurate fulfilment of orders through personalized inventory management. An important novelty in the system, in terms of automated grocery subscription services, is its ability to learn from user feedback and adapt orders appropriately; this study has innovated formulas.*

Keywords - *Grocery, Automation, Statistics, Machine Learning, Subscription.*

1. Introduction

The expansion of the e-grocery market has transformed the shopping behaviour of customers on the most fundamental level, as more automation and personalization of regular purchases are demanded. The conventional subscription-order forms are periodic in time, and they disregard the inconsistency in individual consumption, which causes overstocks, stockouts, or wastage. Such inefficiencies in a business where freshness, on-time reordering and inventory accuracy are critical factors can seriously affect the user experience and operational efficiency [1, 2]. In order to address these challenges, this work presents a smart reordering system in online groceries. It is a statistical modeling with dynamically changing product reordering based on user behaviour via adaptive feedback mechanisms. This system suggests the ideal reorder levels and schedules, based on past purchase history and current consumption trends.

It also incorporates real-time user feedback, products consumed early, lasting longer, or going bad, to generate more accurate predictions in the future [3-5]. The key contribution lies in the design of a cyclic, self-learning algorithm, which adapts over time by means of combining analysis of consumption patterns and user feedback. Other than improving efficiency in inventory management, the shopping process is also streamlined, that is, it has less user intervention. The result is a highly individualised, fact-driven subscription service that can respond to changing needs with a minimum of user intervention.

2. Related Works

The evolving nature of online groceries and services has led to an increase in research with regard to personalized recommendations, intelligent inventory forecasting, and subscription systems via AI. This section highlights some of the main advances in technology that contribute to the advancing state of adaptive automation of grocery orders.

2.1. Subscription Models and Consumer Behavior

Panicker and Mane (2016) proposed a smart grocery recommendation system that used past buying behavior to compile personalized product baskets to improve user experience and satisfaction [6]. Pinto and Amorim (2020) determined how subscription-based commerce affects customer buying frequency and profitability. In their study, they found that although subscriptions can certainly increase customer loyalty, this can result in reduced profits unless constantly optimized [7]. Olumekor et al. (2024) further explored how demographic and other variables, such as income levels, food prices, and internet access, can influence the adoption of patterns in grocery shopping, which demonstrates the need for adaptive personalization for individuals [8].

2.2. AI-Based Personalization in E-Commerce

Artificial intelligence use cases have formed a core part of personalization in the digital commerce space. Aggarwal et al. (2024) have underscored the increasing importance of AI in making sense of customer behavior, making intelligent product recommendations, as well as detecting fraud on online platforms [9]. Singh et al. (2023) proved that AI and IoT are effective in terms of improving real-time inventory tracking and reducing food wastage in grocery operations [10].

According to Alltech Magazine (2024), big e-commerce firms have been allocating more investments towards generative AI tools to perfect customer personalization. Visual product searches, AI-powered price optimization, and hyper-personalized suggestions are some of the innovations that have been associated with significant growth in sales [11]. As Food & Wine (2025) claims, Instacart and similar platforms currently make use of such advances as AI-powered Store Views and on-demand inventory audit to enhance order accuracy and reduce fulfilment complications [12]. Even though the above developments are great strides that enhance shopping experiences, not many systems can dynamically change the frequency of orders and the quantities of products according to the changing shopping behavior, which this study addresses directly.

2.3. Reinforcement Learning and Adaptive Recommender Systems

Modern recommendation engines are gradually becoming driven by Reinforcement Learning (RL) as they can adapt with time. Wang et al. (2023) proposed CDT4Rec, Causal Decision Transformer, which utilizes RL to optimize recommendation personalization and maintain the long-term interest of the users [13]. Ren et al. (2023) equally suggested Contrastive State Augmentations (CSA), a technique that improves RL-based recommendation by adding semantic variety to the state space, to better capture user interaction [14]. Continuing the development of this direction, Mozifian et al. (2023) considered the destructive drawbacks of sequential recommendation (bias, instability, etc.) and overcame them, using proven methods of robust policy learning, demonstrating state-of-the-art results on a number of test sets. Now, although these RL systems have their advantages, they have been largely skewed towards content-driven areas and are yet to be fully exploited in repetitive, need-based applications such as grocery replenishment [15]. The contribution of the research is to extrapolate those RL principles to the case of subscription modeling, thereby designing a responsive system that improves, in real time, the order frequency and quantity depending on the consumption pattern deviations.

2.4. Grocery-Specific Forecasting and Inventory Automation

Gopinathan (2025) suggested a demand forecasting solution specifically in the grocery context, using generative models (GANS and VAEs), taking into consideration variables such as weather, local events and perishability [16]. Likewise, Zhang et al. (2023) also introduce the inventory optimization policy, in which it divides grocery items into categories, depending on their replenishment frequency, e.g., daily, weekly, or monthly, which again depends on consumption rate and seasonality [17].

