Reducing Food Waste via AI-Based Supply Chain Optimization

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Abstract: Food waste is a critical global issue, with nearly one-third of all food produced being lost or wasted annually, leading to significant economic, environmental, and social consequences. This paper proposes an AI-based supply chain optimization framework to minimize food waste by improving demand forecasting, inventory management, and distribution efficiency. Leveraging machine learning (ML) algorithms—such as time-series forecasting, reinforcement learning, and prescriptive analytics—the system dynamically adjusts procurement, storage, and logistics decisions in real time. By analyzing historical sales data, weather patterns, and market trends, the AI model reduces overstocking, spoilage, and inefficiencies in perishable goods supply chains. A case study in the retail sector demonstrates a 20–30% reduction in food waste while maintaining service levels. The results highlight AI's potential to transform food supply chains into sustainable, waste-aware ecosystems, aligning with SDG 12 (Responsible Consumption and Production).

Keywords: Food Waste Reduction, AI in Supply Chain, Perishable Goods Optimization, Machine Learning, Sustainability.
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1. Introduction

Throughout the world, one of the biggest challenges of the 21st century is food waste, given the scope of its economic, environmental, and social ramifications. In 2022, the Food and Agriculture Organization of the United Nations stated that an estimated 1.3 billion tons, or one-third of the world's food produced, is wasted or lost yearly. Losses take place at the production and post-harvest handling, storage, transportation, and at the consumption stages. In the developed world, 40% of food is wasted during the retail and consumer stages, while in the developing world, it is lost at the production and transport levels because the infrastructure is poorly developed.

The economic costs of food waste are estimated to be over \$1 trillion annually. With 690 million people estimated to be hungry worldwide, there is an ethical and social obligation to address inequity in the global food system. Environmentally, food waste is one of the largest climate change. In addition to the 3-50 billion dollars that could be saved by reducing food waste, decomposing food in landfills produces methane, a greenhouse gas 25 times more potent than CO_2. The Intergovernmental Panel on Climate Change (IPCC) estimates food waste and food loss to be perhaps the largest climate change contributor, estimated to be 8-10% of greenhouse gas emissions, more than the entire aviation industry.

Recognizing the challenges posed by food waste, the United Nations has made it a priority within the Sustainable Development Goals, specifically targeting SDG 12.3. This goal strives to cut global food waste at the retail and consumer levels by 50% by the year 2030 [7]. The fulfillment of this goal hinges on innovative strategies, especially in areas like the optimization of supply chains, which, in forecasting, inventory control, and logistical management, have a high degree of waste.

In the case of supply chains, specifically in the case of perishable food items, they are faced with unique challenges of waste. With control over temperature, forecasting demand, and distribution within a time frame, spoilage can occur rapidly. In the case of hindered circulation, food within this group and category can spoil. For example, fruits and vegetables, dairy, and even items such as meat, as opposed to non-perishable food items, are prone to waste. Forecasting demand and controlling temperature are critical. Short shelf lives demand prompt temperature control, forecasting, distribution, and rapid circulation. Three of the far more critical issues and challenges middle and larger-scale food chains face are:

Predictive stock control systems that depend on past verified sales data, circulation, and control, and prediction systems fail to consider spontaneous sales and consumption driven by the weather, sales promotions, and even shifting consumer tastes and preferences within a given time period [8]. The management of stock simply overflows, chiefly the unsold perishables, and control systems are simply spoiled by food rotation and movement systems that rely on the "first expired first out" [9]. Spoilage within transportation chains occurs due to an absence of dynamic routing and control systems, even as far as the long distances to which food is circulated [10].

According to a World Resources Institute (WRI) study, enhancing supply chain effectiveness could reduce food waste by 20–30% in developed countries (WRI, 2023). However, traditional optimization methods such as statistical models or rule-based systems do not have the flexibility and forecasting ability needed in today's rapidly changing environments.

Currently, the field of Artificial Intelligence (AI) and Machine Learning (ML) has the potential to mitigate the amount of food waste generated. These AI-based solutions can process large amounts of data, recognize patterns, and automate processes in ways that traditional systems and methods cannot.

