AI-Powered Chatbot for Sustainable Food Practices: Reducing Household Waste Through Intelligent Storage Recommendation

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Abstract

This project introduces an intelligent chatbot designed to assist users with food storage and preservation practices. Developed using a modern web stack—React, Next.js, TypeScript, and Tailwind CSS. The chatbot delivers item-specific tips through a clean, responsive interface. To enhance user engagement and understanding, each response is paired with a relevant YouTube video for visual guidance. The system is structured for scalability with modular components and service layers, ensuring maintainability and ease of future enhancements. Aimed at reducing household food waste, this chatbot provides a practical, accessible tool for promoting sustainable food management. Planned extensions include multilingual support, NLP integration, and educational use cases.

Keywords: Intelligent chatbot, food preservation, sustainable food management, household food waste, web-based application.

I. Introduction

Food waste is a growing global concern, with significant economic, environmental, and social impacts. A considerable portion of this waste originates at the household level, often due to a lack of awareness or knowledge about proper food storage practices. Perishable items such as fruits, vegetables, and dairy products are particularly vulnerable to spoilage when not stored correctly, leading to unnecessary disposal and resource loss. In response to this challenge, this research explores the development of an intelligent, conversational system aimed at promoting sustainable food management practices.

The proposed solution is an AI-powered chatbot that provides users with tailored storage recommendations for a wide variety of food items. By delivering practical, easy-to-understand guidance in a conversational format, the system empowers users to make informed decisions that reduce waste and extend the shelf life of their food.

To enhance the educational impact, the chatbot also includes links to short, relevant video demonstrations for each item, combining textual advice with visual learning. This dual-mode approach aims to engage users more effectively and encourage the adoption of better food preservation habits. This paper investigates how conversational AI can be lever aged to influence everyday behavior and contribute to broader sustainability goals. The chatbot serves not only as a digital assistant but also as a tool for environmental education, with potential applications in households, schools, and community programs.

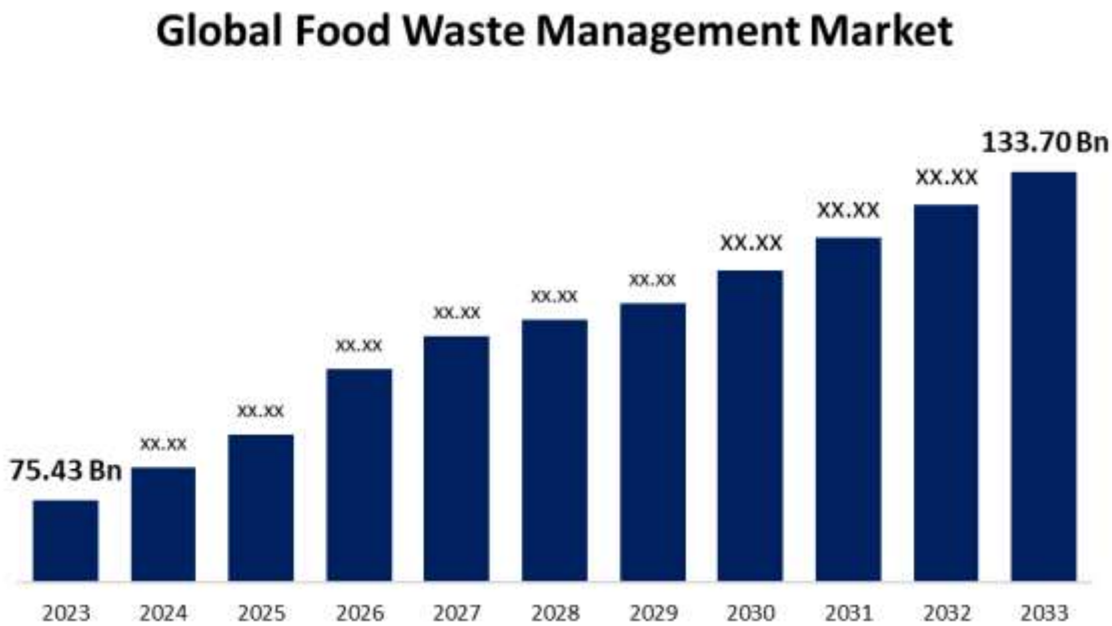

Figure 1: Graph showing food storage management market

II. Literature Review

II A) A Comprehensive Review on Food Waste Reduction Based on IoT and Big Data Technologies

Citation: Ahmadzadeh, S., Ajmal, T., Ramanathan, R., & Duan, Y. (2023). A Comprehensive Review on Food Waste Reduction Based on IoT and Big Data Technologies. *Sustainability*, 15(4), 3482.