2.5. Summary and Research Gap

The current literature provided a good background, including recommendation engines, AI personalization, and demand forecasting in grocery stores. But a decided break is perceptible in systems that are completely integrating:

- Real-time consumption monitoring,
- Real-time user feedback (e.g., spoilage or early exhaustion),
- Intelligent, self-adjusting reorder mechanisms.

As part of this research, a new hybrid architecture is proposed that incorporates the conventional statistical methods with the state-of-the-art machine learning models, such as XGBoost and LSTM, to go beyond predicting the usage patterns and instead dynamically adjust the subscriptions. The contribution is a direct response to the unaddressed need in the automated system of grocery orders.

3. Proposed Methodology

The study proposes a Smart Subscription Algorithm specific to online grocery stores, which is an effort towards automating product refilling in regard to consumeristic patterns of users. The system determines daily consumption rates (CPD), makes predictions of future order volumes, and dynamically adjusts subsequent orders based on user feedback by examining historical purchase records. It is the best way to manage inventory because it reduces the excesses and stock-outs by constantly adjusting the order frequencies and quantities. The proposed system, based on the methodology, is logically split into eight major steps as illustrated in Figure 1.

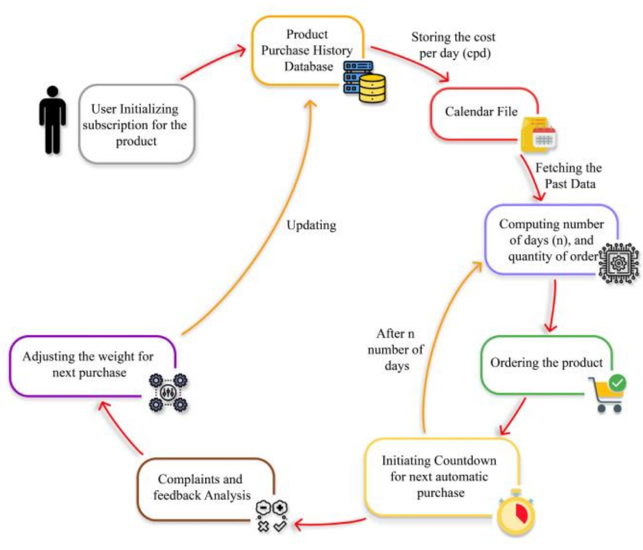

Fig. 1 Smart subscription algorithm flow chart

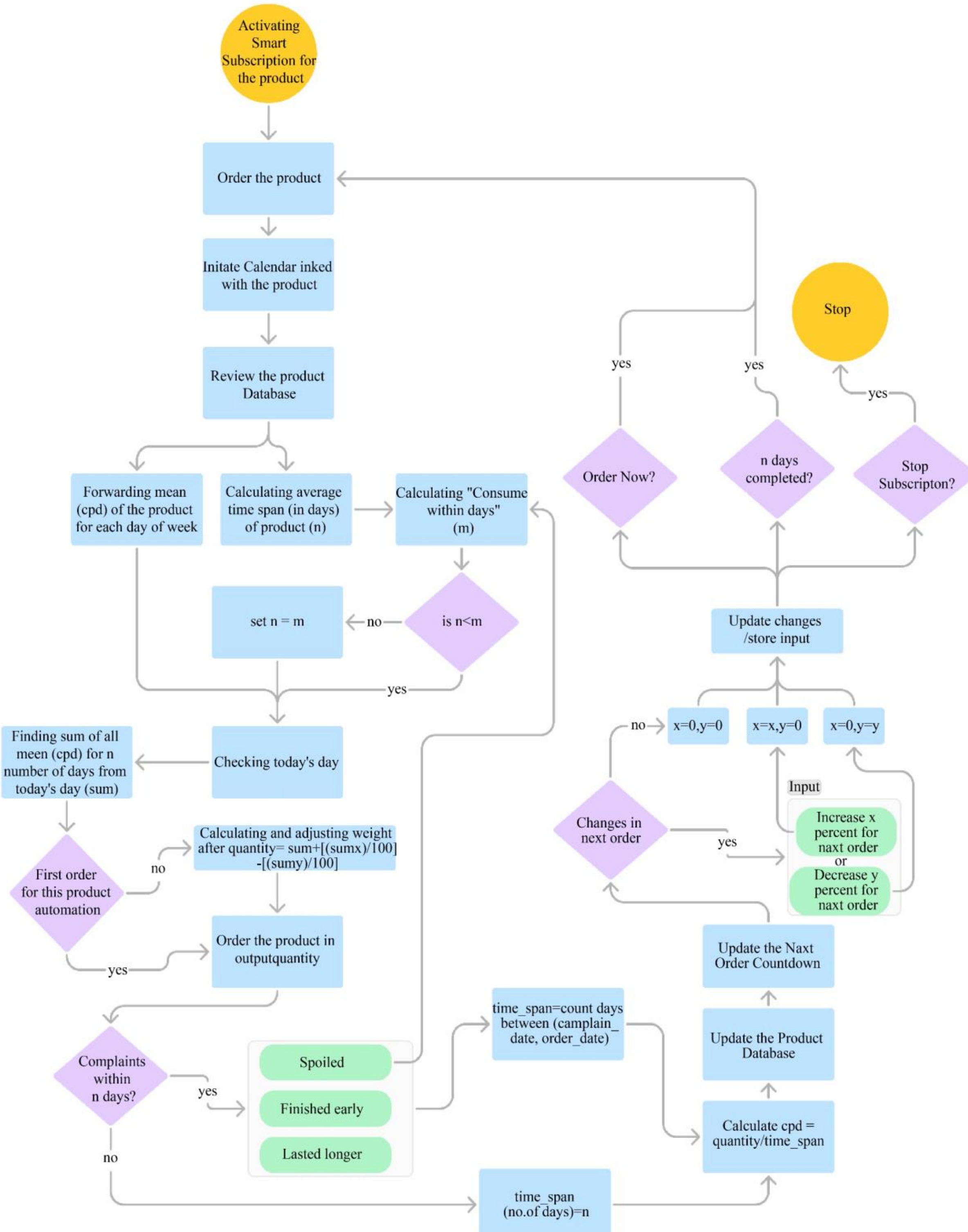

Fig. 2 Detailed algorithm flow

3.1. User Subscription Initialization for the Product

The smart subscription process will start when a user subscribes to a certain product. When the system is activated, it installs the necessary parameters that include:

- n: The time difference between successive orders is estimated based on the user's previous buying history.
- m: The consume-within-days limit can be either preset by the seller or defined by the user.
- mean(CPD): The average rate of consumption of the product per day.
- x and y: Percentage changes specified by the user to either decrease or increase the quantity of the next order.
- Order timestamps: The information about the purchase date, next order date, and spoilage date is used to keep track of the consumption habits.

After this, the system would pull the user's historical purchase data from the database to make predictions on past trends and come up with future order predictions.

3.2. Product Purchase History Database Extraction

The database accessed by the system provides the past history of the orders made by the user of the selected product.

It takes out all the transactions in which the product key matches the selected item (e.g., "tomato"). It then determines the date of purchase and repurchase, and using Equation 1, it determines the consumption per day (CPD):

$$\text{CPD} = \frac{\text{quantity}}{\text{time span between purchase and repurchase dates}} \quad (1)$$

The calculation of CPD is subsequently plotted against the corresponding days of purchase history of the user, making daily consumption behavior highly accurate.

