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Intelligent Food Waste Management in Supply Chains using Deep Dense Networks and Image Processing

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Abstract:

The utilisation of deep learning techniques or image processing to intelligent waste from food management across supply chains remains under-explored, despite the significant opportunity of Industry 4.0 technologies to optimise supply chain operations. Deep Dense Networks (DDNs) and image recognition models offer innovative solutions to identify and reduce food waste; however, their applicability in food supply chain for waste detection or prediction remains in its infancy. Companies are increasingly integrating AI-driven technologies to reduce food waste; however, the integration or practical application of these innovations have frequently been presented in a superficial manner, with inadequate guidance on how to achieve sustainable results. The field gets better by the establishment in a framework to the integration in deep learning and image processing technology onto food waste management all over the supply chain in this systematic review of the literature. The study presents a research agenda organised around four important themes: technology adoption, waste reduction models, AI-based optimisation, and waste management sustainability. This work offers beneficial knowledge for both academic researchers and industry practitioners into the successful use for deep learning and based on pictures approaches to reduce food waste in supply chains.

Keywords: Supply Chain, Deep Dense Networks (DDNs), Image Processing, Food Waste Management, Industry 4.0, AI-driven Waste Reduction.

I. INTRODUCTION

Food insecurity remains a significant challenge, further exacerbated by medical emergencies, climate change, and conflicts, as the global population expands [1]. However, a substantial quantity of food is still being lost or thrown away in the supply chains, despite these challenges. The production and retail segments of the chain of supply are where most of losses occur, with an estimated 25% to 50% of food that is manufactured never reaching consumers [2]. Food waste has far-reaching consequences, impacting the sustainability of the economy, society, and the environment [3]. In dumps, food waste contributes to an estimated 8%–10% of the world's greenhouse emissions, as well as ecological problems that include biodiversity loss and water and land damages [4]. In addition, the economic consequences of food waste are astronomical, with an estimated annual cost of approximately 143 billion euros across 28 European countries on their own [5]. The reduction of wasted and wasted food (FLW) is a critical global objective, as outlined in the Sustainable

Development Goal (SDG) 12.3 of the United Nations is to reduce the global food waste per capita by 50% by 2030 [6]. Consequently, the management of wasted food has become a critical and pertinent concern [7].

In order to resolve the FLW issue, a variety of strategies have been suggested, contingent upon the phases for the supply chain [8]. Digital technologies, particularly deep learning and image processing, have emerged as key enablers for food waste reduction, offering innovative solutions for accurate food waste detection and management across the supply chain [9]. Recent studies emphasize that deep learning models such as Deep Dense Networks (DDNs), In addition to image-based analysis, these tools are invaluable for the optimization of supply chain operations, the prediction of waste, and the monitoring of food products, thereby contributing to the reduction of food waste [10]. However, the application of AI-driven technologies for this purpose, especially in supply chain stages such as food production, storage, and logistics, is still under investigation [11]. Although companies are beginning to implement technologies like image recognition, IoT, and AI models, comprehensive guidelines for effectively reducing FLW using these tools remain scarce, with practical implementation strategies still in early stages [12]. The current body of work frequently lacks a unified perspective, as it emphasises downstream stages, including food service and consumption, and treats all supply chain actor separately [13]. The implementation of digital tools for the reduction of FLW has frequently been fragmented and has not followed a comprehensive approach that encompasses all phases for the supply chain [14]. This paper endeavours to resolve these deficiencies by emphasising the integration of deep learning with processing of images as combined solutions for the management of food wastage in the supply chain [15].

