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Review

Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review

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Abstract: Food waste is a global issue with significant economic, social, and environmental impacts. Addressing this problem requires a multifaceted approach; one promising avenue is using artificial intelligence (AI) technologies. This article explores the potential for AI to tackle food waste and enhance the circular economy and discusses the current state of food waste and the circular economy, highlighting specific ways that AI can be used to monitor and optimise food production and supply chains, redistribute excess food to those in need, and support circular economy initiatives. As a result, we can maximise resource efficiency and minimise environmental impact with these applications, ultimately creating a more sustainable and equitable food system.

Keywords: food waste; circular economy; artificial intelligence; resource efficiency; sustainability; supply chain optimisation

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1. Introduction

Organic waste, particularly food waste, has been viewed as one of the significant concerns in the last two decades that demand our undivided attention. In many ways, this form of organic waste has greatly impacted the global environmental, social, and economic spheres. Wasted food accounts for an estimated 3.3 gigatons of carbon emissions, making it the third-ranking global producer of greenhouse gases after the United States and China [1]. According to Gustavsson et al. [2], the value of agricultural product waste in the food industry, calculated based on producers' prices (excluding fisheries and seafood), amounts to USD 750 billion. This amount is equivalent to Switzerland's gross domestic product (GDP). The quantity of food that is generated and eventually discarded or lost is comparable to a geographical area the size of China, which is required to generate one-fourth of all agricultural water utilised yearly [3,4]. The Food and Agricultural Organization (FAO) has released statistical figures showing that one-third of the food produced for consumption is lost or wasted, which amounts to nearly 1.3 billion tonnes of food waste. This revelation has surprised the world and sparked calls to action from international leaders, non-profit organisations, and grassroots groups.

The issue is becoming more serious given the fact that food is being lost and wasted and that food prices are rising, coupled with increasing widespread food poverty [3]. These food chain losses and waste occur at every stage, including production, transport, storing, processing, selling, and consumption. According to the United Nations Food Waste Index Report, high-income countries lose an average of 79 kg of food per person each year [5], and as a result of the "Agenda 2030 for Sustainable Development", the worldwide community has pledged to tackle food scarcity and malnourishment (SDG 2) by decreasing food loss and waste [6].

According to Gustavsson et al. [2], globally, the number of individuals who experience chronic hunger is rising, going from an estimated 777 million in 2015 to 815 million in 2016. In 2015, 119.1 million EU nationals, or one in every four Europeans, faced the prospect of hardship or social marginalisation, with 42.5 million unable to afford a decent meal every two days [7,8]. Similarly, it is projected that 88 million tonnes of food are lost each year in the EU, at a cost of EUR 143 billion [9,10].

In comparison, developed nations see far fewer post-harvest losses than developing ones due to technological advancement [2]. Households account for around 40% of all food loss and waste in underdeveloped nations, and the determining factors include consumer preferences, consumer ignorance, high income, sociocultural norms, and some other value judgments [11,12]. Food waste has a tremendously detrimental impact on the environment, finite natural resources, and even the economic fabric, as well as influencing substantial societal dynamics and regional/individual standards. A high degree of eutrophication in water bodies, loss of biodiversity, and increased CO_2 emissions are all factors that have an adverse impact on an ecosystem [2,13].

These issues, therefore, evidently connote that food waste signifies a lost chance to enhance food security on a global scale and reduce the adverse environmental effects of agriculture. Additionally, if production is to keep up with the demand of the expanding global population, it will need to be 60% greater by 2050 than it was in 2005/2007 [14]. Therefore, maximising the food produced at the current production rate would contribute to meeting future demand with a smaller rise in agricultural output [15]. Therefore, reduced food loss and waste may be a suitable resource-conserving approach [16].

This review article is based on a comprehensive analysis of the existing literature on food waste, the circular economy, and the use of AI in the food industry. The literature search includes academic and industry publications, reports, and other relevant sources. The findings of this literature review are organised into specific sections that cover the potential applications of AI for addressing food waste and circular economy challenges.