3.3. Calendar-Based CPD Mapping

The system harmonizes the values of CPD with a calendar model of consumption, which is performed by examining the last five weeks of the purchase history.

It estimates the mean CPD on each weekday to increase accuracy. To take a specific example, when an order is received on a Monday, the system will calculate the average CPD of all the previous Mondays over the past four weeks before the order date. The process is used to create a daily CPD prediction of future purchases.

3.4. Computation of Time Span (n) and Order Quantity

This system identifies the following important parameters:

- Mean interval between successive orders (n): The average time duration between each two successive orders.
- Consume within days (m): A fixed number that will not allow excess stocking.

When n is greater than m, the system corrects n to be equal to m to have an optimized system in managing inventory. The estimated total consumption in the next n days will be as calculated in Equation 2:

$$\text{Sum} = \sum(\text{mean CPD} \times n) \quad (2)$$

The final order quantity is then adjusted to user preferences using the formula in Equation 3:

$$\text{Final Quantity} = \text{Sum} + \left(\frac{\text{Sum}\times x}{100}\right) - \left(\frac{\text{Sum}\times y}{100}\right) \quad (3)$$

Here, x and y are user-defined percentage increases or decreases in order quantity.

3.5. Ordering the Product

When the optimum order quantity is established, the system automatically makes the order. A notification pops up on the screen and gives the user detailed order information, including:

- Ordered quantity
- Unit price
- Projected delivery date
- Designated time interval (n) of the following order

On successful delivery, the system will record the transaction in the database and also update the next expected order date.

3.6. Initiating Countdown for the Next Automatic Purchase

When an order is completed, the system initiates a countdown to the next scheduled purchase using the calculated time span (n). The following control options are available to the users:

- Order Now -Enables on-demand restocking at the user's request.
- Modify Next Order – Allows a user to change the quantity of the order by changing x or y
- Pause Subscription- Pauses the subscription momentarily due to vacations or other instances.

Unless manual adjustments are undertaken, the system automatically initiates the next order after the elapse of n days.

3.7. Complaints and Feedback Analysis

When a user gets an order, he/she will be requested to give feedback about his/her consumption experience. The feedback possibilities are:

- Lasted Longer – The product lasted longer in use than expected.
- Finished Early – The product got finished sooner than anticipated

- Spoiled – The product quality got bad before it could be used fully

Depending on the values entered by the user, the system will recalculate the time span (n) through the formula in Equation 4:

$$\text{New Time Span} = \text{Complaint Date} - \text{Order Date} \quad (4)$$

In case of product spoilage, the information is stored and used in subsequent forecasts of consumption in days (m) to enhance the accuracy of prediction.