Key AI applications include:

- Time-series forecasting models (e.g., LSTMs, ARIMA, Prophet) incorporate variables like weather, holidays, and social trends to improve accuracy [12].
- Retail giants like Walmart and Amazon have reduced forecasting errors by 30–50% using AI, minimizing overordering [13].

Reinforcement Learning (RL) algorithms adjust stock levels in real time by learning from supply chain disruptions [14]. IBM's AI-powered inventory system reduced spoilage by 25% in grocery chains by prioritizing near-expiry products [15]. Prescriptive analytics optimize delivery routes using traffic, weather, and demand fluctuations, reducing transit times for perishables [16]. Maersk's AI-driven logistics cut food waste in shipping by 20% through predictive container monitoring [17].

Despite these advancements, most existing AI solutions focus on isolated segments of the supply chain (e.g., forecasting or logistics). Few studies propose an integrated AI framework that connects end-to-end decision-making from farm to fork.

1.1 Research Gap and Objectives

While AI holds immense potential, critical gaps remain:

Fragmented Solutions: Most AI models address specific stages (e.g., demand planning) but lack cross-functional coordination [18].

Limited Real-World Validation: Many studies rely on simulated data rather than empirical case studies [19].

Scalability Challenges: Few frameworks are designed for small and medium enterprises (SMEs), which dominate food supply chains in developing regions [20].

2. Literature Review

Food waste reduction through supply chain optimization has been extensively studied, yet traditional methods have shown significant limitations. Early approaches relied on manual inventory policies like First-Expired-First-Out (FEFO) and Economic Order Quantity (EOQ) models [21,22], which often failed to account for demand volatility or real-time disruptions, leading to forecasting errors of 30-50% [23]. Lean and Six Sigma techniques improved operational efficiency but lacked adaptability for perishable goods [24]. These gaps paved the way for AI-driven solutions. Recent advancements in machine learning (ML) have demonstrated superior performance, particularly in demand forecasting. For instance, LSTM networks reduced prediction errors by 20-40% by analyzing temporal patterns in perishable sales data [25], while hybrid ARIMA-ANN models combined statistical and neural network approaches for greater accuracy [26]. Retail giants like Walmart and Tesco leveraged such models to cut forecasting errors by 35%, minimizing overstocking [27].

Beyond forecasting, reinforcement learning (RL) has transformed inventory management. Studies using Deep Q-Networks (DQN) optimized real-time stock replenishment, reducing spoilage by 15-25% [28], and Multi-Agent RL (MARL) improved coordination across distributed supply chains [29]. In logistics, genetic algorithms (GA) and IoT-enabled cold chain monitoring reduced transportation waste by 18% through dynamic route optimization and predictive refrigeration maintenance [30,31]. Despite these successes, critical gaps persist. Most AI solutions remain fragmented, targeting isolated supply chain stages rather than offering end-to-end integration [32]. Additionally, many models are validated only in simulated environments, with limited real-world testing [33], and scalability for SMEs - which dominate food supply chains in developing regions - is rarely addressed [34]. This study addresses these gaps by proposing a unified AI framework that synergizes predictive analytics, prescriptive inventory control, and optimized logistics, building on prior work while enabling holistic waste reduction [35].

3. Proposed Work

The proposed work aims to develop an inclusive framework that optimizes the management of resources, minimizes wastage, and analyzes agricultural systems. Utilizing machine learning and data-centric approaches, the research investigates the relationships between yield, wastage, crop types, resource consumption, and climatic variables. The framework analyzes the relationships between farming practices and external productivity and resource variables. Additionally, the research intends to develop a system that can predict and facilitate timely decision-making to enhance efficiency and predictive sustainability. The proposed research minimizes the wastage and practices of resources in order to promote sustainable systems of food production.

