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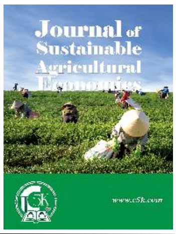

Research Article

Applying Business Intelligence to Minimize Food Waste across U.S. Agricultural and Retail Supply Chains

Most. Sonia Islam[1*]
[1]*Department of Computer Science & Engineering, Bangladesh University of Business and Technology (BUBT), Plot # 77-78, 2 Road No. 7, Dhaka 1216, Bangladesh*

**Corresponding Author: saniaislamsava@gmail.com*

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ABSTRACT

In the United States, food waste remains a significant challenge, with approximately one-third of all food produced for human consumption being wasted. This not only exacerbates issues related to food insecurity but also leads to economic inefficiency and environmental damage. Artificial Intelligence (AI) offers promising solutions to address these concerns by improving predictions of food spoilage and optimizing supply chain management. AI technologies, including machine learning models, predictive analytics, and advanced algorithms, can accurately forecast spoilage, thereby reducing waste. Key innovations include systems for early detection of spoilage indicators, dynamic algorithms that adjust storage conditions, and predictive models for waste forecasting based on real-time environmental data. Case studies, such as those from Shelf Engine and Afresh, show notable improvements, with a 14.8% reduction in food waste per store and a decrease of 26,705 tons of CO_2 emissions. IKEA also achieved a 30% reduction in kitchen food waste within a year using AI-powered monitoring systems. However, challenges remain in data collection, model training, and integrating AI with existing food management systems. These include issues with data quality, compatibility with legacy systems, and regulatory hurdles. The paper concludes by offering recommendations for future research, advocating for collaboration across disciplines to create standardized data protocols, enhance real-time monitoring, and address the ethical concerns surrounding AI adoption in the food sector. By pursuing these strategies, AI can play a pivotal role in minimizing food waste in the U.S. and globally.

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1. Introduction

The World Food Programme (WFP) reports that approximately one-third of food produced globally for human consumption is wasted, which is enough to feed two billion people [1]. This statistic is especially concerning, considering that 30% of the world's population faces moderate to severe food insecurity, and over 900 million people suffer from severe food shortages [2]. Food waste is not only a moral dilemma but also creates significant economic and environmental problems. In the United States, food waste contributes to the instability of the food supply chain by affecting market demand and supply dynamics, which can drive up prices, particularly during periods of scarcity. Furthermore, food waste exacerbates social inequalities as wealthier populations tend to waste more food, widening the gap between different socioeconomic classes. The environmental impact is also immense, as food waste decomposes in landfills, emitting harmful pollutants and contributing to greenhouse gas emissions. Addressing food waste requires effective solutions, and Artificial Intelligence (AI) has emerged as a key tool in mitigating this problem.

AI offers transformative potential in reducing food waste, primarily by predicting food spoilage before it occurs [3]. Through the application of machine learning (ML) models, predictive analytics, and advanced algorithms, AI can enhance the accuracy of spoilage predictions and help optimize supply chain management. These technologies enable real-time monitoring of storage conditions, improving the overall efficiency of food systems and contributing to the sustainability of the global food supply chain. By predicting food spoilage and adjusting supply chain operations accordingly, AI has the potential to significantly reduce

*Corresponding author: saniaislamsava@gmail.com (Most. Sonia Islam)

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waste, which ultimately benefits both the environment and the economy. This approach is particularly important as food waste continues to be a challenge in the United States, where the country alone wastes over 40 million tons of food every year, valued at around $218 billion [4]. As food waste directly correlates with the underutilization of resources such as land, water, and labor, it is crucial to adopt AI to optimize these resources more effectively.

The financial impact of food waste is staggering. Globally, about 1.3 billion tons of food are wasted every year, resulting in an estimated financial loss of US$1 trillion. In the United States, food waste is a major issue at every stage of the supply chain, from production and transportation to retail and consumption [5]. According to Table 1, a detailed summary of food waste distribution across various stages, Chauhan, et al. [6] identify that around 24% of food waste occurs during production and post-harvest stages. This is primarily attributed to inefficient agricultural practices, poor harvesting methods, and inadequate storage facilities. Another 17% of waste arises during transportation, often caused by improper handling and unfavorable environmental conditions, such as temperature fluctuations. At the retail level, food waste amounts to 20%, typically due to overstocking, stringent cosmetic standards, and the tendency to discard imperfect produce. However, the largest share of food waste—35%—occurs at the consumption stage, driven by consumer behaviors such as over-purchasing, neglecting proper storage, and not using food before its expiration. These figures reflect the complexity of food waste, which occurs at multiple stages across the food supply chain, and the economic impact is significant not only in terms of lost food but also in the associated costs of healthcare, waste management, and environmental degradation.

