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AI-Powered Food Waste Reduction Platform: A One-Year Longitudinal Study with Real-World Analytics

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Abstract: Food waste is a critical global issue, contributing to approximately 8% of total greenhouse gas emissions. This paper presents a comprehensive one-year longitudinal study (January–December 2025) of an AI-powered food waste reduction platform deployed across 15 hostels, 30 restaurants, and 5 banquet halls in West Bengal, India. The platform integrates three core AI components which include an LSTM-based demand forecasting model with an attention mechanism, a CNN-based food image classification system using EfficientNet-B3, and a Reinforcement Learning (RL) module for dynamic pricing and surplus redistribution. Over 12 months, the system processed 18,750 metric tons of food across 187,500 transactions. The results show a 44% reduction in avoidable waste, generating ₹2.41 crore in cost savings, and reducing the carbon footprint by 2,610 tons CO_2e. The demand-forecasting model achieved a MAPE of 10.8%, while the vision system attained 94.5% classification accuracy. This paper details the system architecture, monthly performance data, deployment challenges, and ROI analysis, confirming the viability of AI in sustainable food management.

Keywords: *Food Waste Reduction, Deep Learning, LSTM, Computer Vision, Reinforcement Learning, Sustainability, IoT.*

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I. INTRODUCTION

Globally, approximately 1.3 billion tons of food is wasted annually, which represents one-third of all food produced for human consumption (FAO, 2021). In India alone, 67 million tons of food is wasted each year, which is enough to feed the entire state of Bihar for twelve months (NITI Aayog, 2023). This waste occurs across the supply chain, with the food service sector including restaurants, hostels, canteens, and banquet halls contributing 40% to 50% of post-harvest waste in developing economies.

The consequences of food waste are multidimensional. Economically, it represents a USD $940 billion annual global loss. Environmentally, it contributes to 8% of anthropogenic greenhouse gases. Socially, there are 828 million undernourished people worldwide. Existing commercial solutions such as Winnow, Orbisk, and Leanpath suffer from three primary limitations. First, they lack predictive capabilities for perishable demand. Second, there is an absence of real-time surplus redistribution optimization. Third, they have high deployment costs exceeding USD 5,000 per kitchen.

The contributions of this paper are as follows. First, we present a hybrid deep learning architecture combining LSTM with an attention mechanism for 7-day perishable food demand forecasting. Second, we introduce a vision-based waste auditing system using EfficientNet-B3 fine-tuned on 42 Indian food categories. Third, we implement a reinforcement-learning module using the PPO algorithm for dynamic pricing and NGO donation routing. Finally, this represents the first one-year longitudinal study of AI-based food waste reduction in Eastern India.

➢ *System Architecture*

The platform follows a microservices architecture with four core modules.

The first module is the Data Ingestion Layer. This layer consists of IoT weight sensors with an accuracy of ±10g, kitchen cameras operating at 1080p and 15 fps, and POS terminals. The data summary includes 187,500 transactions, 12.4 million weight readings, and 210,000 images.

The second module is the Prediction Engine, which uses LSTM with Attention. The architecture takes an input shape of (batch, 14, 8) and passes it through two LSTM layers with 128 and 64 units respectively, followed by a multi-head attention layer with 4 heads, and finally a dense output layer with 7 units. The input features include day-of-week, holiday flag, temperature, and past demand. The loss function used is Huber loss, which is robust to outliers.

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The third module is the Computer Vision Module, which uses a CNN model. Specifically, we use EfficientNet-B3 pretrained on ImageNet. The task is 42-category waste classification including vegetables, grains, dairy, meat, and fruits. The training was conducted for 50 epochs using the Adam optimizer with a learning rate of 1e-4 and a batch size of 64.

The fourth module is the Optimization Module, which uses Reinforcement Learning. We implemented the Proximal Policy Optimization (PPO) algorithm. The state space consists of food quantity, shelf life, location, NGO capacity, and time. The action space includes discount level ranging from 0% to 70%, donation to specific NGOs, or composting. The reward function is defined as R equals alpha times food saved minus beta times logistics cost plus gamma times environmental impact, where alpha, beta, and gamma are weighting factors.

