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THE ROLE OF ARTIFICIAL INTELLIGENCE IN REDUCING FOOD WASTE IN MODERN FOOD SYSTEMS

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ABSTRACT

This scientific paper examines the urgent global challenge of food loss and waste throughout the entire value chain, highlighting the pivotal role of end-to-end Artificial Intelligence (AI) technologies in mitigating this issue. Food waste exerts a massive destructive impact on the global economy, the environment, and food security. The paper provides a comprehensive analysis of machine learning, computer vision, and predictive analytics techniques used for supply chain optimization, demand forecasting, smart food sorting, and dynamic pricing models. Mathematical and conceptual frameworks for integrating AI into food supply chain management (FSCM) systems are presented. The research demonstrates that the comprehensive deployment of intelligent systems can reduce food waste by 25–40%, positioning AI as a fundamental driver of sustainable development in the agro-industrial sector.

Introduction. In the 21st century, ensuring the sustainable functioning of global food systems has emerged as one of the most critical challenges facing humanity. According to official reports by the Food and Agriculture Organization of the United Nations (FAO), approximately one-third of all food produced for human consumption worldwide is lost or wasted annually. This amounts to roughly 1.3 billion tons of biomass, representing an economic value exceeding USD 1 trillion. These losses occur at every stage of the food supply chain: from

primary agricultural production, post-harvest handling, transportation, and storage, to industrial processing, retail distribution, and final household consumption.

Beyond the colossal economic toll, food waste drives a severe environmental crisis. Organic waste rotting in landfills is a major source of greenhouse gas emissions, particularly methane (CH_4), which has a global warming potential dozens of times higher than carbon dioxide. Food loss and waste account for an estimated 8-10% of total anthropogenic greenhouse gas emissions globally. Moreover, this inefficiency signifies that billions of cubic meters of fresh water, millions of hectares of arable land, and vast quantities of energy and fertilizers are completely squandered on producing food that is never consumed.

Traditional Food Supply Chain Management (FSCM) methods are proving increasingly ineffective in the face of highly dynamic market conditions, volatile weather patterns, and complex consumer behavior. The situation is further exacerbated by a lack of data transparency and poor information sharing among supply chain actors. Consequently, there is an urgent scientific and practical imperative to introduce fundamentally new, high-tech tools for process automation and intellectualization.

The most promising technological frontier for addressing this crisis is Artificial Intelligence (AI) and its core subsets, including Deep Learning, Computer Vision, Natural Language Processing (NLP), and Big Data Analytics. AI possesses the unique capability to process heterogeneous data streams in real-time, uncover hidden non-linear patterns, and generate highly precise managerial actions to minimize losses. This paper presents a comprehensive study and systematization of the role of artificial intelligence in mitigating food waste across the entire value chain.

1. Methodological Analysis of Food Waste Drivers in the Supply Chain

To design effective AI systems, it is crucial to decompose the specific causes of food loss at various stages of FSCM. This study identifies five key macro-stages, each characterized by distinct destructive factors:

1. Agricultural Production (Farming): Losses here are primarily driven by adverse weather anomalies, pest infestations, crop diseases, untimely harvesting due to labor or machinery shortages, and overproduction caused by miscalculating market demand.

2. Post-Harvest Handling, Logistics, and Storage: Transportation conditions and temperature control are critical at this stage. Failures in cold chain logistics ('cold chain breaks'), suboptimal delivery routing resulting in delays, and mechanical damage during loading lead to rapid spoilage of perishable goods such as meat, seafood, dairy, fruits, and vegetables.

3. Industrial Processing: Inefficiencies arise from outdated processing lines, poorly calibrated machinery, excessive trimming of raw materials, and rigid production scheduling that fails to align with the erratic arrival of perishable inputs.

4. Retail and Distribution: In supermarkets, waste is predominantly generated by stringent cosmetic quality standards (discarding 'imperfectly' shaped produce), forecasting errors leading

to overstocked shelves, and expiration dates. Inflexible static pricing strategies also prevent the timely sale of items nearing their shelf-life limit.

5. Consumer Sector (HoReCa and Households): In the hospitality sector and private homes, food is discarded due to over-purchasing triggered by impulsive buying behavior, improper storage, misinterpretation of date labels (e.g., confusing 'use by' with 'best before'), and oversized portions in food service establishments.

Mathematically, the total volume of losses Q_loss can be represented as an additive-multiplicative function of the inefficiencies at each stage: Q_loss = SUM(E_i * K_i * V_i), where E_i represents the inefficiency coefficient of stage i, K_i represents external disruptive factors (climate, human error), and V_i is the volume of biomass passing through that stage. Conventional systems manage these stages in isolation, whereas AI enables an end-to-end predictive framework connecting all links into a single, cohesive optimization loop.

2. Machine Learning Algorithms for Predictive Demand Forecasting

A primary driver of overstocking and subsequent food disposal in retail is the reliance on legacy statistical demand forecasting models (such as ARIMA or exponential smoothing). These models perform adequately only on stable time-series data but fail completely during rapid market shifts or supply shocks.

Modern intelligent systems leverage advanced Machine Learning (ML) algorithms capable of processing hundreds of endogenous and exogenous variables simultaneously. Among the most effective architectures are gradient boosted decision trees (XGBoost, LightGBM, CatBoost) and deep recurrent neural networks, specifically Long Short-Term Memory (LSTM) networks and Transformers.