Table 1: Overview of food waste by stage in the supply chain (Chauhan et al., 2021; Programme, 2020; Xue et al., 2017)

Stage	Percentage of Total Waste	Key Factors Contributing to Waste
Production	24%	Inefficient farming techniques, natural disasters
Post-Harvest	24%	Poor storage facilities, lack of proper infrastructure
Transportation and Retail	17%	Inadequate transportation methods, delays, exposure to unsuitable environments
Consumption	35%	Overstocking, cosmetic standards, improper handling, over-purchasing, lack of planning, poor consumer habits

The environmental impact of food waste is far-reaching. The resources used to produce wasted food, including water, land, and labor, are squandered, making food waste an inefficient use of critical resources. Additionally, when food waste decomposes in landfills, it produces methane, a potent greenhouse gas. According to the Food and Agriculture Organization (FAO), food waste generates roughly 3.3 gigatons of carbon dioxide annually, contributing to climate change [4]. In the U.S., the environmental impact is particularly severe, with over 35 million tons of food wasted each year, contributing to not only greenhouse gas emissions but also the depletion of valuable resources such as water and soil. These environmental costs underline the urgent need for strategic interventions to mitigate food waste and improve the sustainability of the food supply chain [5].

AI can play a pivotal role in addressing food waste by improving food spoilage prediction and enabling better resource management [6]. Recent studies have shown that AI technologies such as machine learning models and predictive analytics are already being successfully implemented in various sectors of the food supply chain to predict spoilage and reduce waste [7, 8]. For example, AI-driven platforms like Shelf Engine and Afresh have been used to reduce food waste at grocery stores by optimizing inventory management and predicting which items are likely to spoil. In fact, AI-powered solutions have led to a 14.8% reduction in food waste per store, with a corresponding reduction of 26,705 tons of CO_2 emissions. Additionally, IKEA, a global leader in home furnishings, achieved a 30% reduction in kitchen food waste within just one year by using AI-based monitoring systems. These real-world examples highlight the potential of AI in reducing food waste and improving sustainability within the food sector.

Despite these successes, integrating AI into existing food management systems poses several challenges. One of the primary obstacles is the quality of data used to train machine learning models. Incomplete, inconsistent, or inaccurate data can result in poor predictions and undermine the effectiveness of AI solutions. Additionally, integrating AI into existing food management systems often requires significant investment in technology and infrastructure, which can be a barrier for small and medium-sized enterprises (SMEs) in the food sector [9]. Compatibility with legacy systems and regulatory barriers also present challenges that need to be addressed for AI to be widely adopted in the food industry. Standardized data protocols, real-time monitoring systems, and the development of interoperable technologies are essential for overcoming these barriers and ensuring the effective deployment of AI in food waste reduction.

The study investigates the potential of AI to improve economic and environmental sustainability by enhancing spoilage prediction and reducing food waste throughout the U.S. food supply chain. It examines how AI can be used to predict food spoilage, adjust storage conditions, and optimize transportation routes. In addition, the paper explores the role of AI in improving decision-making within the food sector by integrating real-time data from various sources, such as sensors, IoT devices, and blockchain technologies. By using AI to dynamically adapt to changing conditions, including fluctuating food demand, variable storage environments, and interactions among stakeholders, the paper proposes a novel AI-driven framework for food spoilage detection and waste reduction. This framework incorporates machine learning, IoT, and blockchain to enhance the efficiency of food systems and minimize waste. In doing so, AI presents a pathway for more sustainable and equitable food systems in the U.S. and globally.

In conclusion, AI offers significant potential in mitigating food waste, improving food spoilage predictions, and enhancing the sustainability of the food supply chain. While challenges remain in terms of data quality and system integration, the successful implementation of AI-driven solutions in various industries proves their potential to address the food waste crisis. By adopting AI technologies across the food supply chain, the U.S. and other nations can reduce food waste, improve resource efficiency, and mitigate environmental harm, contributing to a more sustainable and equitable future.

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2. Methodology

2.1. Research Approach

A thorough literature review was carried out to build a strong foundation for understanding the role of Artificial Intelligence (AI) in reducing food waste. To ensure a comprehensive and detailed exploration of the topic, several databases were consulted. These included PubMed, which offers research on food systems; Google Scholar, which provides access to a diverse range of scholarly articles, including grey literature; and Scopus, known for its extensive interdisciplinary research coverage. The review focused on studies and articles that examine the application of AI technologies to minimize food waste in the United States, addressing key issues like food spoilage, supply chain inefficiencies, and sustainability.

2.2. Search Strategy

To refine the search results and improve the relevance of the gathered research, Boolean operators (AND, OR, NOT) were employed. Key search terms included "AI in food systems," "food spoilage prediction," "machine learning in food waste management," "supply chain optimization," and "AI-driven food sustainability." This search strategy was designed to ensure that the results encompassed a broad spectrum of studies, with a particular focus on those that addressed the application of AI in the context of food waste reduction in the United States.

2.3. Eligibility Criteria

The selection of articles was based on specific inclusion and exclusion criteria to ensure the relevance and quality of the research. The inclusion criteria were as follows: studies must be directly related to the application of AI in reducing food waste, published in peer-reviewed journals, and provide empirical data or well-supported theoretical frameworks. Articles that lacked methodological rigor or did not focus on AI-driven food waste reduction were excluded. The review primarily concentrated on research published between 2020 and 2024 to capture the most recent developments in AI technology and its applications in the U.S. food industry. This timeframe allowed for the inclusion of the latest studies, particularly those up to May 2024, ensuring that the paper’s analysis reflected the current state of research in the field.