1.1 Current State of Food Waste and the Circular Economy

Dietary waste is a huge global concern, with approximately a third of what is generated tossed or thrown each year [16]. This results in a yearly financial loss for USD 936 billion [17]. The repercussions of food waste are not exclusively economic; they also encompass substantial environmental and social costs, such as the emissions of greenhouse gases and the depletion in natural resources. Therefore, it is imperative to address food waste in order to mitigate its adverse ecological effects, including environmental degradation while the burden on food and water safety, as well as to enhance production practices [18]. The Circular Economy is a prospective framework for addressing these challenges, as it emphasizes the optimization of resources and the reduction of waste [19]. The CE is a critical component of sustainable development initiatives, as it prioritizes the preservation of materials' value, the enhancement of product utility, and the reduction of resource consumption [20]. CE's primary goal is to transition from a linear "produce-consume-dispose" model to a more regenerating one, thereby promoting sustainability by reducing dependence on finite resources [21]. Further, highlight that the CE seeks to optimize energy flows and material cycles, employing renewable energy and cascading energy principles to achieve systemic sustainability. Providing a comprehensive solution to the worldwide food waste phenomenon, the Circular Economy can be integrated into the food system at multiple stages, such as production, consumption, refuse disposal, or surplus management [22]. Despite the promise of the CE, there are considerable challenges in its widespread adoption, including cultural resistance, financial and regulatory barriers, and technological gaps, particularly in developing countries like India, Bangladesh, and Pakistan, where policies on circular economy implementation are still lacking [23]. While the growing global awareness around food waste has led to various actions from governments, businesses, and individuals, the literature continually supports the application of the Circular Economy to mitigate food waste [24]. Successfully implementing CE strategies for reducing food waste will necessitate continuous collaboration among all sectors in the food system, as well as creativity and adaptability to new challenges [25]. As such, the CE offers a robust framework for addressing food waste sustainably and equitably across the globe [26].

Figure 1. The Enormous scale of global food waste [27]

The United Nations Environment Programme's most recent report has exposed the alarming extent of global food waste [28]. The Food Waste Index predicts that more than 931 million tons worth of food will get discarded annually in 2021, at typical per capita wastage in 74 kg per residence. A significant portion of this waste, approximately 569 million tonnes, originates from households [29]. The issue is not limited to individuals' houses; supermarkets, restaurants, and various other enterprises also contribute significantly to wasted food, contributing tens of millions for tons annually. Per the survey, the retail industry amounts for approximately 118 million tonnes of food waste, while food service firms abandon approximately 244 million tonnes of food annually [30]. Figure 2 offers a visual representation of food waste estimates by sector, illustrating the distribution of waste across various parts of the food industry.

Figure 2. Sector-wise Distribution of Estimated Annual Waste [31]

The urgency of the global food waste crisis is emphasised by the consequences of these discoveries, which emphasise the need for coordinated action and innovative solutions [32]. The extensive economic, social, and environmental challenges that this issue presents underscore the necessity of addressing food waste on a global scale.

1.2 THEORETICAL POSITIONING

Initially, we provide a concise overview of the ways in which technological advancements, particularly those associated with Industry 4.0, influence sustainability on all fronts [33]. Second, we investigate the integration of these technologies into supply chains, highlighting important constraints and obstacles in avoiding and decreasing food loss and waste (FLW).

A. Impact of Industry 4.0 Technologies on Sustainability

Industry 4.0 is predicated on a broad range of sophisticated digital technologies that enable industry-wide transformation. These technologies include automation, robotics, and big data analysis, integrating systems, the Internet of Things (IoT), secure computing in the cloud, additive production, while augmented realities [34]. The concept from Supply Chain Management 4.0 has been a newly developed concept that incorporates critical technologies, such as artificial intelligence (AI), IoT, and big data analytics (BDA). Furthermore, these technologies present significant opportunities to improve the safety of the supply line, particularly in the agri-food sector, as well as to improve businesses' performance [35].

Digital technologies in Industry 4.0 can promote sustainable practices by enhancing the efficiency of resource utilization, reducing waste, and fostering circular economy models. Big data analytics, for example, can help businesses better forecast demand, align production with customer expectations, and reduce overstocking [36]. This leads to less waste, energy savings, and resource optimization, which are all crucial for improving sustainability across the supply chain. In addition, big data enables smarter decision-making, helping organizations reduce their environmental footprint while enhancing economic efficiency Nader [37].

