Machine Learning-Based Smart Grocery Planner with Dynamic Budgeting and Waste Analytics Under Climate Variability

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***Abstract*— Food waste is a big problem for homes, stores, and food service providers. It costs money and hurts the environment. Most grocery planning tools still use fixed expiration dates, which don't account for how food changes when it's stored and for changes in the weather. This project creates a smart grocery planner that leverages food science, machine learning, and practical budgeting tips to help people waste less food. The system uses daily weather data from Delhi (2022–2023) along with important information about each grocery item, such as how long it usually lasts, the temperature at which it should be stored, and its sensitivity to temperature changes (measured by the Q10 coefficient). Instead of using fixed estimates, the shelf life is updated daily based on current temperature and humidity. A Combined Spoilage Factor (CSF) indicates the level of stress the food is under in its environment. Regression models estimate how long each item will last, while classification models flag items that are close to spoiling. A dynamic budgeting tool helps users decide what to buy and when, so they can avoid spending money on food that might go to waste. Tests show that ensemble machine learning models make more accurate predictions than traditional methods, especially during seasons with large changes in temperature and humidity. Temperature is the main factor, but humidity also has a clear impact during the monsoon.**

Overall, this system is designed to be practical and user-friendly, providing a real way to reduce food waste as the weather becomes less predictable.

***Index Terms*— Food waste analytics, shelf-life prediction, Q10 model, climate-aware systems, random forest, smart grocery planning, dynamic budgeting.**

I. INTRODUCTION

Food waste is a serious global problem that affects the economy, food security, and the environment [1], [2], [3]. Much of this waste occurs at the consumer and retail levels, especially with perishable foods that are sensitive to storage conditions after purchase. Research shows that poor storage and a lack of awareness about how spoilage happens cause people to throw away food that could still be eaten [8]. This problem is worse in places with unpredictable weather, where fluctuations in temperature and humidity accelerate food spoilage. Even so, most expiration labels are based on fixed shelf-life estimates and assume perfect storage conditions, which are rarely the case.

Static expiry labels don't show how factors in the environment affect how quickly food spoils. Temperature is the main factor that affects chemical reactions and microbial growth. Humidity, on the other hand, affects moisture, texture, and how quickly food Static expiry labels don't show how factors in the environment affect how quickly food spoils. Temperature is the main factor that affects chemical reactions and microbial growth. Humidity, on the other hand, affects moisture, texture, and how quickly food goes bad. Because these factors interact in complex ways, fixed-date labels can't capture true spoilage patterns [2], [3], [4]. Because of this, people often don't know how fresh their food is, which can make them throw away good food or eat spoiled food. Most grocery apps offer only basic features, such as shopping lists and expense tracking. They don't account for how fresh things are in real time or for how conditions change. Because of this gap, people buy too much or don't put things that are more likely to go bad at the top of their list. To solve these problems, this study introduces a smart grocery planner that uses food science, climate-aware modeling, and machine learning to help people make better choices every day [2], [3], [4]. The system uses weather data from 2022 to 2023, as well as key information about each food item, such as how long it usually lasts, the optimal storage temperature, and how quickly it spoils as temperatures rise (the Q10 coefficient). This method is better than the old Q10 model because it accounts for humidity and adds a Combined Spoilage Factor (CSF) that shows how both temperature and humidity affect food quality. Regression models estimate how much longer each item will last, and classification models identify which foods are most likely to go bad soon. The planner also has a budgeting tool that changes over time to help people decide what to buy and what to skip based on the real risk of spoilage. The system goes beyond analytics by turning predictions into useful, low-cost advice that helps people make real decisions that cut down on food waste and save money. Here are the main points of this work:

- A climate-aware shelf-life modeling pipeline that combines data about the environment with scientific data about food. * The creation of a single Combined Spoilage Factor (CSF) to measure how temperature and humidity work together to affect spoilage.
- A dual-model predictive framework that uses both regression and classification to better estimate shelf life and find waste risk.
- A flexible budgeting plan that matches how much people are likely to spend with how much food is likely to go bad to cut down on waste and get the most out of their money.

In summary, this work provides a scalable, data-driven solution to food waste in areas affected by climate change, offering new ideas and real benefits for both consumers and retailers.

II. LITERATURE REVIEW

A. Shelf-Life Science and Kinetic Modeling

Chemical kinetics temperature-dependent degradation models have historically been used in classical shelf-life estimation. Among these, T. P. Labuza's Q10 model is still frequently used because of its ease of use and interpretability [4]. For every 10°C increase in temperature, it simulates the multiplicative increase in reaction rates.