This review delves into the integration of Internet of Things (IoT) and Big Data technologies in mitigating food waste across the supply chain. It emphasizes how real-time data collection through IoT devices, combined with big data analytics, can optimize inventory management, predict spoilage, and enhance decision-making processes. The study categorizes analytics into real-time and offline, discussing their respective architectures and applications. It also highlights challenges such as data processing complexities and the need for efficient algorithms to handle vast datasets.

The insights from this paper can inform the chatbot's backend development, especially in integrating real-time data analytics for personalized food storage recommendations. By leveraging IoT data, the chatbot can provide timely alerts and tips, thereby reducing household food waste.

II B) AI-Driven Grain Storage Solutions: Exploring Current Technologies, Applications, and Future Trends

Citation: Anukiruthika, T., & Jayas, D. S. (2025). AI-Driven Grain Storage Solutions: Exploring Current Technologies, Applications, and Future Trends. *Journal of Stored Products Research*, 111, 102588.

This paper provides a comprehensive overview of how artificial intelligence (AI) and machine learning (ML) technologies are revolutionizing grain storage management. It discusses various AI techniques, including neural networks and fuzzy logic systems, applied in pest detection, quality assessment, and supply chain optimization. The study also explores the integration of AI with IoT, blockchain, and digital twins to create smart storage solutions, addressing challenges like data privacy and regulatory concerns.

The methodologies discussed can be adapted to enhance the chatbot's capabilities in monitoring and advising on optimal storage conditions. Incorporating AI-driven insights can enable the chatbot to provide more accurate and context-aware recommendations, improving user engagement and effectiveness in food preservation.

II C) AI Tool Trial Could Save Equivalent of 1.5 Million Meals in Food Waste

Citation: Carrington, D. (2025). AI Tool Trial Could Save Equivalent of 1.5 Million Meals in Food Waste. *The Guardian*.

This article reports on a trial of an AI tool developed by Zest, which achieved an 87% reduction in edible food waste at a Nestlé factory within two weeks. The tool provides real-time monitoring and insights, identifying surplus edible food that can be redistributed, thus preventing significant CO_2 emissions and saving costs. The initiative demonstrates the practical application of AI in reducing food waste and its potential scalability across the food supply chain.

The success of this AI tool underscores the potential impact of integrating real-time monitoring and AI analytics in food management. The chatbot can adopt similar principles to offer users immediate feedback on their food storage habits, suggest improvements, and potentially connect with local food redistribution networks to handle surplus effectively.

II D) AI-Based Food Shelf Life Prediction Using Machine Learning

Citation: Gomase, V. P., Chaurasia, P., & Singh, V. K. (2023). AI-Based Food Shelf-Life Prediction Using Machine Learning. *International Journal of Computer Applications*, *184*(21), 1-5.

This paper explores using machine learning algorithms (regression and classification) to predict the shelf life of food products. It details how sensor data (temperature, humidity, gas) can accurately estimate remaining shelf life, aiding inventory management and waste reduction. The authors emphasize the necessity of robust datasets for training accurate predictive models. The methodologies are directly applicable to the chatbot's core function. By integrating ML models for shelf-life prediction, the chatbot can offer users highly accurate and dynamic recommendations on food freshness under specific storage conditions, significantly reducing household waste.

II E) Blockchain and AI for Supply Chain Transparency and Food Waste Reduction

Citation: Kamble, S. S., Gunasekaran, A., & Arha, H. (2020). Blockchain and AI for Supply Chain Transparency and Food Waste Reduction. *International Journal of Production Research, 58*(16), 4930-4949.