3.8. Adjusting the Weight for the Next Purchase

Feedback from users has a direct effect on future orders. In case the user wishes to change the volume of orders:

- The system designates (x) to increase the percentage.
- The system designates (y) to increase the percentage.

Such updates are taken into consideration when computing the next order. When no adjustments are made, the system restores x=0 and y=0. The process will then go back to Step 2, once the n-day period has elapsed or once the user clicks on the Order Now button manually. For a more detailed explanation of the underlying algorithm, refer to Figure 2.

4. Implementation

The procedure described in the foregoing section offers a novel methodology that is in the process of being refined. An algorithm has been systematically documented, even though the fully functional implementation is still ongoing.

To enable one to grasp its working process better, an example of its application is provided in steps so that one can understand how it is carried out in practice.

4.1. Example: Automated Tomato Subscription Flow

The calendar is shown in Figure 3, and an example of the database to be used in a dry run of the example is illustrated in Figure 4.

Altogether, these figures help to illustrate the workflow of the suggested system.

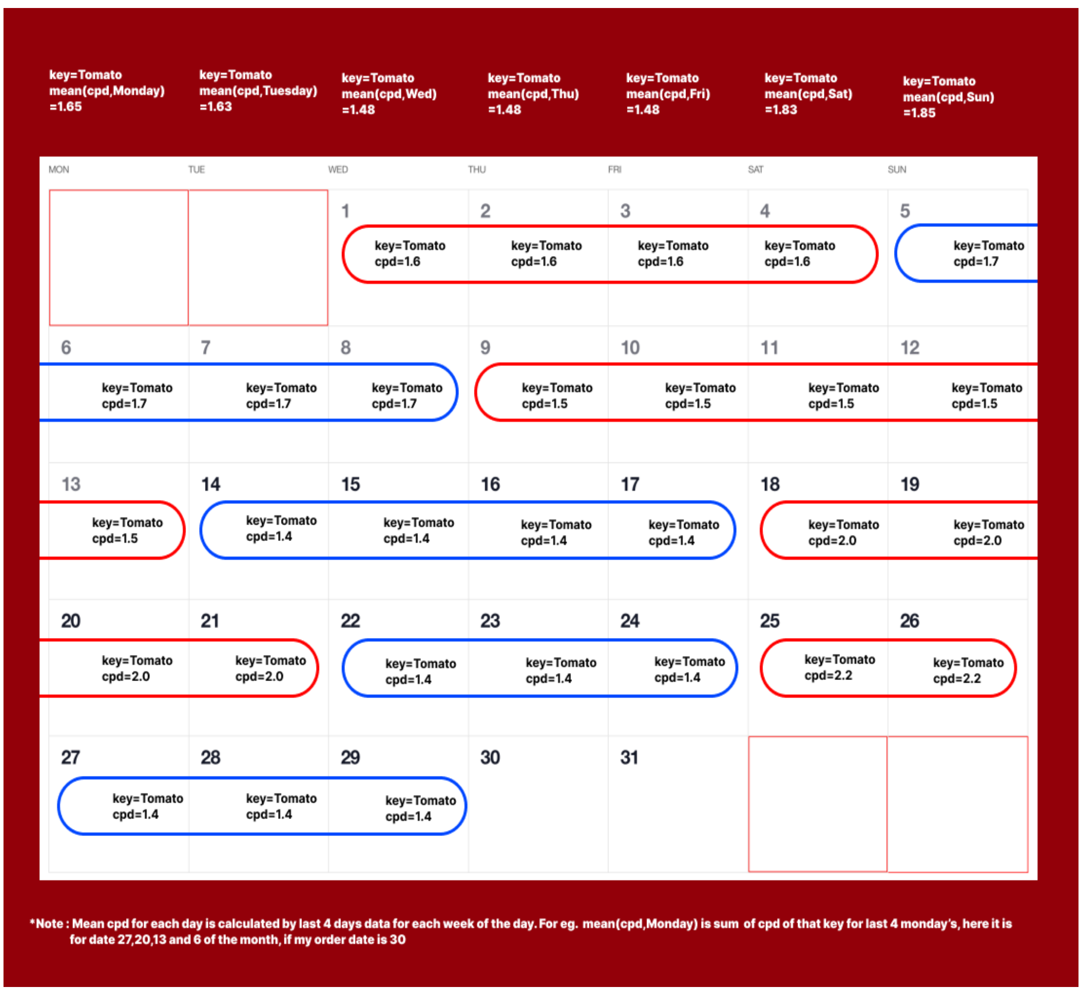

Fig. 3 Calendar for dry run of tomato order

	A	B	C	D	E	F	G
1	Item (key)	purchase_date	repurchase_date	Quantity (kg)	Spoil_Date	time_span	cpd
2	Tomato	01-01-2024	05-01-2024	6.40	null	4.00	1.60
3	Tomato	05-01-2024	09-01-2024	6.80	null	4.00	1.70
4	Tomato	09-01-2024	14-01-2024	7.50	14-01-2024	5.00	1.50
5	Tomato	14-01-2024	18-01-2024	5.60	null	4.00	1.40
6	Tomato	18-01-2024	22-01-2024	8.00	null	4.00	2.00
7	Tomato	22-01-2024	25-01-2024	4.20	null	3.00	1.40
8	Tomato	25-01-2024	27-01-2024	4.40	null	2.00	2.20
9	Tomato	27-01-2024	30-01-2024	4.20	null	3.00	1.40
10							
11							
12		cpd=Quantity/time_span					
13							
14							