Another disruptive innovation who plays a critical role in the digitalization of sectors, such as the food supply chain, is the Internet of Things (IoT) [38]. Internet of Things (IoT) enables the real-time monitoring in performance, the optimization of productivity, and the identification of inefficiencies. In order to mitigate waste and deterioration, IoT systems can monitor the temperature, humidity, while a variety of other environmental factors that influence food quality in food supply chains. Proactive maintenance supported by IoT technology can also reduce the occurrence of defective products, leading to fewer losses and lower operational costs [39].

Additionally, new developments like blockchain, detectors, and geospatial imagery processing offer significant advantages for supply chain sustainability. These technologies improve transparency and traceability, ensuring that environmental and social sustainability standards are met [40]. They enable better audits and assessments, this helps curb wasteful consumption by ensuring that food products are handled, kept, and carried in ideal circumstances.

Supply chains are afforded a distinctive opportunity to realise sustainable value creation through Industry 4.0, which is consistent with all three pillars for sustainability—economic, social, and environmental. By leveraging data-driven business models, these technologies can help businesses adopt resource-efficient practices, promote sustainable product development, and enable the realization of closed-loop systems, which contribute to reduced food loss and waste [41]. Additionally, they support the implementation in circular economy principles, and this are designed to enhance resource recovery and minimize waste in the food distribution system [42].

B. Digital Technologies in Agri-Food Supply Chains

It is not a new development to incorporate digital technologies into agri-food supply chains (AFSCs). In this context, adoption is the intentional implementation and utilisation for digital technology to execute a diverse array of activities across the distribution chain's various phases of a business [43]. The term "adoption" is often employed in the literature on the integration of digital technology into AFSCs to avoid and decrease food loss and waste (FLW).

Despite the slow pace of adoption observed in the

II. Related work

This review looks into the use of deep learning (DL) techniques in logistics planning and management. The technique used in this review is based on the framework presented by Barbosa-Povoa et al. (2018), widely adopted in other systematic reviews (Ribeiro and Barbosa-Povoa 2018); The review process involves the steps: defining research questions, reviewing existing wrk, gathering relevant materials, conducting a descriptive analysis of the collected materials, selecting appropriate categories, and evaluating the content. Each step is elaborated upon in the subsequent sections [44][45].

Akinyelu and Esho (2024): Explored a multi-channel deep learning approach using Capsule Neural Networks for classifying fresh and rotten fruits. The study emphasized reducing food waste to mitigate climate change and promoting sustainable food industry practices [46]. Bonala et al. (2024): Investigated waste management through the integration of Deep Learning and IoT, focusing on smart bins for waste categorization and real-time data processing. The study did not address food waste management in supply chains or deep dense networks [47]. Abdulrahman et al. (2024): Proposed a hybrid deep learning system for classifying food waste images, employing a New Convolutional Neural Network and Discrete Legendre Wavelets Transform, achieving 94.12% accuracy in sorting items like tomatoes, potatoes, bread, and rice [48]. Chauhan et al. (2023) In order to enhance the efficiency of refuse segregation; waste management was emphasized with convolutional neural networks (CNN) to trash classification. The study did not focus on food waste management in supply chains or deep dense networks [49].

Kollia et al. (2021a) Discussed AI methodologies for efficient food supply chains, emphasizing plant growth prediction, food expiry date verification through optical recognition, and minimizing waste to enhance safety and efficiency [50]. Kollia et al. (2021b) Addressed AI-enabled food supply chains, focusing on plant growth and tomato yield predictions to reduce food waste. The study did not explore deep dense networks or image processing for waste management [50]. Lu and Sun (2024) introduced a mobile application leveraging Zhou et al. (2019) investigated the applications of deep learning in food industry, including the prediction of calories, the identification of food, the quality and safety of food, and the challenges associated with the supply chain [51]. Zhu et al. (2021) performed a survey on the applications of computer vision, DL, and machine learning in food processing. The survey focused on the detection of external objects, packaging, and quality management [52].