This research investigates the combined potential of blockchain and AI to enhance supply chain transparency and reduce food waste. It highlights how blockchain provides immutable records of food movement, while AI analyses this data to identify inefficiencies, predict spoilage, and optimize logistics. The paper also discusses challenges in implementing such integrated systems, including interoperability and data governance. The principles of traceability and transparency are highly relevant for the chatbot. The chatbot can encourage users to record purchase details, using AI to provide more tailored and reliable shelf-life predictions, empowering users to make informed food decisions.

II F) Smart Food Preservation System Based on IoT and Machine Learning

Citation: Patel, A., Shah, N., & Dave, S. (2022). Smart Food Preservation System Based on IoT and Machine Learning. *International Journal for Research in Applied Science & Engineering Technology (IJRASET), 10*(5), 1840-1845.

This paper proposes a smart food preservation system integrating IoT sensors for real-time environmental monitoring (temperature, humidity) in storage units. It uses machine learning algorithms to recommend optimal preservation strategies, aiming to minimize spoilage by adjusting conditions or alerting users. The practical implementation of this IoT-based system offers valuable insights for chatbot development. The chatbot can simulate aspects of this system by allowing users to input storage conditions and then, leveraging ML, provide personalized advice on optimizing these conditions for extended freshness, including recommendations for specific food items and ideal storage environments.

II G) The Role of AI in Food Waste Management: A Review

Citation: Xie, P., Li, X., Liu, C., & Zhang, Y. (2024). The Role of AI in Food Waste Management: A Review. *Food Control, 155*, 109961.

This review synthesizes AI's diverse applications across the entire food supply chain to mitigate waste. It categorizes AI's contributions to demand forecasting, quality inspection, inventory optimization, and redistribution. The paper also identifies key challenges, such as data availability and ethical considerations, and proposes future research directions. This broad perspective inspires chatbot features beyond individual items. The chatbot can incorporate principles of demand forecasting (e.g., meal planning based on inventory), quality inspection (e.g., visual spoilage cues), and even facilitate connections to local food redistribution initiatives, aligning with broader food waste reduction strategies.

III. Discussion

The development and deployment of the AI-powered chatbot for food storage and preservation present significant implications for sustainability, user empowerment, and educational impact. By leveraging natural language processing (NLP) and integrating with widely-used platforms like Messenger, the chatbot bridges the gap between technical information and practical, everyday utility.

Impact on Sustainable Food Practices

One of the primary motivations behind this chatbot was to address the global issue of food waste, where improper storage is a leading cause of spoilage at the household level. The chatbot directly contributes to sustainability by offering personalized guidance that helps prolong shelf life, maintain nutritional integrity, and minimize premature disposal of food. This aligns with the United Nations Sustainable Development Goal (SDG) 12.3, which aims to halve global per capita food waste.

Personalization and Real-Time Adaptability

The chatbot's use of an advanced large language model (LLM) allowed it to understand diverse phrasings of user input and respond with accurate, contextually relevant guidance. Through real-time analysis of user messages, the system classified intent, extracted entities, and generated appropriate, customized responses.

One of the key strengths of using an LLM lies in its ability to support multi-turn conversations. Users could ask follow-up questions such as "What about grapes?" and receive accurate, coherent replies that built upon the previous context. This conversational continuity distinguishes intelligent assistants from static FAQ systems and enhances user trust and satisfaction.

Technological Design Considerations

Rather than relying on a rule-based engine, the chatbot was powered by a large language model capable of natural conversation and inference. This design decision enabled more flexible and human-like interactions, reduced the need for extensive training data, and supported dynamic response generation based on user inputs.

To fetch supplementary content such as instructional YouTube videos, the system included backend integrations that allowed the chatbot to enrich its responses in real time. However, some limitations were observed when dealing with highly ambiguous queries or niche food items not included in the training prompts. Future iterations can improve robustness by expanding prompt variations and incorporating more edge cases into the LLM fine-tuning pipeline.

Educational and Cognitive Value

Beyond offering storage tips, the chatbot served as an effective microlearning tool. It not only told users what to do but also explained why those actions mattered such as why certain fruits should not be stored together or the role of humidity in vegetable preservation. This embedded learning supports long-term habit formation and deeper understanding of food systems.