Fig. 4 Database for dry run of tomato order

Dry-run of the given example according to the information and estimations explained:

4.1.1. Initial Order Data

- Order Date: 09-01-2024
- Quantity: 7.5 kg
- Repurchase Date: 14-01-2024

It is the first order; therefore, the system will start with these values and continue to compute consumption per day (CPD) as illustrated in Figure 2, with the formula indicated in Equation 1.

4.1.2. CPD Calculation

Using Equation 2, where let's assume:

- Q = 7.5 kg (Quantity ordered)
- Rd = 14-01-2024 (Repurchase Date)
- Pd = 09-01-2024 (Purchase Date)

The difference between the time of repurchase and the time of purchase is:

Rd - Pd = 14-01-2024 - 09-01-2024 = 5 days

Find the CPD now:
CPD = 7.5 kg / 5 days = 1.5 kg/day

So, the rate of consumption per day is 1.5 kg per day.

4.1.3. Weekly Pattern Analysis

The system will now analyse the consumption pattern of various days of the week over a duration of 4 weeks. We will calculate the average consumption on some sample days (according to the example data) with the help of Equation 3:

For Monday:
mean(CPD, Monday) = (1.4 + 1.5 + 1.7 + 1.4) / 4 = 1.65 kg/day

For Tuesday:
mean(CPD, Tuesday) = (1.4 + 1.5 + 1.7 + 1.6) / 4 = 1.63 kg/day

This would repeat with other days of the week (Wednesday, Thursday, etc.) according to the historical data, which is not exhaustively described here.

4.1.4. Order Quantity Calculation for the Next Cycle

To obtain the next order quantity, the system uses the average daily consumption (CPD) stated in Equation 4 to calculate the quantities needed each day of the next cycle (4 days in this example).

- Base Consumption Sum:
  S = mean(CPD, Monday) + mean(CPD, Tuesday) + mean(CPD, Wednesday) + mean(CPD, Thursday)

  (Assume similar values for Wednesday and Thursday for simplicity, say 1.48 kg/day for both.)

  S = 1.65 + 1.63 + 1.48 + 1.48 = 6.24 kg

Since we now have the base consumption to use in the next 4-day cycle, the system uses any adjustment requested by the user (increase or decrease in order size).

4.1.5. Applying the 20% Increase Request

The system uses Equation 5 to determine the final order quantity, where:

- x = 20% increase request
- y = 0% decrease in request

Plugging in the values:
FinalOrderQuantity = 6.24 kg × (1 + 20/100 - 0/100)

FinalOrderQuantity = 6.24 kg × 1.20 = 7.49 kg

So, the system calculates that the new order quantity should be 7.49 kg for the next cycle.

4.1.6. Feedback Integration and Adjustment

In the event that there was any user feedback regarding the last order (i.e. early depletion, longer-lasting items or spoilage), the feedback would be factored into the order quantity. The shelf life of vegetables and fruit also differs due to environmental factors, as well as the origin of the product. This can be taken care of by providing the user with the option to give feedback on the condition of the vegetables he/she bought, so it can go ahead and update the quantity of the next order.

The quantity will still be 7.49 kg, as the consumption has been calculated, and a 20 percent increase is demanded.

4.1.7. Final Order Quantity

The calculated final order quantity of the next cycle is 7.49 kg. This takes into consideration:

- The previous day-to-day average consumption.
- The user demand is a 20 percent increment.

A prototype User Interface (UI) has been created in order to improve the visualization of how the proposed system will work and how the user will interact with it. This UI is a copy of the main features that should be presented in an online grocery shopping application, which provides a convenient user experience. The designed interface is illustrated in Figure 5 and includes all the elements that have to be incorporated to facilitate automated subscription-based ordering [18].