3. AI in predicting food spoilage

The integration of AI along with other Industry 4.0 technologies, such as big data and the Internet of Things (IoT), is poised to transform the food supply chain significantly. As noted by Romanello and Veglio [4], these technologies are expected to improve food quality and safety, promote environmental sustainability, and enhance operational efficiency throughout every stage of the food supply chain. AI finds application across various phases, including crop monitoring and early pest detection during production, storage monitoring post-harvest, route optimization for transportation, inventory management in retail, and expiry tracking during consumption [5, 6]. This broad application of AI not only addresses quality and efficiency but also plays a pivotal role in reducing food spoilage and waste, providing a potential solution to a longstanding global issue. Figure 1 illustrates how AI and other technologies are deployed at each stage of the food supply chain to optimize efficiency and minimize waste.

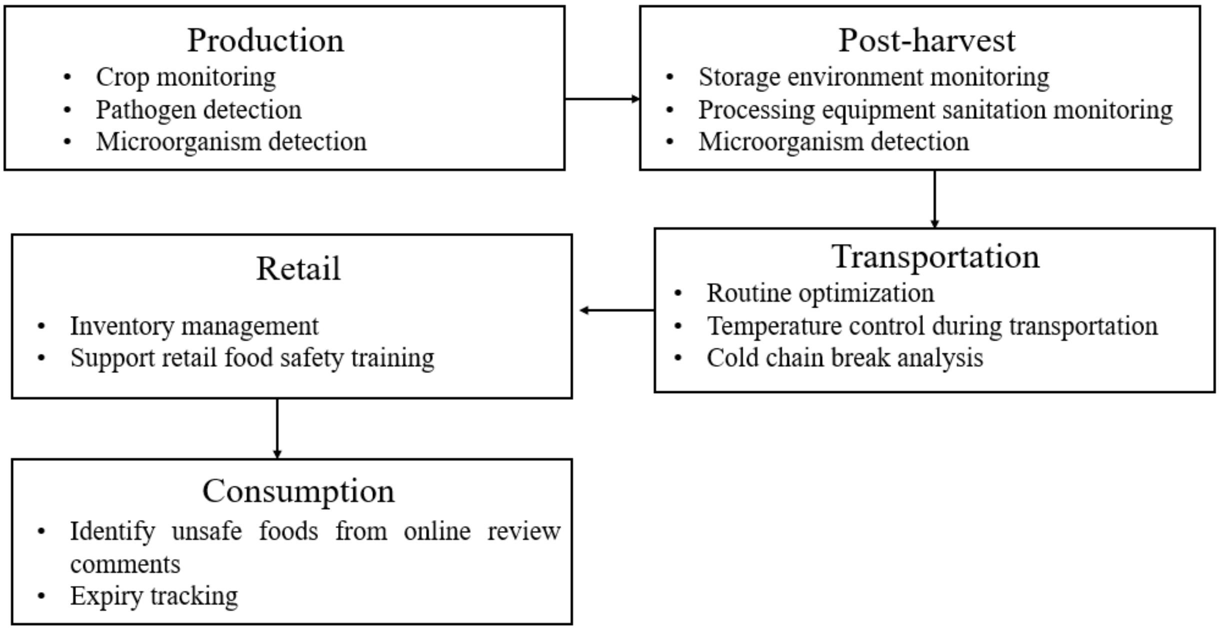

Fig.1. AI application in the food supply chain

AI technologies are crucial at different stages of the food supply chain to ensure food safety and operational efficiency. In the production phase, AI is utilized for crop monitoring, pathogen detection in agriculture, and identifying microorganisms in poultry farms. These applications aim to enhance the quality and yield of agricultural products by preventing disease and pest damage(Kamilaris & Prenafeta-Boldú, 2018). For example, deep learning models have been effectively used for detecting crop diseases, significantly improving early identification and prevention methods (Ferentinos, 2018). Additionally, AI-driven spectral imaging techniques have shown high accuracy in detecting pathogens in poultry farms, thus strengthening biosecurity measures (Park, 2015). During the post-harvest stage, AI helps monitor storage conditions and ensure the cleanliness of processing equipment, reducing spoilage and contamination losses (Pathmanaban et al., 2023). Studies indicate that AI-integrated IoT systems facilitate real-time monitoring of storage environments, allowing for predictions and prevention of spoilage (Afreen & Bajwa, 2021; Siddiqua et al., 2022).

In the transportation phase, AI applications such as route optimization, temperature control, and cold-chain break analysis ensure that perishable goods are transported efficiently and remain fresh, particularly for temperature-sensitive products (Kale & Patil, 2020). Research highlights that AI-powered predictive analytics improve cold-chain logistics by minimizing temperature fluctuations, which can compromise the quality of food products. At the retail stage, AI is used to streamline inventory management and enhance food safety compliance by offering training systems for staff. AI-based demand forecasting techniques have been particularly effective in optimizing inventory, thus reducing food waste in bakeries. Furthermore, AI-driven training platforms help improve food safety practices by providing interactive learning modules for food handlers (Dhal & Kar, 2025).