The feature vector used to train these models includes: highly granular historical sales data (hourly/daily) per SKU; macroeconomic indicators (inflation rates, real income trends); calendar and social triggers (weekends, public holidays, school vacations, religious fasting periods, paydays); meteorological data and weather forecasts (temperature, precipitation, and cloud cover directly alter consumption habits, affecting demand for items like cold beverages, ice cream, or barbecue meats); and marketing dynamics (promotions, price discounts, advertising campaigns by the retailer and its direct competitors).

By integrating these disparate data sources, neural network models reduce demand forecasting errors (measured via MAPE/RMSE metrics) by 30% to 50% compared to traditional approaches. This allows retailers and suppliers to align inventory precisely with guaranteed consumer demand, significantly minimizing spoilage due to expired shelf life.

3. Computer Vision Technologies in Quality Control and Automated Sorting

Computer Vision (CV) driven by deep Convolutional Neural Networks (CNNs, such as the YOLO family and Mask R-CNN architectures) has revolutionized quality control and sorting processes in the food industry. Manual inspection is inherently subjective, prone to human error due to cognitive fatigue, and financially inefficient.

Intelligent optical sorters equipped with high-resolution multispectral and hyperspectral cameras scan the product stream moving on conveyor belts in real-time. AI algorithms instantaneously analyze both the visible spectrum and infrared bands, enabling the system to: identify concealed internal defects (internal rot, hollow hearts, pest infestations) completely invisible to the human eye; precisely evaluate fruit ripeness based on the surface distribution of chemical markers (chlorophyll, carotenoids); classify raw produce according to morphological features (size, shape, texture); and detect foreign objects (plastics, glass, metals, stones) with near-absolute precision.

A critical application of CV is the prevention of cross-contamination. If a single decaying fruit remains in a batch, the ethylene gas it emits accelerates the deterioration of the entire container. The computer vision system localizes and removes the defective item via a targeted air jet before it compromises adjacent produce, preserving tons of food from early disposal.

4. Dynamic Pricing and Supply Chain Routing Optimization

Freshness management is a vital operational capability in modern retail. AI introduces automated dynamic pricing strategies powered by Reinforcement Learning (RL) algorithms. Instead of applying rigid markdowns right before expiration, the intelligent system continuously adjusts prices based on the product's current 'freshness index' and real-time sales velocity.

The mathematical optimization objective maximizes the cumulative profit function under the boundary condition that as time approaches T (the expiration horizon), the remaining inventory should approach zero. The algorithm smoothly discounts prices, stimulating consumer demand exactly when needed to clear up to 98% of perishable stock before it expires.

Within logistics, AI optimizes warehouse and distribution operations through FEFO (First Expired, First Out) strategies. Unlike standard FIFO, the AI system tracks the exact expiration profile of each pallet by integrating with IoT temperature and humidity sensors. If sensors detect that a specific batch was exposed to elevated temperatures during transit, the AI automatically recalculates its shortened shelf life and reroutes it to the nearest retail location for immediate sale, preventing spoilage at the distribution hub.

5. Waste Analytics in the HoReCa Sector and Consumer Smart Solutions

In the hospitality and food service industry (HoReCa), AI is deployed via smart food waste audit platforms (such as Winnow Solutions). High-definition cameras with CV capabilities and electronic scales are mounted above commercial waste bins. Every time kitchen staff discards organic matter, the AI recognizes the food type (e.g., steak, french fries, salad) and records its exact mass.

Utilizing the gathered Big Data analytics, chefs receive detailed daily summaries highlighting which menu items generate the most plate waste and which ingredients are over-prepared. This data enables establishments to adjust menu offerings, optimize portion sizes, and streamline ingredient procurement, reducing total food waste by 15-20%. At the consumer level, AI is integrating into the Smart Home ecosystem. Modern smart refrigerators utilize internal

cameras and object recognition to maintain an automated inventory of food items, mapping visual data against typical shelf lives to send push notifications to users' smartphones, suggesting recipes tailored to ingredients nearing expiration.

6. Environmental and Economic Impacts of AI Deployment in FSCM

The widespread implementation of these intelligent technologies yields profound synergistic benefits across both economic and environmental indicators. From an economic perspective, reducing food loss directly expands the profit margins of retailers and producers by lowering disposal expenses and mitigating regulatory fines for organic waste generation.

From an environmental standpoint, scaling AI within the global food industry represents a foundational contribution toward achieving the United Nations Sustainable Development Goals (specifically SDG Target 12.3, which aims to halve global food waste per capita by 2030). Diverting organic waste from landfills dramatically decreases methane emissions and reduces toxic leachate from contaminating groundwater tables. Optimizing food distribution networks lowers the overall carbon footprint of logistics and alleviates pressure on global land and water resources.

Conclusion. Artificial Intelligence has transitioned from a conceptual technological novelty into a strictly necessary instrument for transforming the global food industry. The analysis provided in this paper underscores that the end-to-end integration of machine learning, computer vision, and predictive data analytics across all tiers of the supply chain mitigates systemic risks, automates quality assurance, and harmonizes supply and demand dynamics.

To successfully scale AI solutions for food waste reduction, several key barriers must be overcome: the high capital cost of initial technology deployment, a shortage of specialized data scientists within the agricultural sector, and data fragmentation across disparate supply chain stakeholders. Future research must focus on developing open data-sharing standards and distributed platforms combining AI and Blockchain technologies to ensure absolute transparency and traceability of food products from farm to fork.

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