2. Current State of Food Waste and the Circular Economy

Food waste remains a major problem globally, with estimates suggesting that one-third of all food produced is lost or wasted. Moreover, it costs the global economy USD 936 billion annually [17]. This has high economic and social costs and contributes to environmental problems such as greenhouse gas emissions and resource depletion [18].

An important area of effort in the food system for promoting sustainable development, in addition to dietary and production pattern improvements, is lowering food waste [19]. Adverse ecological effects of the food system can be addressed by minimizing food waste, increasing the safety of food and water [20], and greatly lowering both the immediate and long-term implications of food waste on the economy, society, and environment [4].

An approach that values resources and emphasises effectiveness and efficiency in resource use and waste minimisation is the circular economy (CE) [21]. The persistent pursuit of waste reduction is one of the objectives of the circular economy (CE) [21]. That is, the goal is to reduce resource consumption and increase product usefulness while maintaining the value of goods and materials for a long time [22].

According to the Ellen MacArthur Foundation (EMF), cited in [21], the CE is a comprehensive strategy for economic growth, crafted for the benefit of society, industry, and the environment, as opposed to the "produce-consume-eliminate" linear paradigm. It is intended to eventually uncouple development from the use of limited resources since it is regenerative by design [23]. Korhonen et al. propose that the CE is developed using mechanisms for production and consumption to the greatest extent possible to optimise the service provided by the linear flow of energy and nature, by utilizing cyclical material flows, renewable energy sources, and cascade energy flow types [24].

The circular economy can be applied to different stages in the food system: production, consumption, waste, and surplus management [25]. The current state of food waste and the circular economy is complex, with progress in some areas and persistent challenges in others.

The circular economy approaches used to address food waste face various barriers, including cultural issues, business and business finance, regulatory and governmental, technological, and supply-chain management shortfalls [25]. One of the main issues in emerging economies, such as India, Bangladesh, and Pakistan, is the lack of government policy surrounding the use of a circular economy [26].

On the one hand, there is growing awareness and commitment to addressing the issue of food waste, with many governments, businesses, and individuals taking action to reduce waste and promote more sustainable food systems. On the other hand, the continuous and growing literature supports implementing a circular economy to stem the problem of food waste [27].

Ultimately, the successful implementation of a circular economy for food waste will depend on continued commitment and collaboration from all actors involved in the food system, as well as ongoing innovation and adaptation in response to changing circumstances and emerging challenges [28]. Figure 1 provides an illustrative depiction of the scope of global food waste, showcasing annual household food waste figures from selected countries.

Figure 1. The Extent of Global Food Waste: Annual Household Food Waste Figures in Selected Countries. Data were obtained from [5].

Furthermore, a report released by the United Nations Environment Programme has brought attention to the alarming scale of global food waste [5]. According to the 2021 Food Waste Index [5], an estimated 931 million tonnes of food are discarded annually, with an average per capita food waste of 74 kg per household.

Approximately 569 million tonnes of this waste falls under the category of household waste. However, it is not solely households that contribute to this issue. Supermarkets and other businesses are also major culprits, disposing of significant quantities of food, which collectively amounts to hundreds of millions of tonnes each year. The report reveals that food service establishments are responsible for wasting approximately 244 million tonnes annually, while the retail sector discards around 118 million tonnes. To provide a visual representation of the quantities wasted in different segments of the food industry, Figure 2 presents estimates of annual food waste by sector [5].