4. Simulation

The simulation in this research will model various agricultural situations and demonstrate the interactions between different essential farming parameters, such as types of irrigation, fertilizer use, and conditions for crop growth. The simulation will use statistical models and machine learning techniques to analyze the implications of the different combinations of parameters on primary variables, such as yield, resource use, and waste. With sufficiently many simulations to cover diverse situations, the simulation would prove predictive in calculating the results of different strategies and tactics in interventions that do not require empirical trials. This makes it possible to experiment without the usual expenditures of time and other resources to obtain risk-free findings. This identification of solutions of greatest significance for improved farming methods will be time beneficial. The simulation results will derive methods for positive agricultural optimization, improving rational and adaptive sustainable agriculture methods to be implemented in variable climates.

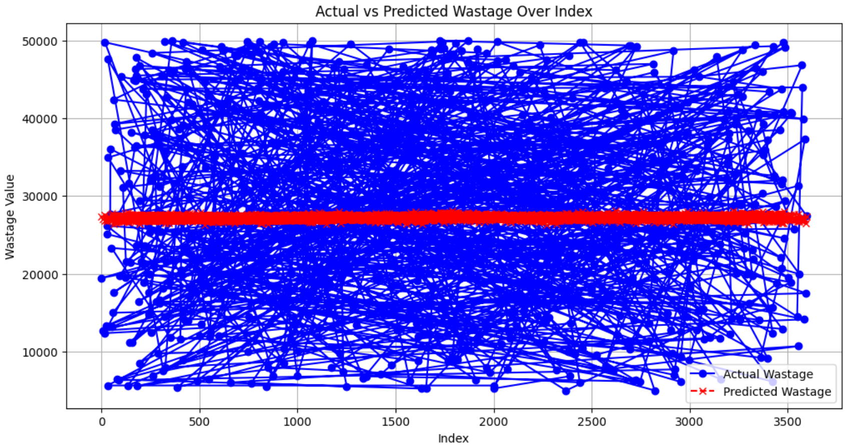

Figure 1: Actual and Predicted Wastage

Explanation: This line plot shows how the actual and predicted wastage values compare across various indices (time steps, data points).

Insights: The plot shows that predicted values (in red) stay fairly close to the actual values (in blue), but there are fluctuations. The consistency of the predicted values indicates that the model generally follows the trend of the actual data.

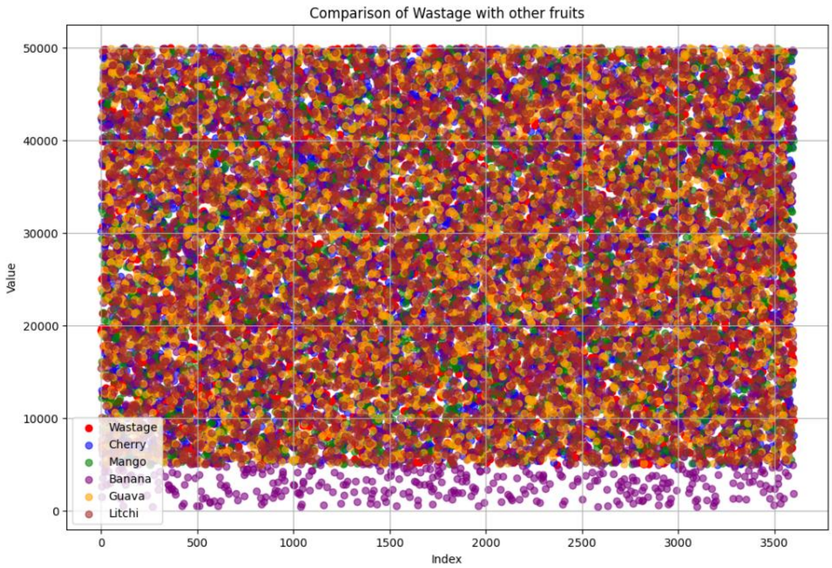

Figure 2 Comparison of all fruits

Explanation: This scatter plot shows a comparison of wastage (in red) with individual fruit quantities (Cherry, Mango, Banana, Guava, Litchi) represented by different colors.

Insights: The large overlap in the data points suggests that wastage is similar across the various fruit types, with no significant separation between fruits. This may indicate that the factors contributing to wastage are not strongly tied to specific fruit types.