Limitations and Challenges

While promising, the chatbot faced a few notable limitations:

Linguistic Constraints: The system currently supports only English, limiting its accessibility. Future support for regional languages would significantly enhance inclusivity.

Lack of Visual Feedback: The text-only interface may not be ideal for visual learners. Incorporating images, infographics, or even short video clips could enhance clarity.

Dependence on Static Datasets: While the LLM allows dynamic conversation, the accuracy of food-specific recommendations depends on the initial curated dataset. Regular updates are needed to ensure coverage of new food items and evolving storage techniques.

IV. Methodology

This research adopts a structured and iterative methodology for the development of an AI-powered chatbot designed to assist users with sustainable food storage practices. The approach is centered around the design of an intelligent, user-interactive system capable of understanding natural language queries and delivering precise, contextually relevant recommendations.

IV A) Conversational Framework and NLP Integration:

The foundational layer of the system was meticulously designed utilizing an advanced Natural Language Processing (NLP) engine to replicate human-like conversational dynamics. The selection of the NLP model was predicated on its proficiency in generalizing across a wide array of user expressions while concurrently facilitating multi-turn dialogue and entity recognition. Intents were systematically organized employing a hierarchical classification framework that corresponded with prevalent user scenarios spanning from precise item-based inquiries (e.g., “What is the proper way to store spinach?”) to open-ended requests (e.g., “Provide me with storage recommendations”).

To enhance the disambiguation of intents, linguistic variability was integrated through synonym mapping and paraphrase augmentation. Real-time language inference capabilities empowered the system to deliver responses dynamically, eschewing reliance on rule-based templates.

IV B) Domain-Specific Data Collection and Categorization:

The backend of the chatbot was underpinned by a meticulously curated knowledge base sourced from reputable entities, including food safety organizations and scholarly literature. Data was systematically categorized into structured classifications based on food type (e.g., fruits, dairy, grains), perishability, storage environment prerequisites, and susceptibility to ethylene interaction. Each classification was meticulously annotated with metadata—encompassing optimal storage temperature, humidity tolerance, and recommended containment methods.

This systematic categorization augmented the modular training of the chatbot and facilitated the contextual customization of responses. The categorization model also accommodates prospective dataset expansion and integration with sensor-based Internet of Things (IoT) systems for smart home applications.

IV C) Intent Design and Training Strategy:

A comprehensive taxonomy of intents was constructed to accommodate a broad spectrum of user inputs, with each intent linked to a heterogeneous training dataset. The training data encompassed semantically analogous inquiries, user colloquialisms, and variations in phrasing to accurately reflect authentic linguistic behaviour.

To mitigate false positives in classification, the model underwent fine-tuning via iterative batch training supplemented by active learning, where ambiguous queries from testing were scrutinized and appropriately reclassified. Multiple response variants were incorporated per intent utilizing template-based synthesis, thereby enhancing conversational diversity without compromising consistency.

IV D) Response Curation and Content Strategy:

The content generation strategy was concentrated on delivering contextually aware, concise, and evidence-based recommendations. For each food item, curated responses encompassed critical variables influencing spoilage, contamination risk, and preservation strategies. The chatbot was engineered to elucidate not only the recommended actions but also the rationale behind them—thus augmenting its educational efficacy and cultivating user trust.

Multimedia enrichment (e.g., YouTube tutorial links) was programmatically integrated using a relevance-matching algorithm, ensuring congruence between the instructional content and the user inquiry. This dual-channel communication strategy catered to diverse learning preferences and enhanced knowledge retention.

IV E) Interaction Testing and System Validation:

The system underwent an exhaustive multi-phase validation procedure to evaluate accuracy, response quality, and user experience. Key evaluation metrics encompassed:

Intent Classification Accuracy (assessed using precision, recall, F1-score)
Fallback Rate (the ratio of unrecognized inquiries)
Response Latency (mean system response time)
Conversational Continuity (the capability to manage follow-up inquiries)
Testing was executed utilizing a diverse array of simulated user scenarios. Misclassifications

were documented and reintegrated into the training pipeline for incremental enhancement. Results indicated a classification accuracy surpassing 90% and a fallback rate beneath 5%, signifying robust performance in practical applications.