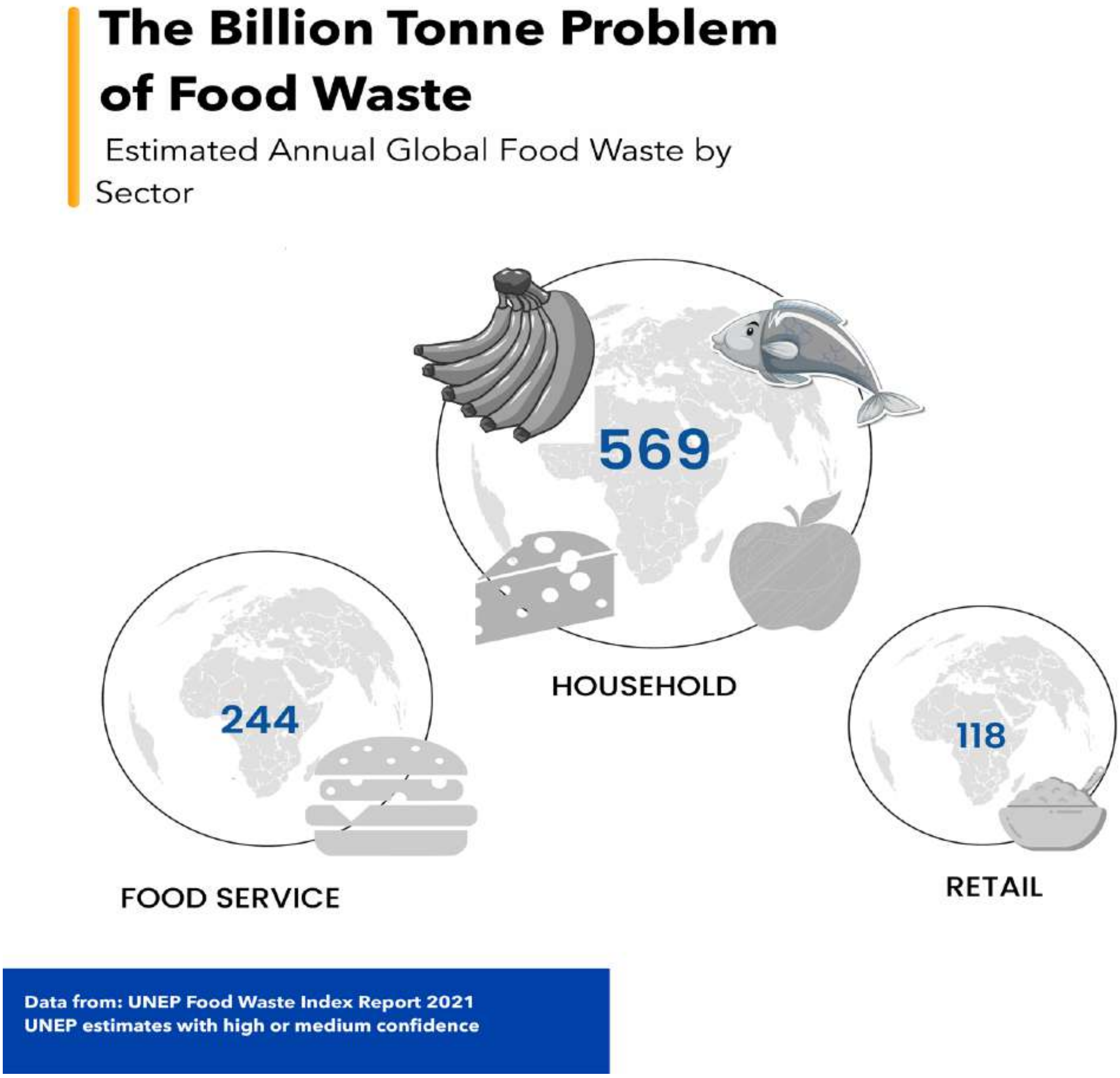

Figure 2. The Billion Tonne Problem of Food Waste: Estimated Annual Global Food Waste Across Different Sectors.

These findings underscore the pressing need for concerted efforts and innovative solutions to combat global food waste. Addressing this issue is crucial, as it poses substantial economic, social, and environmental challenges on a global scale.

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

The circular economy (CE) has gained traction over the past few centuries and gathered momentum in recent times as a model that supports more ethical production and consumption patterns. However, natural resources have been overused due to the increased growth in global goods consumption. By establishing a system that emphasises material reduction, reuse, recycling, and recovery across manufacturing, distribution, and consumption, the CE responds to the need to separate environmental pressure from economic growth [29].