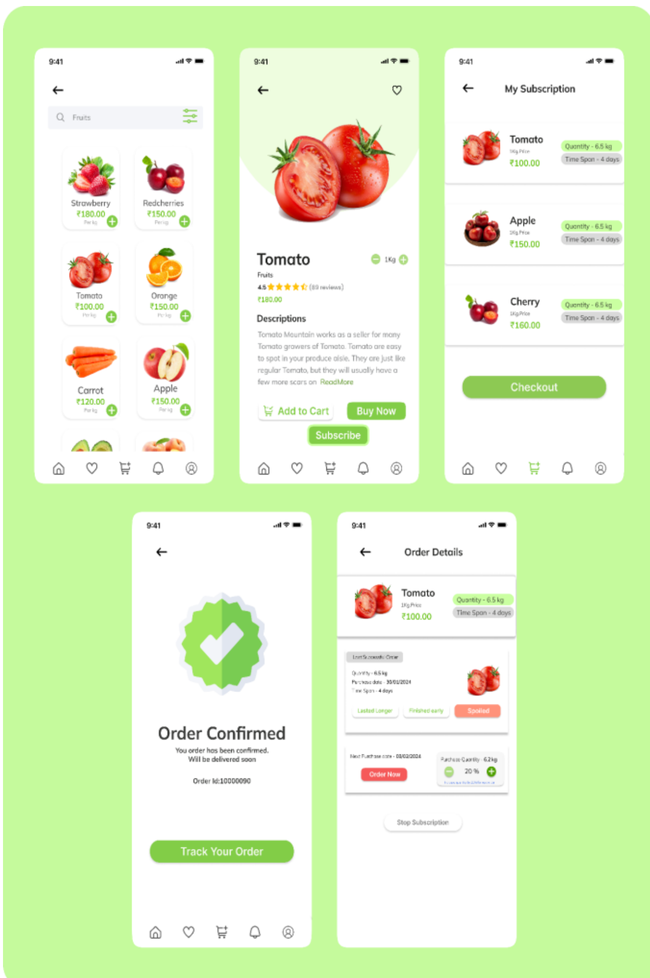

Fig. 5 Prototype UI for the grocery automation integrated in application

4.2. Experimental Setup

In order to test the Smart Subscription Algorithm with the help of Machine Learning based approaches, a synthetic dataset has been generated, simulating the grocer's purchasing behavior in the real world. The dataset used was 50 transactions of 10 different users. The variables stored on each record included purchase date, quantity, computed Consumption Per Day (CPD), feedback flags, shelf life and user-designated reorder preferences.

Python 3.11 was used to deploy the system. The main data processing and analysis were performed with the help of pandas and numpy libraries, and visualization was carried out using seaborn and matplotlib. The development and testing of two predictive models were done:

- XGBoost – a Gradient boosting algorithm, which is optimized on tabular data.
- LSTM - sequential neural network (time-series prediction).

All the simulations were carried out on a local machine that had an Intel i7 processor and 16GB RAM. The standard regression measures, namely, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the coefficient of determination (R^2 score), helped to evaluate the model performance.

4.2.1. Results and Metrics for Evaluation

Table 1 shows the comparative results of both tested models:

Table 1. Comparison of the performance of XGBoost and LSTM models based on RMSE, MAE, and R 2 measures on grocery consumption data

Model	RMSE	MAE	R^2 score
XGBoost	0.0095	0.0062	0.7951
LSTM	0.0323	0.0257	-0.2221

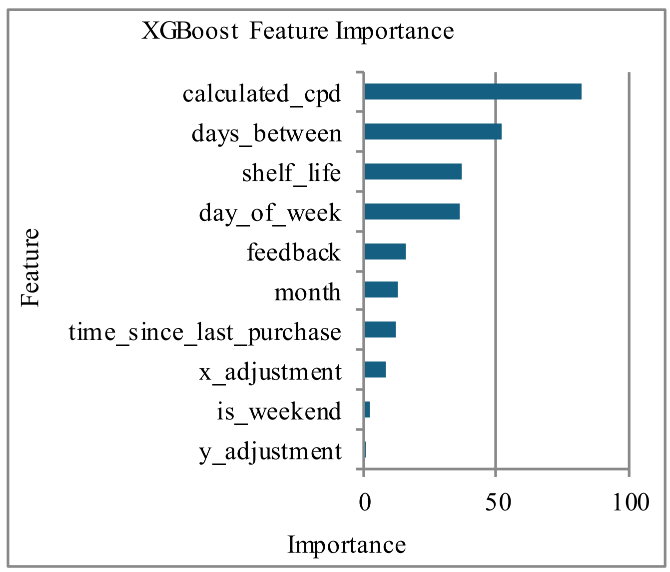

Fig. 6 Importance plot of features as determined by the XGBoost model, which indicates shelf life, feedback and time-based features as important factors in predicting CPD

The XGBoost model performed better than the LSTM model, and it provided the best compromise between predictive accuracy, computational efficiency, and interpretability. Analysis of feature importance revealed that the variables, including shelf_life, feedback, and time_since_last_purchase, were the strongest factors to influence the CPD prediction (see Figure 6). Also, learning curves indicated consistent convergence after 20 epochs, and the plots of error distribution depicted a low prediction variance. Table 1 and Figure 8 visualize the general performance of the models. At the same time, the learning behavior of the LSTM model is depicted in Figure 7. According to these findings, XGBoost is supposed to be the most efficient model in terms of simulated grocery subscription use cases and will be chosen as the default prediction engine for the proposed system.