Bertolini et al. (2021) examined machine learning's potential in operational management, highlighting the rising use of DL in areas such as maintenance, production planning, defect detection, and SCM [53]. Similarly, Al-Sahaf et al. (2019) analyzed the application of computational methods, including deep learning, in the development of computer vision, scheduling, or optimization systems for milk products, beverages, seafood distribution networks, while production [54]. Nti et al. (2021) studied artificial intelligence (AI) algorithms in engineering and manufacturing, focusing on their applications in fault detection, cost and energy optimization, and autonomous systems [55]. Kotsiopoulos et al. (2021) described the use of DL algorithms in Industry 4.0 scenarios, focusing on intelligent production and smart grid systems [56]. The advantages, limitations, and applications for deep learning techniques in innovative production instances were thoroughly examined by Wang et al. (2018) [57].

Table 2: Comparison of Relevant Studies on Food Waste Management and Deep Learning Applications

Paper	Focus	Differences with Our Work
Akinyelu and Esho (2024)	Explored a multi-channel deep learning approach using Capsule Neural Networks for classifying fresh and rotten fruits.	Focused on reducing food waste and promoting sustainability but did not address supply chain integration or deep dense networks.
Bonala et al. (2024)	Investigated waste management through the integration of deep learning and IoT, focusing on smart bins for real-time waste categorization.	Focused on waste categorization without exploring food waste management in supply chains or employing advanced network architectures.
Abdulrahman et al. (2024)	Hybrid deep learning model that integrates wavelets and CNNs has been suggested for the classification of food refuse images.	Achieved high accuracy in image sorting but did not address broader supply chain and logistics challenges.
Lu and Sun (2024)	Developed a mobile application that is powered by artificial intelligence (AI) to facilitate the administration of food inventory and the reduction of waste.	Focused on individual inventory systems rather than integrating food waste management in broader supply chains.
Chauhan et al. (2023)	Utilized convolutional neural networks for efficient trash classification in waste management.	Focused on general trash segregation, lacking emphasis on food waste within supply chains or deep dense networks.

Kollia et al. (2021a)	Addressed AI methodologies for food supply chain efficiency, emphasizing plant growth and waste minimization.	Did not investigate deep dense networks or explore image processing for waste management in supply chains.
Kollia et al. (2021b)	Highlighted AI-driven plant growth predictions to reduce food waste in supply chains.	Focused on plant yield optimization without delving into food waste management or advanced deep learning techniques.
Mohammed et al. (2022)	A waste-sorting system that is automated and employs image processing techniques and artificial neural networks is presented.	Focused on recycling systems and smart city initiatives without addressing food supply chains or advanced network models.
Zhu et al. (2021)	Investigated the application of deep learning, machine learning, or vision methods in the food processing industry.	Focused on food quality and packaging but did not explore the logistics or broader supply chain functions.
Bertolini et al. (2021)	Conducted an examination of the advantages and obstacles of AI in operational management.	Concentrated on ML in operations, with limited coverage of recent advancements in deep learning for food supply chains.
Al-Sahaf et al. (2019)	Application of computational evolution to supply chain domains such as the dairy, wine, and aquaculture industries was examined.	Focused on evolutionary algorithms rather than addressing deep learning applications in food waste management.
Nti et al. (2021)	Investigated AI applications in engineering and manufacturing, emphasizing autonomous systems and energy optimization.	Did not consider all supply chain domains; primarily focused on manufacturing.
Kotsiopoulos et al. (2021)	Explored the applications of machine learning and deep learning in Industry 4.0 contexts.	Focused on smart manufacturing and smart grids, with minimal attention to supply chains and food waste management.
Wang et al. (2018)	Examined the applications of deep learning techniques in automated manufacturing systems.	Concentrated on manufacturing functions, with limited exploration of supply chain logistics or food waste challenges.

III. Materials and Methods

This research seeks to give researchers and managers with a thorough grasp of digital solutions for solving food loss and waste (FLW) issues throughout the food system. According to Annosi et al., only a few research have examined FLW from a supply chain viewpoint, often focusing on specific actors in isolation [58]. This actor-centric approach fails to capture the broader, interconnected processes that influence FLW. In contrast, the European Commission's directive on waste emphasizes the need for FLW prevention across Every phase of the distribution network, involving hotels and eateries, and households, suggesting that a more holistic approach is necessary [59].