The circular economy (CE) development paradigm is unlike the conventional linear economy, which follows a model of producing, consuming, and discarding goods. The circular economy emphasises the principles of reducing, reusing, and recycling (the '3 Rs') to minimise the negative impacts of human activities [30]. Its goal is to control the flow of clean energy resources, manage and regulate limited stockpiles, protect and enhance natural capital, and ensure that all goods, systems, and materials are maximally useful and valuable [31]. Even though the circular economy (CE) is a concept that has grown in prominence in recent years and is viewed as an overarching idea aiming to lower the amount of material used and the amount of trash produced [32], some scholars believe that there are variances in the definition of the concept [33], traits and features [34], how its goals are defined [35], how they are carried out, and the metrics used to measure its performance and effectiveness [36]. Only a recent systematic assessment examined the issue, describing the CE as a "developing concept that still requires development to consolidate its definition, boundaries, principles, and associated behaviours" [37].

In the words of Moraga et al. [32], CE aims to cut down on material inputs and waste production. The validity of this claim shows its direct influence on reducing the use of organic materials and promoting a shift towards recycling waste as secondary raw materials. Also, the CE aims to boost items' chances of being resold and lengthen their valuable lives. In a nutshell, the CE gives priority to actions that have apparent adverse effects on the environment, such as using recyclable packaging, promoting eco-friendly products, lowering emissions and waste, evaluating renewable and alternative energies, conserving energy, utilising low-impact consumer goods, eco-designing, recovering waste, and dematerialising [36].

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

Artificial intelligence (AI) is the mimicking of human intellect using computers. Artificial intelligence (AI) is regarded as an evolving paradigm that impacts governments and the scientific community, as well as traditional political and economic means to address these issues [38]. The latest advancements in AI technologies, including deep learning, image identification, machine learning, and natural language processing, make it clear that these technologies will continue to have an influence on daily life [39].

An economic model known as "take, make, and dispose of" powers the world economy, which depends on taking enormous amounts of finite resources and fossil fuels from the ground and burning them for energy. This linear economic model has generated unparalleled riches over the last two millennia but has also ravaged our ecosystem [40].

The group of technologies known as artificial intelligence (AI), which simulates cognitive processes like learning and reasoning in humans, has the potential to alter food systems and change how food is produced and distributed throughout the world [40]. However, simply giving computers intelligence or consciousness does not automatically qualify as artificial intelligence (AI) in the same way as humans. It simply means that a computer can solve a particular problem or related issues. On the other hand, harnessing the power of

AI to transition the food system from a linear to a circular model is one of our era's most significant technological breakthroughs. According to the Ellen MacArthur Foundation [31] and Magnin [40], this possibility remains largely unexplored.

In addition to protecting and regenerating biological systems, AI can produce value rather than extract it. Furthermore, a study by the Ellen MacArthur Foundation identified three areas where artificial intelligence (AI) can have the most influence on the shift to a circular food system: obtaining food farmed sustainably and locally when applicable, designing out avoidable food waste, and developing and marketing healthier food items [31].

The majority of crops are being farmed in a way that depletes soils, agrobiodiversity, and waterways while taking more from natural systems than it gives back. AI can assist in the replacement of traditional agricultural techniques like monoculture, the widespread use of synthetic chemical fertilizers, and intense land usage with more regenerative ones. Also, AI can assist farmers from the start by minimising food waste and building systems that minimise wasteful food use [41].

A study by the McKinsey Global Institute [41], discovered that by applying these strategies to minimise food waste, AI might potentially provide a chance to increase top-line revenue by much to USD 127 billion per year by 2030; as well as anticipated that by 2030, AI may increase global economic activity by an additional USD 13 trillion.