Finally, at the consumption stage, AI plays a vital role in identifying unsafe or expired foods by analyzing online reviews and tracking expiration dates, helping consumers avoid spoiled or unsafe products. Sentiment analysis of online reviews has proven to be a useful tool in detecting foodborne illness outbreaks, enabling timely interventions (Sadilek et al., 2018). In addition, AI-powered smart labeling systems assist consumers in tracking product freshness and expiration dates, significantly reducing household food waste. Overall, Figure 1 underscores the interconnected role of advanced technologies in optimizing each stage of the food supply chain, with the primary goal of reducing waste and ensuring food safety from production to consumption. These technological advancements not only aim to boost efficiency at each stage but also contribute to sustainability by reducing the environmental impact of food waste and spoilage.

4. AI for early detection

Food spoilage occurs due to a variety of factors, including the presence of pathogens, chemical and biochemical reactions, physical damage, and enzymatic activity. These factors affect the pH, nutritional content, flavor, texture, color, and water activity of food, ultimately making it unsafe or undesirable for consumption [15]. Artificial Intelligence (AI) and machine learning technologies offer promising solutions to reduce food waste by accurately predicting spoilage before it happens. These machine learning models are trained on large datasets that include food characteristics, optimal storage conditions, and indicators of spoilage [16]. These advanced models not only estimate the shelf life of food products but also analyze environmental factors such as temperature, humidity, and ventilation to recommend the best storage conditions, thereby preventing premature spoilage. Additionally, AI plays a crucial role in microbiology by enabling early pathogen detection, enhancing food safety, and reducing the risks associated with foodborne illnesses [17].

Moreover, AI and big data technologies, characterized by the volume, speed, and variety of information they process, are critical in identifying early warning signs of food safety risks during production. For example, harmful algal blooms in seafood or fungal growth in crops, which could lead to the formation of mycotoxins, can be detected early with AI. Big data tools like machine learning algorithms, cloud computing, and predictive analytics process vast amounts of real-time data from sources such as IoT sensors, satellite imagery, and microbiological analysis. These technologies help identify contamination patterns, optimize food distribution, and enhance risk assessment in food safety. This enables the food industry to monitor and assess product quality and safety in real-time, ensuring both product integrity and consumer health [18]. In the United States, AI-enabled systems have been successfully applied in practical scenarios, such as the U.S. Food and Drug Administration (FDA) using AI to detect problematic seafood imports and vegetable growers utilizing AI to manage crop risks based on environmental factors [19, 20]. AI not only improves food safety but also contributes to reducing food waste by providing more precise management of food quality and safety risks throughout the entire food supply chain.

5. AI for optimizing food storage and distribution

AI technology plays a vital role in enhancing food preservation by predicting and preventing spoilage, which aligns with sustainable agricultural practices. One notable example is a machine learning model developed by Sonwani et al. [21], which assesses whether fruits and vegetables are stored under optimal conditions. By analyzing images of produce at varying temperature and humidity levels using convolutional neural networks (CNNs), the model predicts the shelf life of these items. This not only supports the development of intelligent inventory systems that reduce waste but also allows for real-time adjustments to storage conditions to maintain freshness. The system uses image recognition algorithms to detect subtle signs of spoilage, such as changes in color and texture, and integrates environmental sensor data to improve predictions regarding produce deterioration. Moreover, AI's predictive capabilities are also utilized to forecast consumer demand patterns, improving the alignment of food production with actual consumption needs, thereby reducing the risk of overproduction [22]. Recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM) models, can identify seasonal fluctuations and predict future demand, further optimizing production and reducing waste [23]. These technologies ensure that proper storage conditions are maintained across the supply chain by adjusting factors such as temperature and humidity in real time. Additionally, AI facilitates efficient food redistribution to areas of high demand, such as shelters, through logistics optimization algorithms that prioritize deliveries based on freshness and need.

AI is also crucial in managing microbiological risks during storage, transportation, and consumption by analyzing environmental conditions and detecting patterns that could lead to foodborne illnesses. Predictive models, including support vector machines (SVMs) or random forests, can flag potential risks by correlating storage conditions with microbiological data, enabling early identification of contamination or spoilage risks. These AI-driven systems not only enhance food safety but also help reduce waste caused by contamination or spoilage.

In addition to improving food safety, AI technologies offer significant environmental and economic advantages. For example, Bhatia et al. [24] report that the use of AI in food management has notably reduced CO_2 emissions, with one case showing a reduction of 26,705 tons annually. Economically, AI-driven tools such as demand prediction models and dynamic pricing algorithms have proven to be effective in the grocery sector. These tools help reduce costs related to unsold inventory and waste disposal while enhancing profitability. According to the Pacific Coast Food Waste Commitment, the adoption of AI technologies for inventory management has led to an average profit increase of 14.8% per store (see Table 2) [25]. These advancements highlight the diverse benefits of AI, underscoring its role in both improving environmental sustainability and increasing economic efficiency within the food industry.