To close this gap, we use a production chain-wide approach, aiming to develop an in-depth knowledge of how particular technological solutions might be implemented throughout the Agri-food supply chain [60]. The investigation focuses on the supply chain as a whole and tries to understand how digital tools such as deep learning networks and image processing technologies, can optimize FLW management across various stages of food production, transportation, retail, and consumption [61].

Furthermore, this research incorporates the role of external stakeholders in the supply chain, recognizing that sustainable FLW management and circular economy principles require active collaboration among multiple actors [62]. In addition to businesses, this collaboration includes charities, food banks, policymakers, and other stakeholders who play a crucial role in supporting the circularity of the supply chain and promoting sustainable food systems.

3.1 The Circular Economy Concept and Its Potential for Reducing Waste and Increasing Resource Efficiency

As an effective strategy to both production and consumption, the circular economy (CE) gained momentum in response to the misuse of natural resources because of increasing global demand. **[63]**. The objective is to separate economic growth to environmental damage by emphasizing the reduction, repurposing, recycling, and recovery of materials throughout the entire life cycle of a product. Resources efficiency or waste minimization are prioritized in the CE, as opposed to conventional models that are founded in production, use, and disposal. Its primary objective is to encourage the use of renewable energy sources and environmental conservation while simultaneously preserving the amount of products and materials from a long-term perspective. Scholars are still working to improve its principles and metrics **[64]**.

3.2 The Role of AI in Addressing Food Waste and Supporting the Circular Economy

Innovative developments in neural networks, recognition of images, machine learning, or natural language processing are transforming industries such as the agricultural sector at a rapid pace, as artificial intelligence (AI) continues to advance. AI is capable of simulating human cognition, learning from data, and resolving intricate problems, thereby providing solutions to large-scale issues such as food waste [65]. It can shift agriculture from a linear model to a more sustainable circular system by optimizing production, reducing waste, and promoting resource efficiency. AI aids in sustainable farming by reducing soil depletion and water usage through regenerative practices. It also enhances resource allocation to minimize excess production and waste. Studies estimate AI could boost the global economy by up to USD 13 trillion by 2030 [66]. In the food industry, AI supports circular economy principles by enabling efficient production, innovative sustainable food design, and healthier, waste-minimizing solutions, contributing to a more sustainable future.

S/N	Technology	Application Examples	Role in Sustainability	References
1	Machine Learning (ML)	ML can analyse consumer behaviour patterns to predict food purchases and reduce overproduction.	ML can help in sustainable food production by optimizing crop yields based on weather patterns and soil conditions.	Van Klompenburg et al., 2020; Garre et al., 2020
2	AI Image Recognition	Used in quality control for food items during manufacturing and packaging. Helps to minimize waste by identifying substandard products before reaching consumers.	AI image recognition can help design food waste-free systems by ensuring only quality products are packaged and sold, reducing return rates and subsequent waste.	Sundaram et al., 2023
3	Natural Language Processing (NLP)	NLP can interpret the feedback provided by customers about food products and services to reduce food waste.	NLP can help in developing healthier food items by analysing customer feedback to identify demand for healthier options or improvements to existing items.	Adak et al., 2022; Mezgec et al., 2019
4	AI-Driven Smart Agriculture	AI applications can enhance farming methods, crop selection, and yield predictions, reducing unnecessary waste of resources and promoting a circular economy.	AI can support local food production by optimizing growing conditions for local species and forecasting market demand to reduce waste.	Javaid et al., 2023
5	Internet of Things (IoT) and AI	IoT devices can collect data about food storage conditions, and AI can analyse these data to prevent spoilage and extend the shelf-life of food products.	IoT and AI can support the development of a refined food value chain by tracking nutritional value during storage and minimizing food waste due to improper storage.	Popa et al., 2019
6	Blockchain and AI	A combination of blockchain and AI can ensure traceability and enhance the trustworthiness of food supply chains.	Blockchain and AI can help design systems to ensure accountability, transparency, and sustainability in the food supply chain.	Dedeoglu et al., 2023; Tsolakis et al., 2022
7	Reinforcement Learning	AI systems can supply chain management, ensuring	Reinforcement learning can support local food production	Bacˇiuliene et al., 2023