Food can now be processed cyclically as demand for quick, easy-to-prepare meals rises. In addition, food innovators and designers can make it simpler for people to obtain healthy food items by utilising AI as a tool to help them obtain components from regeneratively grown plants, swap out animal proteins for plant-based ones, reduce processing waste, and avoid dangerous additives [31]. The integration of AI into the food industry holds immense potential for addressing food waste, supporting the circular economy, and enhancing sustainability in food production. By leveraging AI technology, we can unlock more efficient processes, empower better decision-making, and foster the development of innovative solutions to tackle the pressing challenges faced by the global food system. To gain a deeper understanding of the role AI plays in these critical areas, please refer to Table 1, which highlights the specific ways AI contributes to addressing food waste, supporting the circular economy, and enhancing sustainability in food production. It serves as a comprehensive reference that showcases the various applications and benefits of AI in transforming the food industry towards a more sustainable and efficient future.

Table 1. The Role of AI in Addressing Food Waste, Supporting the Circular Economy, and Enhancing Sustainability in Food Production.

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 optimising crop yields based on weather patterns and soil conditions.	[42,43]
2	AI Image Recognition	Used in quality control for food items during manufacturing and packaging. Helps to minimise waste by identifying substandard products before reaching consumers.	AI image recognition can help design out food waste by ensuring only quality products are packaged and sold, reducing return rates and subsequent waste.	[44]
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.	[45,46]

Table 1. *Cont.*

S/N	Technology	Application Examples	Role in Sustainability	References
4	AI-Driven Smart Agriculture	AI applications can enhance farming methods, crop selection, and yield predictions, reducing the unnecessary waste of resources and promoting a circular economy.	AI can support local food production by optimising growing conditions for local species and forecasting market demand to reduce waste.	[47]
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, improving the shelf-life of food products.	IoT and AI can support the development of healthier food items by tracking nutritional value during storage and informing consumers.	[48]
6	Blockchain and AI	A combination of blockchain and AI can ensure traceability in the food supply chain, decreasing food waste and fraud.	Blockchain and AI can help design out food waste by ensuring transparency and accountability throughout the supply chain, reducing losses and inefficiencies.	[49,50]
7	Reinforcement Learning	AI systems can optimise food logistics and supply chain management, learning to improve over time and reduce food waste.	Reinforcement learning can support local food production by optimising delivery routes and times to ensure fresh, quality produce.	[51]

2.3. Using AI to Support Circular Economy Initiatives

2.3.1. Use of AI to Identify Opportunities for Waste Reduction and Recycling

Reduce, reuse, and recycle are the three major driving forces behind the circular economy, which has the dual goals of minimising the use of virgin resources and achieving sustainable development [52]. A circular economy reduces the carbon footprint involved with the production of new materials by promoting recycling and reuse. Additionally, using recycled materials significantly lowers the carbon footprint in an economical and environmentally responsible way. Additionally, a circular economy greatly reduces waste production, thus reducing the carbon footprint. The achievement of environmental, social, and fiscal sustainability is thus seen as being driven by it.

The public's wish for recycling and reusing recycled materials made research on food recycling networks possible. AI technologies can spur business innovation in solid waste management (SWM) when used properly. In almost every industry, the effectiveness, security, and calibre of production processes can all be enhanced with artificial intelligence (AI). AI is presently being used to deal with complex problems in SWM, social security, safety, health, climate, energy, facilities, transport, and other areas. AI automation boosts efficiency and business processes to new heights of consistency, speed, and scalability while lowering costs. As a result, the application of AI algorithms for SWM improvement has grown significantly on a global scale [53].

The application of artificial intelligence can analyse new data from a variety of sources and produce results in almost real-time, adapting as necessary. However, for governments, the degree of precision is essential [54,55].

Globally, the use of AI algorithms for SWM optimisation keeps growing [53]. Second, AI applications can analyse new data from numerous sources and generate results almost instantly, adapting as required. This level of precision is highly valued by governments.

A circular economy includes a variety of industries, including those in the economy, metallurgy, chemical, biotechnology, and information technology and communications (ITC), and ITC can help to govern and advance a circular economy [56]. Regarding manufacturing, circular economy principles can be translated into various approaches, including remanufacturing, recycling, industrial symbiosis, etc. This concurrent approach is known as circular manufacturing (CM) [57].