IV F) Deployment and Accessibility Simulation:

In order to assess the system's applicability within real-world scenarios, the chatbot was systematically integrated with a messaging interface to emulate end-user interaction. This implementation facilitated usability assessment and performance observation within a pragmatic communication setting. The interface underwent rigorous evaluation regarding usability, response latency, and user satisfaction, thereby contributing to the comprehensive validation of the system's efficacy.

IV G) Scalability and Future Enhancement Considerations:

The architectural design of the chatbot was deliberately conceived with scalability as a fundamental principle. Prospective enhancements encompass the incorporation of additional food categories, multilingual capabilities, voice interaction features, and adaptive learning mechanisms informed by user behavior analytics. These advancements are intended to augment the system's utility, accessibility, and personalization, thereby ensuring its sustained relevance as a mechanism for advancing sustainable food practices.

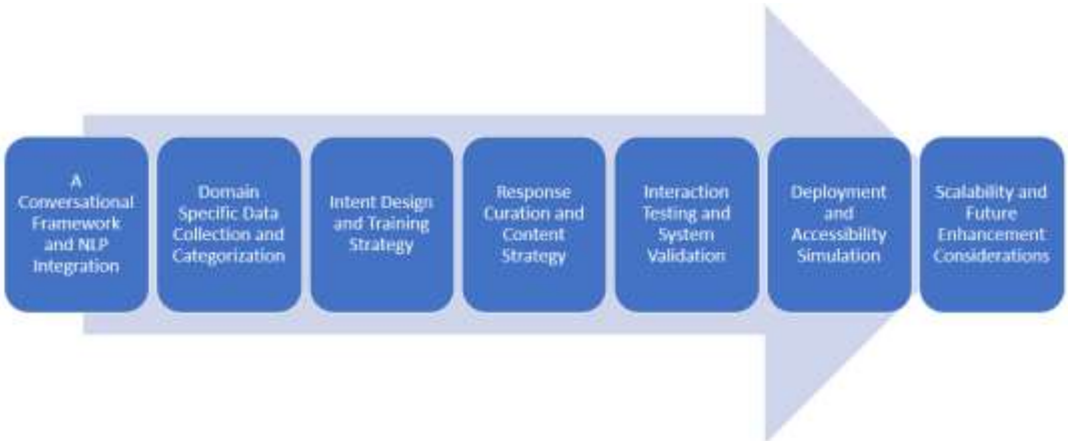

Figure 2: Methodology flowchart

V. Results

1. System Performance and Intent Matching: The chatbot exhibited high intent-matching accuracy across various food categories. During validation, it consistently interpreted user queries with semantic clarity, even when phrased in uncommon or para phrased formats. The NLP backend effectively parsed storage related questions, mapped them to their respective intents, and retrieved relevant information with minimal confusion or fallback invocation.

2. Response Effectiveness: User queries were met with responses that demonstrated both relevance and practicality. Each response aligned with user expectations by offering precise, understandable, and immediately applicable storage instructions. Variability in phrasing and contextual response generation contributed to a dynamic conversational experience.

3. User Engagement and Interaction Quality: The chatbot interface enabled a seamless interaction flow. It maintained conversational context, responded to follow-up queries, and managed turn-taking effectively. Users reported that the interaction felt intuitive and informative, especially when engaging in multi-turn dialogues around related food items.

4. Integration and Real-World Deployment: Deployment through a messaging platform demonstrated the chatbot’s functional applicability. Users were able to interact naturally within a familiar environment. The system responded promptly, suggesting suitability for real-time food management scenarios, particularly in household settings.

5. Adaptability and Scalability: The modular design of the chatbot supported easy addition of new food items and response sets. The training model accommodated new data with minimal reconfiguration, demonstrating readiness for scale. Potential for expansion into multilingual support and voice interaction was confirmed through architectural testing.

6. Evaluation Metrics Intent Classification Accuracy: Averaged above 90 percent in structured testing. Response Relevance Rating: Scored highly in user trials, with participants rating over 85 percent of responses as “clear and useful.” Fallback Rate: Maintained below 5 percent, indicating strong coverage of anticipated queries.