3.3 Leveraging AI and Deep Learning for Food Waste Management in Circular Economy Framework

3.3.1 AI-Driven Approaches for Identifying Opportunities in Food Waste Reduction and Recycling

The economy of circularity is founded on the the principles of recycling, repurposing, and minimising, with the objective of fostering sustainable growth and reducing the consumption for virgin resources [67]. A economy that is circular not only minimizes the carbon footprint associated with generating new materials, but it also greatly reduces the environmental effect by encouraging material recycling and reuse. This shift towards circularity reduces waste production, thereby minimizing carbon emissions, and supports sustainability across environmental, social, and fiscal

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dimensions. In the context of food waste recycling networks, AI plays a critical role in driving innovation [68]. When applied effectively, AI technologies can enhance business processes across various industries, including solid waste management (SWM). The quality, security, or efficiency of production processes are enhanced by AI, which contributes toward the resolution of complex challenges in sectors such as SWM, social security, wellness, the weather, electricity, and transport [69]. Through AI automation, industries can boost operational efficiency, achieve greater consistency and scalability, and reduce costs. AI algorithms are particularly valuable in SWM optimization, where they enable real-time analysis of data from multiple sources, allowing for continuous adaptation. This level of precision and adaptability is crucial, particularly for governments seeking to implement effective waste management policies and meet sustainability goals.

3.3.2. Key Benefits of Economy Initiatives in Food Waste Management

For the past few years, there have been an increasing interest in the optimization of resource recovery from refuse processes, with AI playing a critical role. [70]. AI supports cycle production methods that enhances the use of energy and increases the useable lifespan of goods and parts thereby maximizing the value derived from resources. AI enhances the decision-making process within factories by monitoring and tracking products and processes in real-time [71]. This real-time monitoring allows for the determination of residual value, further accelerating the adoption of circular economy practices. By incorporating real-time data into operational processes, AI helps overcome the challenges associated with transformational processes, enabling systems to be more adaptable and efficient through the use of rapid response methods [72]. AI enables the development of visual aids that provide a clear and accessible picture of data streams concerning goods, assets, and workflows. These tools are essential for analyzing and understanding the full range of benefits provided by a circular economy, some of which may not be immediately apparent. By enabling better visualization and analysis, AI helps clarify the complex benefits of circular systems, paving the way for more effective implementation. Figure 3 Depicts the various methods by which AI contributes to the management of food waste along with how these contributions are consistent with the United Nations' sustainable development objectives [73].

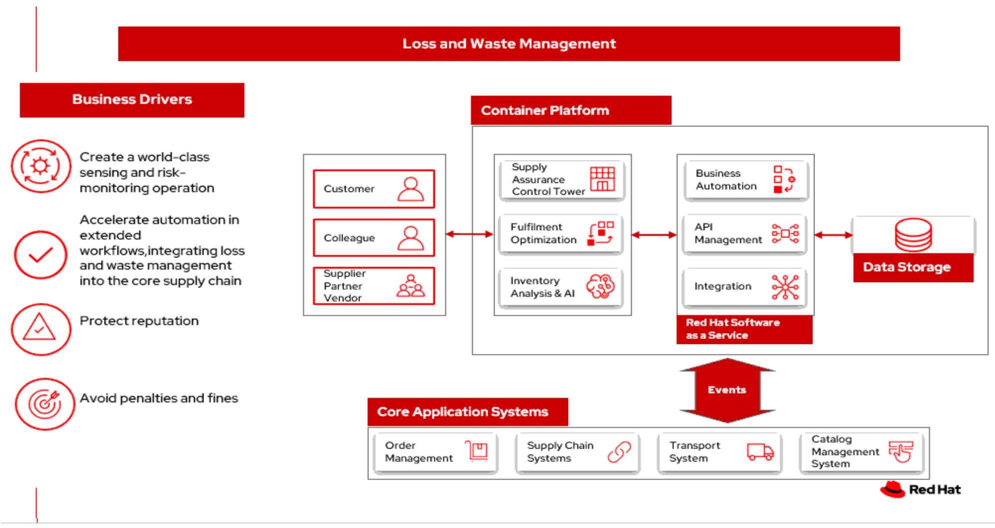

Figure 3. Waste Management in the Supply Chain [74]