Table 2: Financial and environmental impact of AI in food waste reduction

Impact Type	Quantitative Benefit	Reference	Case Study
Reduction in CO_2 Emissions	Reduction of 26,705 tons annually	(Nu et al., 2024)	Case Study involving AI implementation in retail grocery
Cost Savings	Decrease in costs associated with food disposal and unsold inventory	(Cicculo et al., 2022)	Grocery retail sector through AI forecasting tools
Increased Profitability	The average increase in profits by 14.8% per store	(Nu et al., 2024)	AI-enhanced inventory management in multiple stores

6. Challenges in implementing AI for food spoilage prediction

Implementing AI to predict food spoilage presents significant challenges, primarily due to the need for diverse, high-quality data required to train accurate predictive models. Collecting data on various variables such as temperature, humidity, storage conditions, and microbial activity is essential, but obtaining extensive and representative datasets proves difficult. As highlighted by Anwar et al. [32], the variability in food types, spoilage processes, and storage conditions makes data collection complex. Each food type has distinct characteristics and degradation patterns, necessitating custom datasets for accurate modeling. Furthermore, ensuring the consistency and reliability of the data collected remains a challenge. Data can come from various sources, including sensors, manual observations, and historical records, each with varying levels of accuracy. Any errors, biases, or missing entries in these datasets can significantly impair the performance of AI models, leading to inaccurate predictions and unreliable outcomes [33]. The lack of universally accepted protocols for data collection across the food industry further complicates efforts to standardize data, an essential step for developing robust AI applications. These challenges highlight the complexity of deploying AI for food spoilage prediction and underscore the need for efforts to improve data quality and standardization in this field. Table 3 outlines the key challenges and potential solutions for implementing AI in food spoilage prediction.

Table 3: key challenges and solutions in implementing AI for food spoilage prediction

Category	Challenge Description	References	Solutions
Data Collection	Difficult to collect comprehensive data on temperature, humidity, microbial activity across food types.	(Anwar et al., 2023)	Develop universal protocols for data collection (e.g., FoodON) to improve data consistency.
Data Variability	Different food types require tailored datasets, making data collection complex.	(Anwar et al., 2023)	Use active learning and synthetic data to fill gaps and reduce bias.
Data Quality Issues	Inaccurate or missing data from sources like sensors or records affects AI predictions.	(Wang et al., 2022)	Implement federated learning to protect data privacy while training models.
Data Standardization	Lack of universal protocols for data collection complicates consistency.	(Wang et al., 2022)	Standardize data formats for international collaboration.
Data Accessibility & Sharing	Ethical and legal barriers hinder data sharing, especially sensitive personal data.	(Taheri Gorji et al., 2023)	Use fairness-aware algorithms to monitor and correct biases in deployed AI models.
Bias in AI Models	Skewed or incomplete datasets result in biased predictions.	(González-Sendino et al., 2024)	Continuous model monitoring is needed to detect and correct emerging biases.
Integration & Operations	Difficulty integrating AI with existing food management systems.	(Patel et al., 2024)	Adapt workflows and train staff for AI adoption.
Financial Constraints	High initial costs and maintenance expenses create financial barriers.	(Rejeb et al., 2022)	Financial barriers can be addressed through collaborative efforts.
Regulatory & Legal Barriers	Lack of regulatory frameworks for AI in food safety standards.	(Thakkar et al., 2023)	Harmonize data protocols and establish regulatory frameworks.
Ethical & Fairness Issues	AI models may perpetuate societal biases if trained on biased data.	(Thomas et al., 2022)	Develop fairness-aware algorithms to ensure AI equity in food systems.

AI's integration into food spoilage prediction also faces barriers related to data accessibility and sharing. Ethical concerns regarding data privacy, proprietary interests, and adherence to regulatory standards often impede the free exchange of data resources. The reliance on large and varied datasets sourced from different devices, such as sensors, cameras, and smartphones, introduces additional complexities related to data security and the potential exposure of sensitive personal information. Furthermore, collaborative projects frequently encounter difficulties in forming data-sharing agreements, navigating legal frameworks, and reconciling concerns over data ownership and intellectual property rights. To overcome these obstacles, strategies such as data standardization, the promotion of open data platforms, and fostering partnerships among stakeholders are essential. Standardizing data formats, ontologies, and metadata is crucial to ensure consistency and interoperability across diverse sources. Open data initiatives that prioritize transparency while protecting privacy through anonymization and encryption are also vital. Additionally, collaboration between industry stakeholders, academic researchers, and regulatory authorities is necessary to facilitate data sharing, establish best practices, and address legal and ethical concerns.

A promising solution to these challenges is the use of decentralized, privacy-preserving technology, as demonstrated by Taheri Gorji, et al. [35]. This approach utilizes federated learning alongside fluorescence imaging technology and deep learning models to detect invisible residues on food preparation equipment, classifying them as clean or contaminated. This model operates without sharing data across clients or storing it on a centralized server, thus enhancing data privacy and addressing one of the critical issues in deploying AI for food safety applications.