Although Q10-based methods work well in controlled settings, they have drawbacks in real-world settings. In particular, they disregard other important factors, such as humidity, airflow, and microbial variability, in favor of assuming that temperature is the only factor causing spoilage. In humid climates, especially in tropical regions like India, this leads to a systematic overestimation of shelf life. Although the literature currently in publication recognizes these limitations, it lacks standardized extensions to include multi-factor environmental stress.

To fill this gap, new research suggests adding correction factors to kinetic models. But these changes are often based on experience and don't apply to other types of food. The current study makes the Q10 formulation more useful in real life by adding humidity-based corrections and a composite spoilage metric.

B. Food Waste, Climate Change, and Risk to Operations

Reports from the United Nations Environment Programme and the Food and Agriculture Organization show that food waste is not just a problem with people's behavior; it is also a problem with the way the system works that is caused by exposure to the environment [1], [2]. The Intergovernmental Panel on Climate Change also says that climate change makes spoilage more likely by changing storage conditions in ways that are hard to predict [3].

FIFO (First-In-First-Out) and other traditional inventory methods assume that storage environments are stable when used in business. But FIFO doesn't keep quality when the temperature and humidity in the air are not at their best. This leads to hidden waste buildup, especially in supply chains for things that go bad quickly.

Gap Found:

- Current systems don't have real-time climate integration
- There is no link between being exposed to the environment and making decisions as a consumer.
- Budgeting systems work on their own, without taking into account the risk of spoilage

This study fills in these gaps by combining climate-aware spoilage modeling with economic decision support. This lets people change their buying and consumption habits.

C. Machine Learning for Quality and Shelf-Life Analysis

Machine learning has become a useful tool for figuring out how nonlinear relationships work in food systems. Ensemble methods like Random Forests, which Leo Breiman came up with, are very good at dealing with data that isn't all the same and features that interact with each other [5]. Using frameworks like Scikit-learn makes it even easier to deploy on a large scale [6].

Recent research shows that artificial intelligence can help with predicting shelf life, sensory analysis, and classifying food quality by modeling complex, nonlinear relationships in spoilage processes. This makes it possible to assess food quality more accurately and on a larger scale [9]. For example: Estimating the shelf life of fruits based on sensors [9] Deep learning models for predicting ripening [10] Modeling spoilage in a controlled environment [11]

These methods show that ML works, but they also have some major problems:

- Concentrate on individual product categories
- Work in environments that are under control
- Not being able to work with climate-scale datasets
- Do not include frameworks for making economic decisions

This research advances the discipline by integrating urban climate data, multi-item modeling, and budget-conscious analytics. This means that ML can be used in more places than just labs.

Table 1: Comparison with existing approaches

Approach	Climate Inputs	ML Layer	Budget Link
FIFO/Static expiry	No	No	No
Demand-only apps	Limited	Partial	Yes
Q-10 only models	Temp only	Rare	No
Proposed Framework	tem+hum+rain	Regr. +classif.	Yes

III. METHODOLOGY

A. Putting together information

- Dataset of Delhi weather from 2022 to 2023 [13]
- Food metadata from the Food Safety and Standards Authority of India [7], the U.S. Food and Drug Administration [8], and divisive analysis for user recommendation [15]. You can run simulations in different weather by using a cross-join to mix items and days.

B. Modeling Shelf Life That Takes the Weather into Account

The methodology improves traditional Q10 modeling by:

- Decay that depends on temperature (Q10 model)
- A number that you can use to fix humidity
- The Combined Spoilage Factor (CSF) looks at how things affect each other.

For item i on day d, temperature-adjusted shelf life is:

$$SL_{i,d} = SL_{i,d}^{(T)} \cdot (1 - \alpha \max(0, H_d - H_0))$$

where SL^0_i is baseline shelf life, T_d is ambient temperature, and T_i^{ref} is ideal storage temperature.

Humidity correction is then applied:

$$SL_{i,d}^{(T)} = SL_i^0 \cdot Q10_i^{\frac{T_d - T_i^{ref}}{10}}$$

where H_d is relative humidity, H_0 = 60%, and α = 0.003.

To represent compound environment stress, CSF is:

$$CSF_{i,d} = Q10_i^{\frac{T_d - T_i^{ref}}{10}} \cdot (1 + \beta \max(0, H_d - H_0))$$

with β = 0.004. High CSF values indicate accelerated deterioration.