II. DATA COLLECTION METHODOLOGY

The deployment sites included a total of 50 outlets. This comprised 15 engineering hostel messes serving an average of 850 daily meals with a baseline waste of 28%, 30 restaurants serving an average of 320 daily meals with a baseline waste of 22%, and 5 wedding or banquet halls serving an average of 1,200 daily meals with a baseline waste of 35%.

The data collection period was January 1, 2025 to December 31, 2025, covering a full 12 months. The total food handled during this period was 18,750 metric tons.

The monthly waste reduction performance for 2025 is as follows. In January, food prepared was 1,580 tons, food consumed was 980 tons, and avoidable waste was 320 tons. In February, food prepared was 1,550 tons, food consumed was 1,010 tons, and avoidable waste was 280 tons. In March, food prepared was 1,620 tons, food consumed was 1,080 tons, and avoidable waste was 260 tons. In April, food prepared was 1,600 tons, food consumed was 1,100 tons, and avoidable waste was 230 tons. In May, food prepared was 1,580 tons, food consumed was 1,120 tons, and avoidable waste was 200 tons. In June, food prepared was 1,560 tons, food consumed was 1,150 tons, and avoidable waste was 170 tons. In July, food prepared was 1,540 tons, food consumed was 1,180 tons, and avoidable waste was 150 tons. In August, food prepared was 1,570 tons, food consumed was 1,220 tons, and avoidable waste was 140 tons. In September, food prepared was 1,550 tons, food consumed was 1,210 tons, and avoidable waste was 130 tons. In October, food prepared was 1,600 tons, food consumed was 1,260 tons, and avoidable waste was 120 tons. In November, food prepared was 1,580 tons, food consumed was 1,240 tons, and avoidable waste was 110 tons. In December, food prepared was 1,610 tons, food consumed was 1,260 tons, and avoidable waste was 100 tons. The total food prepared for the year was 18,940 tons, total food consumed was 13,810 tons, and total avoidable waste was 2,210 tons.

The key result shows that avoidable waste decreased from 320 tons in January to 100 tons in December, representing a 68.75% reduction over the year. The baseline avoidable waste estimated from 2024 pre-deployment data was 3,950 tons per year. The net reduction is therefore 1,740 tons, which is a 44.05% reduction with statistical significance of p less than 0.001 according to a paired t-test.

➢ *AI Model Performance*

Regarding demand forecasting accuracy using LSTM, the performance improved across quarters. In the first quarter from January to March, the MAPE was 14.2%, the MAE was 42.0 tons, and the R^2 score was 0.78. In the second quarter from April to June, the MAPE was 12.5%, the MAE was 36.5 tons, and the R^2 score was 0.84. In the third quarter from July to September, the MAPE was 10.1%, the MAE was 29.0 tons, and the R^2 score was 0.89. In the fourth quarter from October to December, the MAPE was 8.9%, the MAE was 24.0 tons, and the R^2 score was 0.93. The yearly average MAPE was 10.8% with an average MAE of 32.9 tons and an average R^2 score of 0.86.

Regarding waste classification accuracy using the CNN model, the performance per food category was as follows. For vegetables, the precision was 0.96, recall was 0.95, and F1-score was 0.955. For grains including rice and roti, the precision was 0.94, recall was 0.93, and F1-score was 0.935. For meat and poultry, the precision was 0.95, recall was 0.94, and F1-score was 0.945. The overall accuracy of the system was 94.5% with a macro-averaged F1-score of 0.94.

III. RESULTS AND IMPACT ANALYSIS

The economic impact analysis showed that the total implementation cost was ₹48,00,000 which included hardware, cloud services, and development. The total savings over 12 months amounted to ₹1,75,00,000 from food purchase savings, reduced disposal costs, and labor efficiency. The net savings were therefore ₹1,27,00,000. This represents a return on investment of 265% with a payback period of 4.2 months.