Bias in AI models is another issue that has gained attention as AI and machine learning become more prevalent in food spoilage prediction. González-Sendino, et al. [36] emphasize that biases can arise at various stages of the AI development process, from data collection to model training and deployment. During data collection, biases may emerge if the dataset is incomplete, non-representative, or if there is an inconsistent interpretation of labels by different annotators, leading to skewed outputs. Similarly, biases can occur during model training if the data is unbalanced or if the model is not equipped to handle diverse inputs. To mitigate these biases, it is crucial to continuously monitor and test AI models with a variety of inputs after deployment. Thomas et al. [40] note that these biases can perpetuate social inequalities if the data reinforces existing prejudices. For example, AI models may display discriminatory patterns against marginalized groups if training data is biased or lacks diversity. Addressing these biases is essential to ensure fairness and equity in AI applications, particularly in food safety.

Figure 2 illustrates the various sources of bias in AI deployment within food systems. Data-related biases, such as incomplete or skewed datasets, can arise from an over-reliance on historical sales data that fails to account for emerging consumption trends, leading to inaccurate demand forecasting. Algorithmic biases may emerge if AI models overemphasize certain spoilage factors, such as temperature fluctuations, while neglecting others like microbial growth, reducing predictive accuracy. Operational and human biases further exacerbate inefficiencies when decision-makers either over-rely on or dismiss AI recommendations based on subjective judgment. Moreover, external factors, such as regulatory inconsistencies and economic disparities, hinder equitable access to AI technologies, particularly for small-scale retailers who may not have the resources to implement sophisticated predictive analytics. Larger grocery chains can leverage AI-driven demand forecasting to optimize inventory management, while smaller vendors may experience higher food waste due to less accurate stock adjustments. Addressing these biases requires a comprehensive approach that integrates diverse datasets, enhances algorithmic transparency, and ensures equal access to AI technologies across the food supply chain.

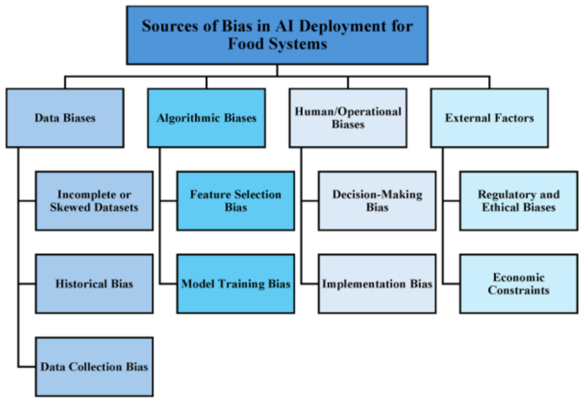

Fig. 2. Sources of bias in AI deployment for food systems [41]

To overcome the challenges in AI-driven food spoilage prediction, targeted strategies are needed to enhance data standardization, reduce bias, and improve integration. Establishing universal data collection protocols is crucial for ensuring consistency and comparability across datasets. Standardized ontologies, such as the FoodON framework [42], can improve interoperability and data quality. Techniques like active learning and synthetic data generation can help fill gaps in real-world datasets, reducing bias and improving model generalization. To address ethical concerns related to data sharing, federated learning, which allows AI models to be trained across decentralized devices without sharing raw data, has been successfully used in medical imaging and can be adapted for food safety. Furthermore, continuous monitoring of AI models using adversarial testing and fairness-aware algorithms can help identify and correct biases that emerge post-deployment. Collaboration between industry stakeholders, regulatory agencies, and technology developers will also foster the adoption of best practices and regulatory frameworks that balance innovation with ethical considerations [43]. Implementing these solutions will enhance the accuracy and fairness of AI models, supporting a more sustainable and equitable food supply chain.

Achieving high accuracy and reliability in AI models is essential for their effective application in predicting food spoilage. This requires comprehensive training datasets that cover a wide range of food types, storage conditions, and spoilage factors. Jarray, et al. [44] emphasize the importance of improving data collection methods, refining feature selection techniques, and advancing algorithmic approaches to improve prediction accuracy. Additionally, real-world validation of AI models is essential to ensure their robustness and applicability across various operational environments. This validation process involves rigorous testing in real-world settings to evaluate model performance, identify limitations, and adjust algorithms accordingly Hassoun, et al. [43].

Integrating AI into existing food management and supply chain systems also presents several challenges. These include technological issues related to compatibility with legacy systems, concerns about interoperability, and the need for specialized infrastructure to support AI implementations [37]. Operational challenges arise from the need to adapt current workflows and processes to incorporate AI insights, which requires organizational commitment, workforce training, and change management strategies. Financial barriers also exist, including high initial investment costs, ongoing maintenance, and uncertain returns on investment [46]. Additionally, the regulatory framework has yet to fully address the integration of AI technologies, as many regulatory agencies lack the necessary scientific knowledge and assessment practices to manage AI-driven food safety systems [39]. To facilitate international collaboration and data exchange, researchers suggest harmonizing data formats and establishing cooperative platforms and databases, which could help mitigate some of these challenges. These efforts are essential to fully harness AI's potential to improve food safety and reduce waste effectively.