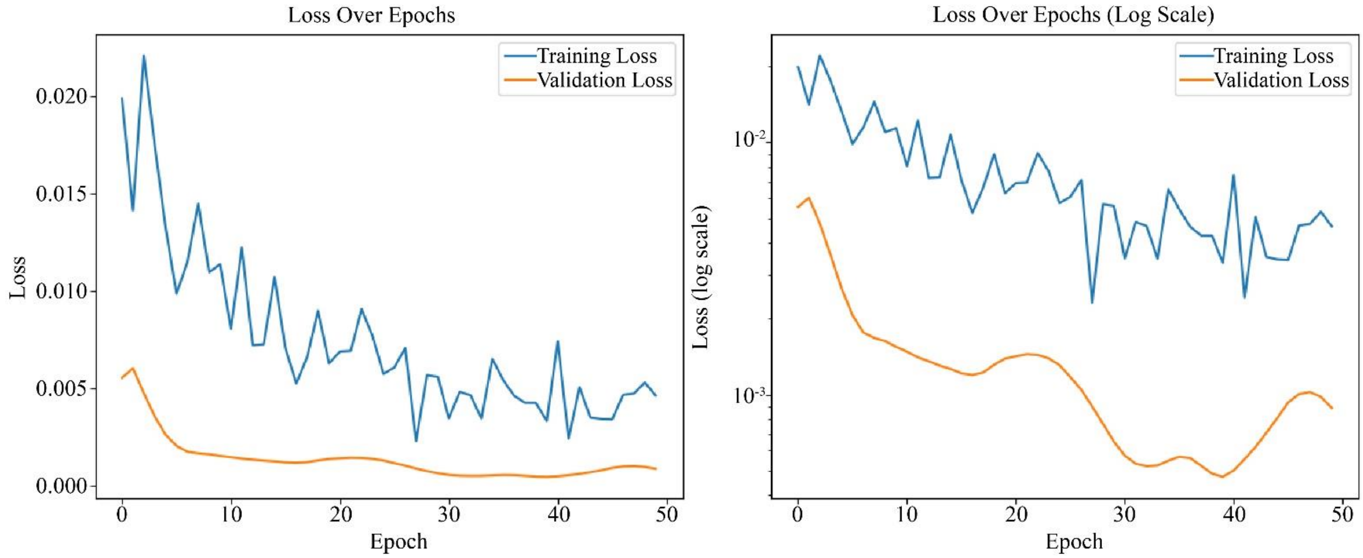

Fig. 7 LSTM learning curves of training and validation loss over epochs, wherein the model exhibits convergence behavior