Waste-risk labels are generated as

$$y_{i,d}^{risk} = \begin{cases} 1, & \text{if } SL_{i,d} < 3 \\ 0, & \text{otherwise} \end{cases}$$

C. Learning Models and Evaluation

Three regressors are trained for $SL_{i,d}$ prediction: Linear Regression, Decision Tree, and Random Forest. Waste risk is modeled using Random Forest classification. Performance is measured with R^2, MAE, RMSE, precision, recall, F1, ROCAUC, and five-fold cross-validation [5], [6].

i where c_i is unit price, q_i is purchasing quantity, the model estimates spoilage probability, and λ controls risk aversion. This converts shelf-life intelligence into budget-aware action

$$J = \sum_i c_i q_i + \lambda \sum_i q_i \hat{p}_{i,d}^{waste}$$

Fig.1. Overview of the System

The system is built in layers, which makes it easy to see how data flows and add new modules.

A. Layers in Modules

Data Acquisition: gets weather feeds and product metadata from curated storage standards [[3], [7].

2) Preprocessing and Feature Engine: This part takes care of missing values, encodes seasonality, calculates Eq. (1)–Eq. (3), and makes features that are ready for the model, such as authentication and user personalization. Predictive Analytics Layer: uses trained regression and classification services to figure out how long something will last and how dangerous it is. 4) Decision Layer: makes a list of priorities for restocking and consumption and meets the budgeting goal (Eq. (5)). 5) The Visualization and Interaction Layer shows insights through dashboards, alerts, and suggestions for weekly planning.

B. An explanation of how the data moves

The steps in the process are: gathering weather data, combining features, making inferences about shelf life and risk, optimizing the budget, and making dashboard recommendations. You can upgrade each module separately, like by replacing tree ensembles with temporal deep models, without having to redesign the whole pipeline. and predictive analysis.

IV. PROPOSED SYSTEM

1. System Extensions and Data Acquisition

The proposed framework should be adaptable and work in many different places and for many different people. Adding more data sources, such as real-time IoT sensors, smart refrigerators, and weather APIs that know where you are, can make the system even better. These extensions would let you always keep an eye on storage conditions like changes in temperature, humidity, and power outages. This would make predictions more accurate.

The dataset used in this research was generated by combining publicly available daily weather data for Delhi (2022–2023) with an organized grocery metadata repository. Some examples of weather attributes are temperature, humidity, and precipitation. On the other hand, item-specific metadata has information like the item's baseline shelf life, the best temperature for storage, and the Q10 coefficients. The model learned how to handle different weather conditions by using a cross-join strategy to show how grocery items would be affected by different types of weather in real life.

2. User-Specific and Climate-Aware Design

The system is designed to work well in different climates and be unique to each user. The size of the user's household, their eating habits, their dietary preferences, and their weekly budget are all things that are taken into account when making a decision. This lets the model give you personalized suggestions instead of general ones.

The system works best in places where the weather changes a lot, like Delhi, where the temperature and humidity change a lot from season to season, which affects how quickly food goes bad. For example, during the hottest months of summer, higher temperatures speed up biochemical breakdown, and during the monsoon season, higher humidity speeds up the growth of microbes even more. The model will be more accurate if it looks at both temperature and humidity at the same time.

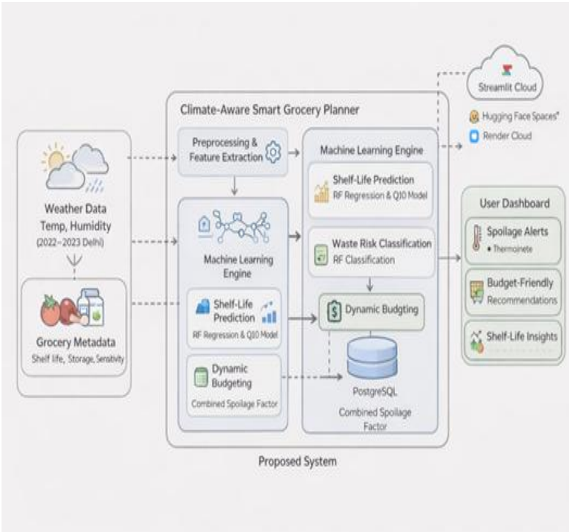

Fig 2: Architecture Diagram

3. Adaptive Learning and Scalability

The system lets people learn in a flexible way by changing its predictions all the time based on new weather data and user interactions. Even when the weather changes or people change their routines, this makes the model strong. Also, because the architecture is modular, it's easy to add to or replace the climate dataset and change the model parameters as needed to cover more areas.