7. Case Studies

The adoption of AI technologies in the grocery retail sector is becoming a key strategy for reducing food waste, improving operational efficiency, and minimizing environmental impact. AI systems employ advanced algorithms to analyze large datasets, including sales records, historical trends, and external factors like weather patterns and seasonal fluctuations, to accurately forecast consumer demand. This ability allows retailers to optimize their inventory levels, preventing over-ordering and minimizing the occurrence of unsold or spoiled products. As a result, food waste and shrinkage are reduced, which contributes to both operational efficiency and profitability. According to the Pacific Coast Food Waste Commitment [30], avoiding the disposal of unsold inventory and reducing shrinkage not only addresses food waste but also enhances profitability, demonstrating AI's value in the retail sector.

In addition to improving inventory management, AI also automates labor-intensive processes such as ordering and restocking, further boosting efficiency and reducing operational costs. The successful implementation of AI solutions in pilot programs and across multiple stores proves the scalability and effectiveness of these technologies in the grocery retail industry.

Several case studies demonstrate the concrete impact of AI in reducing food waste in the U.S. For example, retailers using AI-powered solutions from Shelf Engine and Afresh reported an average reduction of 14.8% in food waste per store. This led to lower shrinkage, higher profits, and improved labor efficiency, all of which offset the costs of implementing AI [30]. Furthermore, these initiatives helped prevent 26,705 tons of CO2 emissions from reaching landfills, showcasing the significant environmental benefits of AI-driven solutions. Another example comes from Winnow Solutions, which partnered with large grocery chains such as Walmart and Whole Foods to deploy AI-powered waste monitoring systems that helped reduce food waste by 20% within just six months. These efforts also prevented significant carbon emissions, underscoring the environmental impact.

Another example is IKEA, which used AI to monitor and analyze food waste in its kitchens, resulting in a 30% reduction in food waste within a year [41]. Furthermore, a project by Kroger, one of the largest grocery chains in the U.S., utilized AI and machine learning to track inventory and reduce food waste. By integrating AI into its inventory management system, Kroger was able to predict demand more accurately, reducing overstock and spoilage by 25% over a year [45]. This project not only led to cost savings but also aligned with Kroger's sustainability goals by reducing the waste sent to landfills.

These case studies highlight the potential of AI to predict spoilage, optimize inventory management, and foster sustainable practices, significantly reducing food waste across various retail environments in the U.S. By leveraging AI technologies, U.S. retailers are not only boosting their profitability but also contributing to more sustainable and environmentally friendly operations.

8. AI for food spoilage prediction

Building on the successful case studies and applications of AI in reducing food waste, it is essential to delve into the ML models that drive food spoilage prediction and inventory management. The choice of AI model depends on various factors, including the nature of the data, the complexity of the environment, and the specific goals of the food system. Understanding the strengths, limitations, and practical applications of these models is key to advancing AI's role in addressing food waste.

Supervised learning models, such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), form the backbone of food spoilage prediction. These models learn from labeled historical data to identify spoilage patterns based on factors like temperature, humidity, and microbial conditions. For example, RF excels in handling diverse and heterogeneous datasets, making it ideal for different food products. However, RF's reliance on large labeled datasets and its struggle with high-dimensional data can pose challenges in real-world applications. SVMs, known for their binary classification abilities, can distinguish between fresh and spoiled food by identifying an optimal hyperplane to separate the two classes. While they are effective for smaller datasets, SVMs can be computationally intensive when applied to large-scale systems. To overcome these hurdles, researchers have sought to improve the efficiency of SVMs. Pouladzadeh, et al. [46] explored SVMs for food recognition applications, which are integral to tasks like calorie estimation. Meanwhile, ANN models, especially deep learning networks, have shown potential in detecting subtle spoilage signs from complex data, such as hyperspectral images, but they require large datasets and come with high computational costs.

On the other hand, unsupervised learning models, such as K-Means Clustering and Principal Component Analysis (PCA), offer unique advantages in anomaly detection and spoilage prediction. These models do not require labeled data and can identify outliers in environmental conditions that may cause spoilage. K-Means clustering, for instance, helps segment food products based on spoilage characteristics, improving inventory management [66]. However, it struggles with non-spherical data distributions. PCA, useful for dimensionality reduction, helps improve computational efficiency but may overlook critical spoilage indicators if important features are discarded.

Deep learning models, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have revolutionized spoilage prediction by analyzing image and time-series data. CNNs are particularly effective for visual assessments of food quality, such as detecting microbial contamination in fresh produce using hyperspectral imaging, enabling early spoilage detection. RNNs, especially Long Short-Term Memory (LSTM) networks, excel at analyzing time-dependent data, such as temperature and humidity trends in cold storage, providing high temporal accuracy in spoilage predictions. While these models have significant advantages, they require large labeled datasets and substantial computational resources, making them challenging to implement for smaller-scale operations.