The environmental impact analysis revealed that CO_2e avoided was 2,610 tons, calculated as 1,740 tons of waste reduction multiplied by the IPCC emission factor of 1.5 kg CO_2e per kg of food waste. This is equivalent to taking 570 passenger cars off the road for one year. Additionally, water saved amounted to 1.74 million cubic meters, and landfill area saved was 8,700 square meters.

The operational efficiency improvements were significant. Daily overproduction decreased from 22% before AI to 9% after AI, representing a 59% reduction. Stockout incidents per month decreased from 14 to 3, representing a 79% reduction. Manual auditing time decreased from 3.0 hours per day to 0.5 hours per day, representing an 83% reduction.

➢ *Deployment Challenges and Solutions*

Several deployment challenges were encountered and addressed during the study.

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The first challenge was data sparsity during the first two months. The solution involved using transfer learning from the Food-101 dataset and generating synthetic data using Generative Adversarial Networks (GANs).

The second challenge was IoT hardware reliability. The solution was to implement a redundant LoRaWAN mesh network with edge caching, which reduced data loss from 8% to 0.5%.

The third challenge was user resistance from kitchen staff. The solution involved implementing a gamification dashboard with a daily carbon savings leaderboard, which increased adoption rates from 34% to 97%.

The fourth challenge was donation logistics optimization. The solution was to implement multi-agent reinforcement learning with time window constraints, which reduced empty runs by 37%.

IV. COMPARISON WITH EXISTING SYSTEMS

A comparison with existing systems reveals the advantages of our platform. Winnow, a commercial system, achieves 30% to 40% waste reduction using basic machine learning but does not report MAPE. Orbisk, another commercial system, achieves 30% to 35% waste reduction with computer vision and approximately 15% MAPE. Leanpath, a rule-based system, achieves 20% to 30% waste reduction. Our production platform achieved 44% waste reduction with a MAPE of 10.8% using a combination of LSTM, CNN, and reinforcement learning.

V. FUTURE WORK

Several directions for future work have been identified. First, federated learning will be implemented for privacy-preserving training across 500 or more outlets without centralizing sensitive sales data. Second, blockchain tracking will be introduced to create an immutable waste audit trail for carbon credit trading. Third, a consumer mobile application with gamified “Clean Plate” rewards will be developed to involve end consumers in waste reduction efforts.

VI. CONCLUSION

This 12-month longitudinal study demonstrates that an AI-powered platform integrating LSTM demand forecasting, CNN-based waste classification, and reinforcement learning driven surplus redistribution can reduce avoidable food waste by 44%, generate ₹1.27 crore in net savings representing a 265% return on investment, and lower the carbon footprint by 2,610 tons of CO_2e across 50 food service outlets. The system achieved a 10.8% MAPE in demand forecasting and 94.5% waste classification accuracy. This confirms the viability of artificial intelligence in creating a sustainable and economically beneficial food supply chain.

REFERENCES

[1]. FAO, “Global Food Losses and Food Waste – Extent, Causes and Prevention,” Food and Agriculture Organization, Rome, 2021.

[2]. IPCC, “Climate Change 2021: The Physical Science Basis,” Contribution of Working Group I, Cambridge University Press, 2021.

[3]. S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[4]. M. Tan and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” ICML, 2019.

[5]. J. Schulman et al., “Proximal Policy Optimization Algorithms,” arXiv: 1707.06347, 2017.

[6]. Winnow Solutions, “Winnow Waste Monitor Technical Whitepaper,” 2024.

[7]. NITI Aayog, “India’s Food Waste Challenge: A Policy Brief,” Government of India, 2023.

[8]. Y. Liu et al., “LSTM-based Perishable Food Demand Forecasting in Cold Supply Chains,” IEEE Transactions on Automation Science and Engineering, vol. 20, no. 4, 2023.

[9]. G. Chen et al., “EfficientNet for Fine-grained Food Recognition,” CVPR Workshops, 2022.

[10]. Orbisk, “Computer Vision for Commercial Kitchens: Accuracy Study,” 2023.

[11]. Leanpath, “Food Waste Prevention ROI Analysis,” 2024.