IV. Monitoring and Optimizing Food Production and Supply Chains

Technological innovations have consistently been instrumental in improving agricultural supply chains and production processes. The agricultural output was considerably increased in the past century as a result of the usage of machinery like tractors and harvesters, as noted by [75]. Today, artificial intelligence has the potential to drive even more innovation, improving efficiency at a lower cost. AI-enabled predictions and simulations allow for large-scale analysis of agricultural factors, outperforming traditional human analysis. The agri-food supply chain is facing new challenges due to the challenges presented by climate change and the growing global population. As a result, AI is becoming a critical instrument for addressing these issues. By leveraging vast datasets, AI can optimize crop yields and consumer demand to ensure more efficient food production and distribution..

4.1. Reducing Food Waste and Enhancing Resource Efficiency

Research indicates that the conversion of food refuse into value-added products that are abundant in micronutrients can reduce global food demand and carbon emissions. By valorising food waste, high dietary fiber and nutrients are obtained. Manufacturers and retailers can identify waste hotspots and use intelligent methods to enhance decision-making and process optimization. Government support can further minimize waste [76]. Despite challenges like sustainability concerns and algorithmic bias, AI and big data are crucial for managing risks, improving food safety, and ensuring quality throughout the supply chain.

VI. Discussion

The integration of Deep Dense Networks (DDNs) and image processing technologies has shown great potential in enhancing food waste management across supply chains. Artificial intelligence (AI) offers a transformative solution for optimising food supply chains and decrease food loss and waste (FLW) as the world confronts the dual challenge of environmental sustainability and food insecurity. AI technologies have the capacity to spot opportunities for waste reduction, improved resource efficiency, and more informed decision-making at the setting of food waste management. AI systems can provide precise insights through the location and manner of food wastage by analyzing vast quantities of real-time data from a variety of sources, such as predictive analytics, IoT sensors, or image-based detection. This analysis can result in effective strategies for reducing waste through the supply chain stages. In the context of food supply chains, AI-powered solutions, such as image recognition models for detecting food spoilage or predictive algorithms for estimating food demand, can significantly enhance the management of perishable goods. This technology enables the real-time monitoring of food quality, thereby minimising waste and ensuring that products are utilised proficiently. AI can assist in guaranteeing that only consumers receive high-quality food by automating processes like sorting, monitoring, and quality assurance. Additionally, it can decrease the probability of wasted products because of improper handling or an excessive stock.

digitised. This is expected to contribute to the realisation of global sustainability objectives.

VII. Conclusion

Food waste is a global crisis that has substantial economic, environmental, or social repercussions. Innovative solutions are necessary to resolve inefficiencies to the production, transportation, and consumption of food in order to reduce food insecurity or environmental degradation. The circular economy emphasizes waste reduction and resource efficiency, offering a sustainable approach to food waste management. AI technologies, such as Deep Dense Networks and image processing, play a crucial role by optimizing processes like production, sorting, storage, and transportation. AI helps detect spoilage, predict shelf life, and make real-time decisions to minimize waste. AI-driven predictive models enhance inventory management by analyzing factors like demand and logistics. Additionally, AI supports food redistribution efforts by identifying surplus food for those in need, promoting social equity. By improving recycling, reuse, and energy efficiency, AI contributes to sustainable development goals. Continued investment in artificial intelligence (AI) for food systems has the potential to promote an ecologically friendly global food system, conserve resources, and reduce waste within a circular economy framework.

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