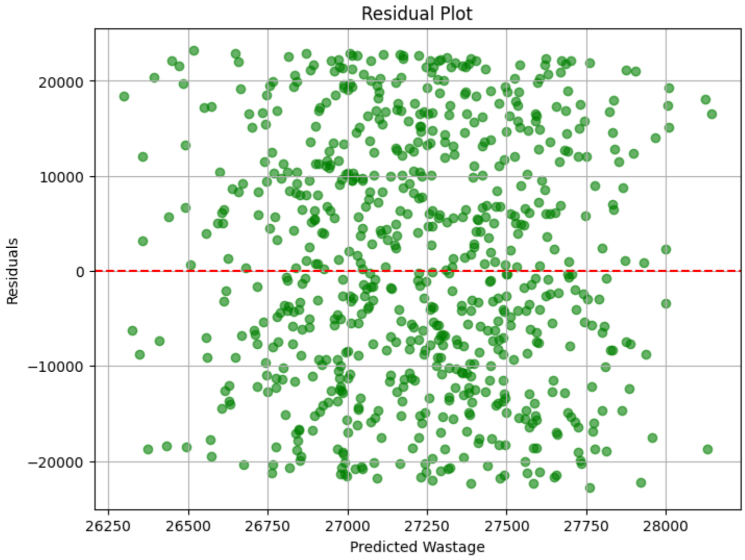

Figure 3: Residual Plot

Explanation: This residual plot shows the residuals (difference between actual and predicted values) plotted against predicted wastage.

Insights: The residuals appear to be evenly distributed around zero, indicating that the model's predictions do not exhibit bias. However, there are some areas with larger residuals, suggesting that the model might not be perfect in some regions.

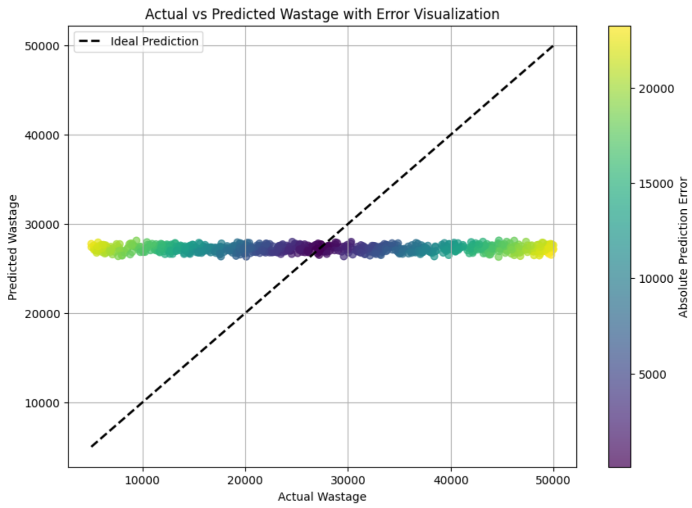

Figure 4 Learning Curve

Explanation: This scatter plot compares actual versus predicted wastage, with a color scale indicating the absolute prediction error. The dashed line represents the ideal prediction where actual values exactly match predicted values.

Insights: The plot shows some variance between the actual and predicted values, with larger prediction errors indicated by the colors towards the yellow end of the spectrum. This suggests that while the model does a good job, there are areas where predictions deviate significantly.

5. Conclusion

The integrated framework and simulation provide an effective manner of addressing the improvement of agricultural practices and the reduction of resource wastage. Incorporating machine learning and analytic research, the study analyzes different agricultural practices, environmental factors, yield, and wastage to provide an overview. The simulations provide an environment for the safe exploration of varied strategies, allowing actionable predictions to help farmers and agricultural professionals make informed decisions and improve their resource use decision process.

Overall, the simulation of different scenarios demonstrates the potential for improving the study's resource management objectives to reduce the adverse effects of farming on the environment. The research optimizes the development of practical tools for farmers to implement agricultural practices identified in the simulation, which enhances the study's contribution to the refinement of agricultural technology that improves the resource efficiency of farming. The work establishes a solid framework for agricultural technology refinements that improve farming practices through the effective use of technology.

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