Reinforcement learning (RL) models, such as Deep Q-Networks (DQN), are used to optimize inventory management by dynamically adjusting ordering patterns based on spoilage risks and demand fluctuations. These models can reduce food waste while maximizing profitability by continuously learning the best strategies for decision-making. Hybrid approaches, which combine AI models with IoT sensors, offer real-time monitoring and adaptive control over food storage conditions. For example, integrating LSTM with IoT-based temperature sensors significantly improves spoilage prediction accuracy by accounting for real-time environmental changes. However, RL models require substantial training time and ongoing real-world feedback, making scalability difficult in some cases.

Despite the promising results seen in case studies, there are several challenges and limitations in using AI to reduce food waste. A major hurdle is the reliance on large, high-quality datasets, which may not be available for smaller businesses with limited historical data. The initial costs associated with AI systems, including computational and maintenance expenses, can also be prohibitive for many. While AI technologies can scale well in large operations, their complexity and resource demands may make them difficult to implement in smaller environments. Additionally, AI systems often rely on real-time data inputs, such as sensor readings, which can be prone to inaccuracies or malfunctions. Issues with model selection, computational efficiency, and potential job displacement further complicate the widespread adoption of AI in the food sector. As such, while AI offers immense potential, these challenges need to be addressed for more widespread and effective deployment in the food industry.

9. Future Recommendation

Future research in AI and food spoilage prediction is set to evolve through several integrated and strategic avenues aimed at improving the effectiveness and practical applications of these technologies.

One of the key areas of focus will be technological advancements. Researchers will concentrate on refining AI algorithms to enhance the accuracy and reliability of food spoilage predictions. This includes developing more sophisticated deep learning models that can analyze complex datasets to identify subtle signs of spoilage with greater precision.

Integration with emerging technologies will also play a crucial role in advancing AI applications. The combination of AI with technologies such as the Internet of Things (IoT) and blockchain is essential for improving predictions. IoT sensors provide continuous monitoring of environmental factors and food quality metrics, feeding real-time data into AI models, thereby enabling more accurate spoilage predictions. Blockchain technology, on the other hand, can improve traceability and transparency across the food supply chain, making it easier to track food products and intervene promptly to prevent spoilage. This transparency helps AI systems to process data with greater precision by tracking key variables like temperature, humidity, and transit times, which are critical for spoilage prediction. By ensuring the integrity of data throughout the supply chain, blockchain helps AI models make more reliable predictions, reducing waste by preventing overstocking and mishandling of perishable goods.

Another promising research direction is multi-modal data fusion. Integrating various data types—such as sensory, chemical, and microbiological data—into AI models can greatly enhance predictive accuracy and provide a deeper understanding of the factors contributing to food spoilage. This approach allows researchers to capture the full range of influences on spoilage, providing a more holistic view of the issue.

Real-time monitoring and adaptive control are also critical for advancing AI systems. AI models equipped with real-time monitoring capabilities can dynamically adjust storage conditions, packaging materials, and distribution logistics based on predictive insights. This proactive approach helps to minimize waste and ensure food safety and quality, improving overall food management.

Finally, collaborative research initiatives will accelerate innovation in AI for food spoilage prediction. Collaboration between food scientists, data scientists, engineers, and industry stakeholders will enable the pooling of diverse expertise and resources. These interdisciplinary efforts will help overcome complex challenges and develop practical, sustainable solutions for managing food waste.

By focusing on these areas, researchers and industry professionals can significantly enhance the role of AI in reducing food waste, which will have far-reaching positive effects on both the economy and the environment.

10. Conclusions

AI has become a game-changer in the fight against food waste and spoilage, providing innovative solutions to improve food safety and sustainability across the global supply chain. By leveraging advanced algorithms and real-time data analytics, AI allows for the early detection of spoilage, enhances inventory management, and significantly reduces waste through more precise demand forecasting. These advantages are not just theoretical; companies such as IKEA, Shelf Engine, and Afresh have already achieved notable reductions in food waste per store, resulting in substantial environmental benefits, including the prevention of thousands of tons of CO2 emissions. These real-world successes demonstrate AI's practical effectiveness and its potential to drive large-scale improvements in food systems.

The unique contribution of this study is its demonstration of AI's ability to deliver tangible, measurable changes in both operational efficiency and environmental outcomes. The findings offer compelling evidence that AI can transform food waste management, providing solutions that not only reduce waste but also foster a more secure and sustainable global food supply. Optimizing resources, minimizing waste, and lowering carbon footprints are essential steps in meeting the growing global food demands while mitigating environmental harm.

However, to fully unlock AI's potential, several challenges must be addressed, including issues related to data quality, model training, and the integration of AI with existing systems. Overcoming these obstacles requires collaboration among technologists, researchers, policymakers, and industry stakeholders. The combination of AI with complementary technologies such as IoT and big data presents further opportunities to create a smarter, more efficient food system. Future research should focus on overcoming barriers such as data privacy concerns, model biases, and regulatory compliance, ensuring that AI's transformative potential is fully realized. By promoting interdisciplinary collaboration and standardizing data protocols, we can develop a more sustainable, efficient, and resilient food supply chain that benefits both people and the planet for generations to come.

CRediT Authorship Statement

Declare the credit and contribution of each author in this research. For example:

First author: Conceptualization, writing original draft, methodology. **Second author:** data curation, writing original draft, validation, analysis.

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