Improvements that could happen in the future are:
Making predictions about the future with deep learning models like LSTM, learning to transfer between different climates and adding supply chain data to improve performance at the retail levelity, and sustainability of surplus food recovery at scale.

V. RESULTS AND DISCUSSION

A. Experimental Setup

After preprocessing, the combined dataset contained 13,140 date-item observations. The train and test sets were split 80:20, and there was a five-fold cross-validation [12], [14]. Feature vectors included season encodings, item metadata, temperature, humidity, precipitation, and CSF.

B. Shelf-life Regression Performance

Table II provides a brief summary of how well the tests performed. In both absolute and squared terms, Random Forest always had the best fit and the fewest mistakes. It performs better than linear regression, indicating that spoilage dynamics are highly nonlinear, especially under both heat and humidity stress.

Table 2:

Model	R2	MAE (days)	RMSE (days)
Linear Regression	0.81	1.96	2.57
Decision Tree Regression	0.90	1.24	1.78
Random Forest Regression	0.95	0.82	1.21

C. Risks of Sorting Waste

The Random Forest classifier did a great job of finding cases that were probably dangerous (Table III). Most of the high-risk observations happened during the hottest and most humid weeks of summer and the monsoon.

Table 3:

Metric	Value
Accuracy	0.92
Precision	0.90
Recall	0.88
F1-score	0.89
ROC-AUC	0.95

D. Information about the seasons and their features

Three helpful trends showed up. First, the expected shelf life for classes that spoil quickly dropped by 35% to 45% in the summer compared to the winter. Second, when the humidity was over 75%, the temperature effects were even worse, with an extra 12–18% drop. This showed that the humidity correction term was correct. Third, the ranking of feature importance put temperature first, humidity second, and CSF among the top composite predictors.

E. What it does to the business

The dynamic budgeting tool cut down on food waste by about 11% each week [17] compared to static planning. This change is important for homes and stores because it changes how much people buy. The framework helps people make decisions faster and works better than systems that stay the same. It tells people ahead of time when food might go bad, so they can eat it sooner or buy fewer things that might go bad. The results show that planning with the weather in mind is a good way to cut down on food waste in cities [18].

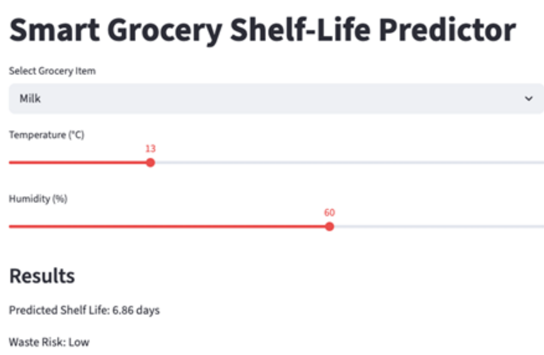

Fig.3. User Interface

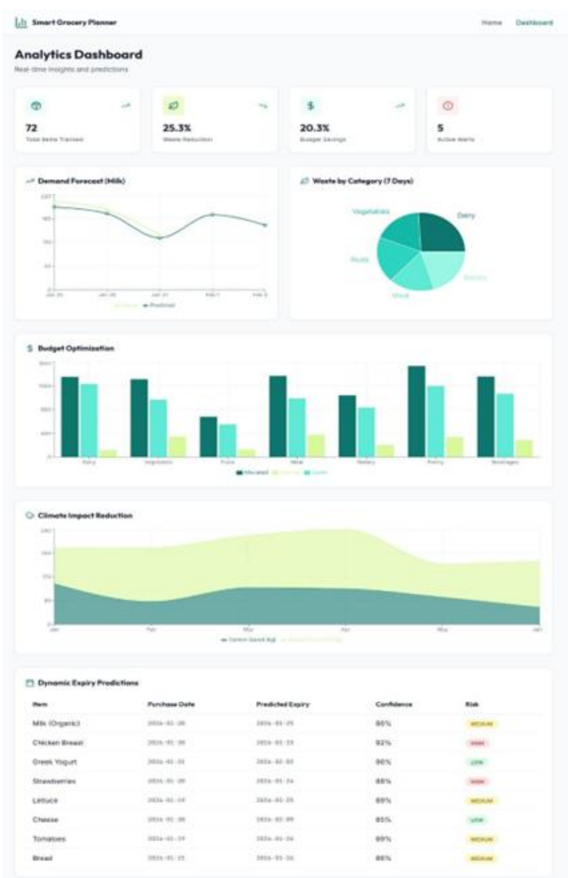

Fig.4. Dashboard Diagram

Overall, the results validate FoodLink as a practical and high-impact solution for surplus food redistribution. The system's end-to-end automation reduces food wastage, supports faster decision-making, and enhances the transparency and scalability of donation networks. These findings demonstrate the platform's ability to serve as an intelligent coordination infrastructure for NGOs, municipalities, and community food programs.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