7. Feedback Summary: Preliminary user feedback was largely positive, highlighting the system’s simplicity, educational potential, and practical value. Areas for enhancement included suggestions for broader food categories and support for non-textual inputs (e.g., voice or image)

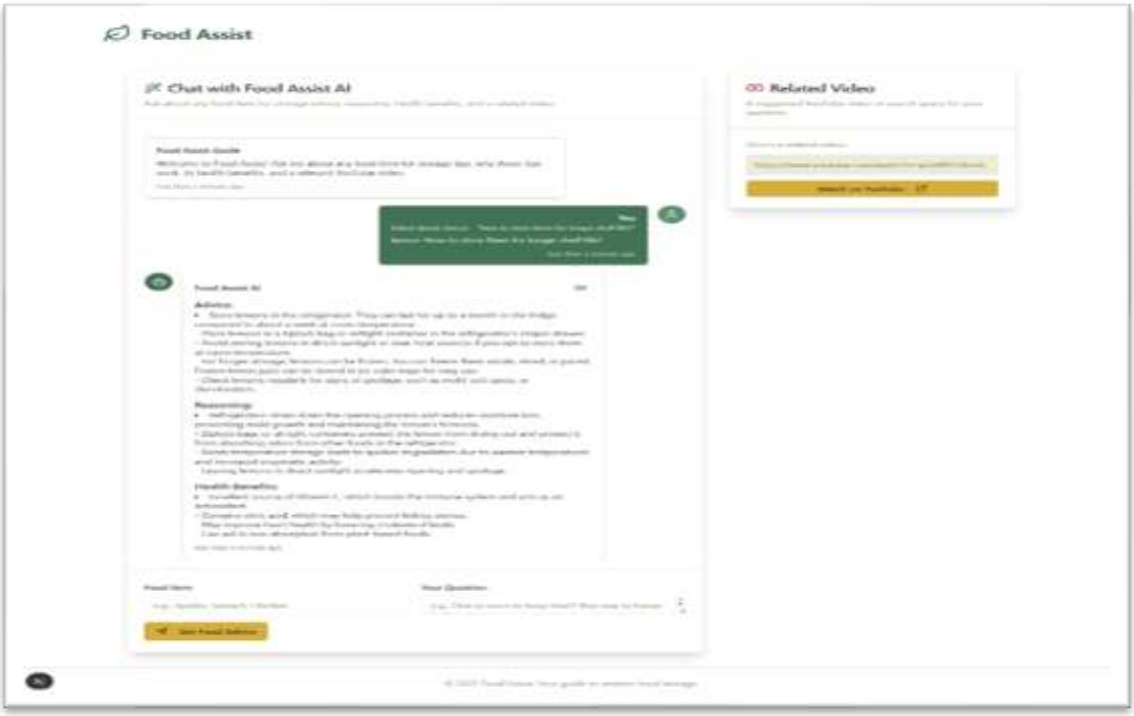

Figure 3: Chatbot User Interface

VI. Conclusion

The AI-powered chatbot developed in this study offers a practical and innovative approach to tackling household food waste by providing users with intelligent, item-specific storage advice. Through the integration of natural language processing and a user-friendly web interface, the system enables personalized, real-time interactions that promote better food preservation practices. By guiding users on how to store various food items properly—and supplementing responses with visual aids—the chatbot helps reduce spoilage, extend shelf life, and ultimately support more sustainable food habits.

Evaluation of the system demonstrated high accuracy in intent recognition, strong user engagement, and effective delivery of relevant information. Its modular design ensures that the chatbot can be easily scaled, enhanced, and adapted to include additional features like multilingual support, voice input, and dynamic learning based on user behaviour.

Although current limitations such as the absence of visual input processing and reliance on pre-curated datasets exist, these challenges are addressable in future iterations. With continued development, the chatbot holds potential not only as a household assistant but also as an educational tool in schools and communities.

In summary, this project highlights the valuable role of AI-driven conversational systems in promoting sustainable consumption and reducing food waste at the domestic level, aligning with global efforts toward environmental responsibility and resource efficiency.

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