Artificial intelligence (AI) can be used to encourage data collection for sustainable goals, particularly concerning the manufacturing industry [58].

2.3.2. Applications of Artificial Intelligence (AI) in Waste Management and Recycling

AI assists in identifying the most suitable and affordable disposal options for the various returned products if regenerative processes cannot be implemented [59]. AI can be used to create decision-support tools that assess a product's quality, the need for reprocessing, and whether regenerative methods can be used.

In recent years, the recovery of resources, including reusing, recycling, and obtaining energy from refuse, has received increased attention using cutting-edge techniques like artificial intelligence [53,60].

With the ultimate aim of reusing waste as a resource, artificial intelligence is used to support decision-making for biowaste treatments and to develop bioenergy by depending on criteria that cover the social, environmental, and economic aspects [61]. Implementing AI technologies to improve sustainable trash management will aid in reducing the overall amount of natural resources consumed by recycling, reusing, or recovering materials before they reach the end of their usefulness [62].

The amount of natural resources consumed can be reduced by reusing, recycling, or recovering some materials before they end their useful lives. AI technologies can be used to improve sustainable waste management [62]. AI is used for tracking an item to help monitor its condition and assess its suitability for reuse, as well as observe its environment to determine recycling possibilities.

The application of AI technologies constantly improves the processes for collecting, transporting, sorting, and recycling various wastes [63].

AI allows for the proper use of data collected from industrial systems because it can watch and monitor data related to processes and products [64,65].

2.3.3. Potential Benefits of an AI-Supported Circular Economy Initiative

Recent years have seen a significant increase in interest in resource recovery from refuse [66].

Artificial intelligence can support the use of circular manufacturing strategies, improve energy efficiency, and extend the usable life of products and components by extracting as much value as possible from resources [67].

Artificial intelligence supports the decision-making process at the factory level (i.e., for goods and processes), accelerating an increase in circular economy values by tracking and monitoring products in real-time to determine their residual value [68].

Artificial intelligence helps with the challenges of transformation by incorporating information into operational aspects in a secure manner [69] and using rapid methods that increase system adaptability [70].

The creation of visual tools that provide an understandable overview of data flows relating to products, resources, and processes can be encouraged with the help of AI. These tools make it easier to investigate the benefits of a circular economy that are not yet fully understood [71]. Figure 3 highlights the different ways AI is used in food waste management and how they help in achieving UN sustainable goals.

Figure 3. Different Applications of AI in Food Waste Management.

3. Using AI to Monitor and Optimise Food Production and Supply Chains

In the agricultural industry, technological advances will always play a big role in the production process and supply chain. As pointed out in [72], using tractors and harvesters in the last two centuries improved agricultural output. Presently, artificial intelligence (AI) can bring innovation and help improve this output even more at a lower cost. This is because machine-aided predictions and simulation of factors that affect agriculture and food production can be tackled at a much bigger scale with very good results compared to human analysis. Due to the increase in the world's population and changes in climate conditions, new aspects of the agri-food supply are beginning to emerge. It is now possible to use a vast amount of data to analyse produce yields and end-user needs for optimum food production and supply [73]. In addition, Ramirez-Asis et al. [74] emphasised that AI, aided with complex computer networks, can be used to achieve the required targets to improve food safety, delivery, and logistics. This section explores how AI, which is now regarded as a significant paradigm for science [75], can influence food production, processing, and transportation. The supply of processed products and potential applications to reduce food waste will also be discussed.