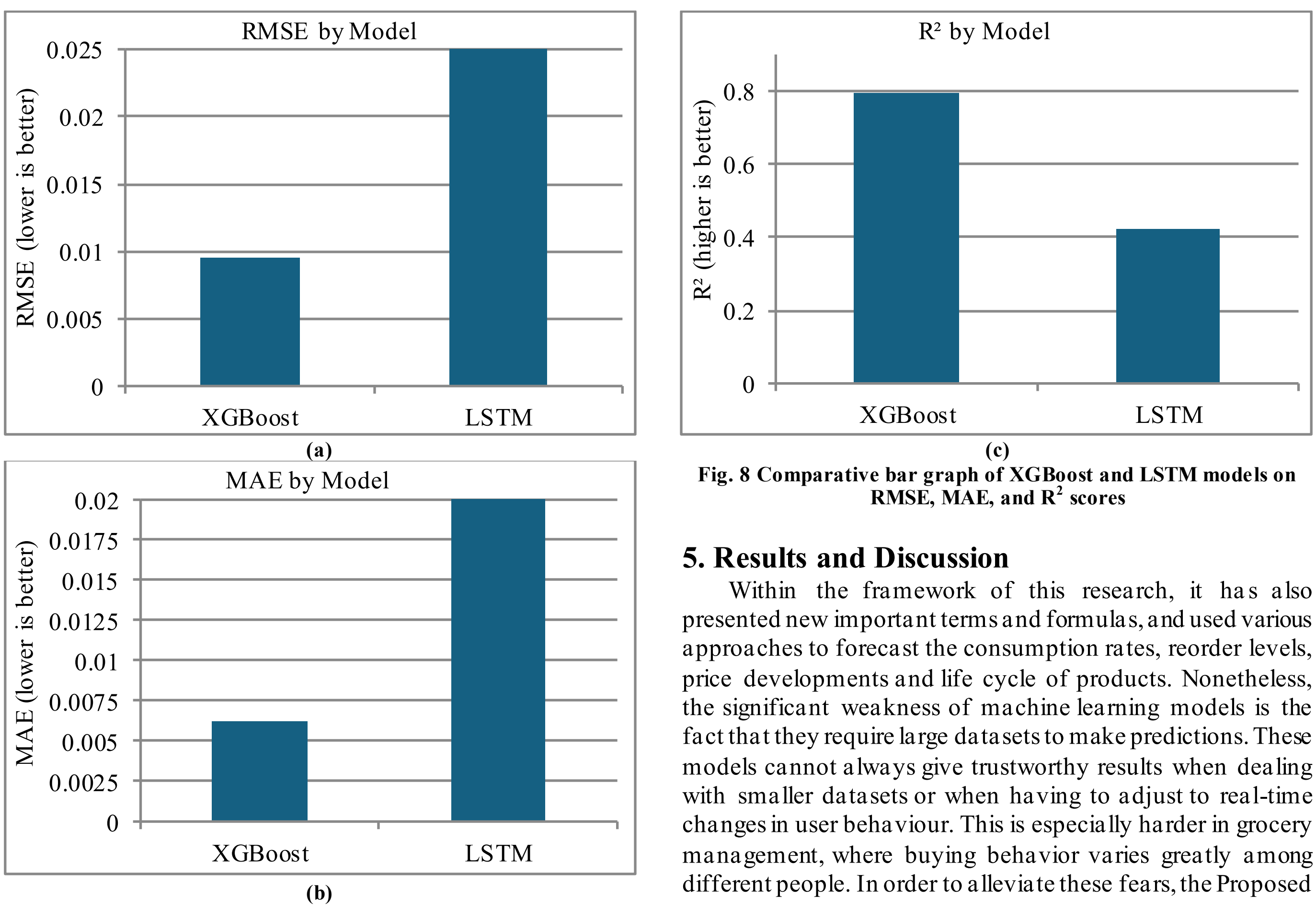

Fig. 8 Comparative bar graph of XGBoost and LSTM models on RMSE, MAE, and R^2 scores

5. Results and Discussion

Within the framework of this research, it has also presented new important terms and formulas, and used various approaches to forecast the consumption rates, reorder levels, price developments and life cycle of products. Nonetheless, the significant weakness of machine learning models is the fact that they require large datasets to make predictions. These models cannot always give trustworthy results when dealing with smaller datasets or when having to adjust to real-time changes in user behaviour. This is especially harder in grocery management, where buying behavior varies greatly among different people. In order to alleviate these fears, the Proposed

Methods section of this paper will provide a statistical way of determining consumption rates and the restocking schedule. This approach contrasts with standard machine learning approaches that have been described in the Related Works section, as it uses recent consumption data that is dynamically updated on a weekly basis. This constant adding or updating of new data makes predictions accurate and reliable, even without large datasets. This flexibility renders the statistical solution a more practical implementation of real-time tracking of grocery consumption.

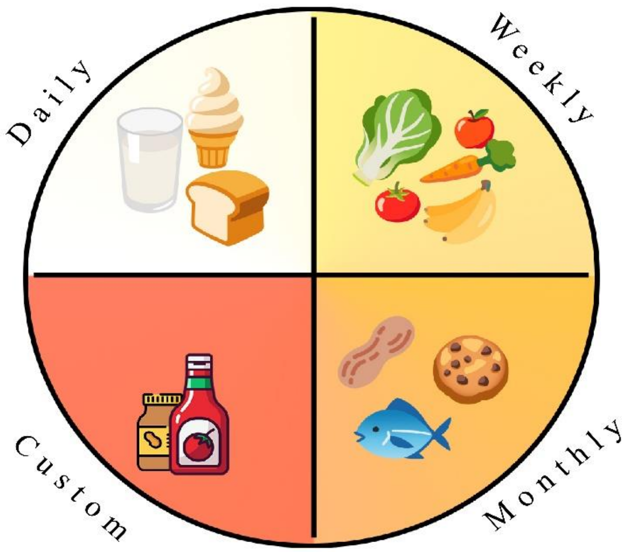

Fig. 9 Clustering based on product time span

Though the models of machine learning, XGBoost and LSTM, have been tested in this project, the next step will include making these models a part of the live system, thus automating real-time predictions. The first opportunity for enhancement can be seen in the automation of product categories and grouping of items into daily, weekly, and monthly order cycles through ML classification methods, as exemplified in Figure 9.

Moreover, a hybrid implementation in future work will consider combining the statistical model implemented in this work with the tested machine learning approaches to realize a real-time and adaptive order automation based on the corresponding advantages, as a follow-up of the presented work. Such incorporation will allow the system to make more accurate forecasts in datasets of different sizes, which will further enhance the effectiveness and integrity of grocery inventory handling. These breakthroughs will play a significant role in perfecting the system, making it more adaptable and scalable to suit the different needs of various users.

6. Conclusion

To summarize, the postulated statistical system, which is tested as part of this research on automating the subscription-based management of orders on online grocery platforms, can bring important changes to the optimization of the accuracy of app predictions and user experience. With dynamic consumption rate analysis, predictive ordering and adaptive feedback mechanisms, the system demonstrates excellent results in minimizing wastes, out-of-stocks and ensuring timely deliveries. The data is processed in real-time, and user feedback can be incorporated to constantly optimize the quantities of the order, making the subscriptions constantly adjusted to the personal consumption habits. With the development of the system, further improvement, including intelligent product classification, delivery design, and price forecasting, might optimize the subscription process and business performance even more and lead to the creation of smarter and more sustainable grocery systems.

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