This study introduces a climate-conscious smart grocery planner that amalgamates food science, machine learning, and pragmatic budgeting tools to address the widespread problem of household food waste [1],[13]. This planner is different from others that only use fixed expiration dates because it changes how long something will last be based on the temperature and humidity. This is more accurate for real kitchens, especially where the weather is hard to predict. Says that the weather and how food is stored can make it less fresh. Machine learning doesn't take over; it just makes predictions that are already based on established food science more accurate and tailored to each person. The system is both reliable and easy to use, so people can trust the advice they get.

Tests show that temperature is still the main reason food goes bad, but humidity is also important, especially at certain times of the year. When making plans, the planner takes both factors into account and gives people clear and helpful advice on what to buy and eat first. This helps people save money and not waste as much.

Streamlit made the dashboard for the system, which is easy to use. It lets regular people do technical analysis. The platform makes predictions easier to understand by turning them into pictures and giving clear advice. This helps people make better decisions about how to buy, store, and use food. This helps you plan better and more efficiently at home, and it also cuts down on waste.

This planner links scientific models of shelf life with real-world needs to make it easier to deal with food in a changing climate. It gives you a good foundation for managing food at home and elsewhere in a way that is better for the environment.

What the future holds for research and what it can't do? The results are good, but this system can still improve and grow in the future. One issue with the system right now is that it uses general weather data, which may not be completely accurate for the conditions in a person's kitchen or fridge. In the future, the planner could be even more accurate and personalized for each user if it had cheap sensors that could keep track of temperature and humidity in real time. It could send out daily updates that show what's really going on in each house. In the future, the planner could use advanced time-series machine learning models to not only guess when food will go bad, but also how quickly it will go bad over the course of days or weeks. This would be even better for users.

The planner could get smarter over time by using more advanced AI techniques like reinforcement learning or deep learning. For example, it could learn from how people really use their groceries and change its suggestions to fit each family's needs. This would make it even more useful in daily life. s-regional flexibility. Because spoilage behavior changes depending on the climate zone, future research may look into transfer learning methods that let trained models work in new places with little retraining.

You can also add features that help people make choices that are better for the environment, like keeping track of how much carbon their grocery shopping makes or showing them options that save energy and are good for the environment. Adding PostGIS and other spatial databases to the system can improve it by letting you do analytics that look at where things are. This can help with things like figuring out how the weather changes in different places, making the supply chain work better, and planning for delivery. This would make the app useful for food systems in homes, communities, and cities.

REFERENCES

[1] United Nations Environment Programme, *Food Waste Index Report 2024*. Nairobi, Kenya: UNEP, 2024.

[2] Food and Agriculture Organization, *The State of Food and Agriculture 2019*. Rome, Italy: FAO, 2019.

[3] Intergovernmental Panel on Climate Change, *Climate Change 2023: Synthesis Report*. Geneva, Switzerland: IPCC, 2023.

[4] T. P. Labuza, “Application of chemical kinetics to deterioration of foods,” *Journal of Chemical Education*, vol. 61, no. 4, p. 348, 1984.

[5] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[6] Pedregosa *et al.*, “Scikit-learn: Machine learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[7] Food Safety and Standards Authority of India, “Food storage and safety guidelines,” 2023.

[8] U.S. Food and Drug Administration, “Food safety and storage,” 2024.

[9] S. Srinivasagan *et al.*, “TinyML-sensor for shelf-life estimation of fresh date fruits,” *Sensors*, vol. 23, no. 16, 2023.

[10] P. Xavier *et al.*, “Shelf-life management of Hass avocado using deep learning,” *Foods*, vol. 13, no. 8, 2024.

[11] S. Ruan *et al.*, “Shelf-life prediction of fresh-cut radishes,” *Foods*, vol. 13, no. 15, 2024.

[12] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed., 2021.

[13] Kaggle, “Delhi Weather Dataset (2022–2023),” 2024. [Online]. Available: https://www.kaggle.com

[14] Hariharan *et al.*, “Machine learning techniques for fault detection,” *Energies*, vol. 18, no. 19, 2025.

[15] M. B. C. and R. K. B., “Cost-effective analytical modelling,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 5, 2019.