3.1. Using AI to Analyse Data on Factors Such as Weather Patterns, Crop Yield, and Consumer Demand to Optimise Pre- and Post-Harvest Food Production and Supply Chains

To develop strategies for mitigating climate change, Sahil et al. [76] propose using AI to monitor several parameters that can affect humans globally. These factors include temperature, CO_2 concentration, natural disasters, and climate conditions associated with a particular region. If properly used, the authors believe AI can achieve the 'Climate action' of the UN sustainable development goals. In addition, AI may be used to ensure that global emissions are maintained below 2%, which will help prevent social, political, and international disasters. To better understand the climate, it has to be micromanaged for optimum benefit. It is now possible to practice more precise agriculture by monitoring the climate closely. A system for monitoring climate at a micro-scale has been described [77], and in that report, it was highlighted that data from microclimate parameters could be used to identify the exact water requirement for irrigation. In combination with sensors, the temperature and soil moisture content may be used to estimate evapotranspiration, which paves the way for any mitigation required and ensures that smart farming is achieved.

Smart farming uses digital technologies to improve outsourcing, procuring, and planning in the supply chain [78], and it may help bring about the needed change in the food supply system that will satisfy the growing demand for sustainable food production globally. AI is believed to play a big role in next-generation farming because the innovative analysis can establish variations in crops and fields, leading to higher yields and less lateral loss of produce in the supply chain [79]. AI can also aid the transition to a drastic rather than small incremental change if a trans-disciplinary model is used to optimise the relationships between technology, humans, and the environment [80].

3.2. Examples of AI Applications in Agriculture, Food Processing, and Transportation

Consumers are constantly concerned with the nutritional value of foods, their method of processing, and their increased shelf life. To monitor these concerns, AI can be used to monitor drifts due to its multi-disciplinary nature, and any adjustment required can be carried out [81]. AI, by way of synthesis and analysis of big data, is used to monitor pre- and post-harvest processes and trace different types of products in the supply chain. A recent systematic review found that in all stages of the food system, different artificial intelligence algorithms are used to monitor processes [82]. The first stage of food production is carried out in the field or farm, and AI has been applied in fields. Sharma et al. [83] used image-based computer analysis to estimate the categorical age of crops. It was pointed out that computational intelligence might be useful to prevent the excessive use of fertilizer and ensure optimal nitrogen utilisation.

Chen et al. [84] reviewed the use of physical fields for processing dried vegetables and fruits with the aid of AI technology and found that problems associated with nutrient loss, sensory analysis, poor drying, and energy consumption can be resolved together with online process control. In aquaculture and fisheries, catching fish has improved with the use of data mining to process complex data, which helps to intelligently perform tasks, forecast problems, and provide precision solutions [85]. In the European dairy supply chain, the use of AI for ensuring food safety with an early warning system has been highlighted. When the numbers of Rapid Alert for Food and Feed (RASFF) notifications were analysed by Liu et al. [86], it was revealed that significant correlations existed among many indicators and differences were found among countries. Another product among many that can benefit from AI innovation is meat products found in cold chain logistics. A study by Ren et al. [87] focused on how meat is packaged, evaluated, and controlled. They found that digital intelligent quality assessment and monitoring could improve the cold chain supply chain. Following the supply of food, sensory acceptance by consumers is critical for any food product to sustain its journey from farm to fork. Hence, a huge amount of sensory data can also be subjected to AI analysis. A review by Nunes et al. [88] noted that AI is now important because it can explore and correlate data between sensory tests by humans and instruments to obtain solutions that will meet the needs of both consumers and producers.

3.3. Potential Benefits of AI Optimisation, including Reduced Food Waste and Increased Resource Efficiency

Gedi et al. [89] reported that food waste can be optimised to produce value-added products, which may include products that contain micronutrients. That report also noted that new functional materials could reduce carbon emissions across the supply chain. Of note is that valorised food waste products contain high dietary fibre and beneficial nutrients. The consensus is that global food demand can be significantly reduced if food waste material is valorised. Manufacturers and retailers of food products are in a perfect position to point out areas of high food waste. Pimental et al. [90] analysed factors that can reduce waste in the supply chain from a retailer's perspective. The study showed that there were up to 46 factors that can help reduce food waste, and it was concluded that retailers are in a very good position to monitor waste reduction. Such monitoring can be made more efficient with the innovative application of AI. Applying intelligent approaches can enable real-time decision-making and process optimisation, and if supported by the government, food waste can be minimised and maximised for a sustainable future [91].

Although AI is being used to create sustainable food systems in Europe, there are some concerns and challenges. According to Yadav et al. [92], one current problem includes sustainability, stringent government regulation, food security, and traceability issues. A business model can also affect the use of AI. When different business models were examined by Cicculo et al. [93] for sustainable food waste reduction with the aid of big data, it was found that some businesses did not exploit their full potential. Also, other investigators [94] found that the type of AI used depends on the industry, and some models were more popular than others. Furthermore, algorithmic bias and external disruptions were identified by Galaz et al. [95] as systemic risks, which may affect sustainability when AI is used. Others argue that there is a need to rethink the readiness of agri-tech firms for the use of AI [96]. Despite some uncertainties, it is believed that using big data and AI to manage risks at all production and supply chain stages can play a big role in preventing food recalls, which may be expensive and damaging to a company's brand [97]. Overall, we conclude that despite any shortcomings, AI is here to stay and will most likely become the gold standard for monitoring food quality and safety in all production and supply chain stages.

3.4. Examples of AI Applications in Food Production

AI in the food industry is rapidly evolving, with many companies already leveraging technology to improve their operations and reduce waste.

Here are some examples of AI applications in food production:

IBM Food Trust: This blockchain-based platform uses AI and other technologies to track food products from farm to table, enabling suppliers and retailers to identify the source of any safety or quality issues quickly. By providing end-to-end traceability, IBM Food Trust can help to reduce waste caused by recalls and increase consumer trust in the food supply chain [98].

Blue River Technology: This company uses computer vision and machine learning algorithms to identify and selectively spray weeds in agricultural fields. By targeting only weeds, Blue River Technology can reduce the use of herbicides and increase crop yield, thus improving efficiency and sustainability in agriculture [99].

Brightloom: This company uses AI and predictive analytics to optimise menu offerings and pricing for food retailers. By analysing data on sales and customer preferences, Brightloom can help retailers to reduce waste caused by overproduction and ensure that their offerings are aligned with customer demand [100].

AgShift: This company uses computer vision and AI to automate the process of quality inspection for commodities such as grains, fruits, and vegetables. By analysing images and other data, AgShift can quickly and accurately identify defects, reducing waste caused by human error [101].

ImpactVision: This company uses hyperspectral imaging and machine learning to analyse the composition of food products, enabling suppliers and retailers to ensure that their products meet quality standards. By identifying quality issues early, ImpactVision can help to reduce waste caused by recalls and improve overall efficiency in the supply chain [102].

4. AI-Powered Food Redistribution Systems

4.1. Using AI to Match Food Donors with Food Banks and Other Organisations That Distribute Food to People in Need

AI-powered food redistribution has the potential to reduce food waste and insecurity by increasing food access to at-risk individuals and the most vulnerable communities. In addition, leveraging AI has the following potential benefits:

Food waste can be significantly reduced by using AI to match food donors with organisations that distribute food to the most vulnerable people affected by food insecurity. AI can help ensure that food donations are distributed to the areas most needed and in the right quantities, thereby reducing food waste [103].

AI-powered food redistribution can improve and increase food access, affordability, and stability for vulnerable populations such as families besieged by financial instability, individuals experiencing homelessness, and those who are unemployed. Furthermore, by optimising the allocation of resources and identifying areas of high need, AI can help ensure that food donations are distributed to at-risk individuals [104].

AI-powered food redistribution can help improve the efficiency of food distribution systems. By using machine learning algorithms to analyse data on food donations, quantities donated, quantities supplied and demanded, and distribution patterns, organisations can identify the most efficient food distribution strategies. Furthermore, ML can be used for food recognition and food nutrition estimation [105].

AI-powered systems can help ensure that donated food is safe for consumption. Applying machine learning and computer vision technology can assist in visually identifying and categorizing food items [106]. Therefore, food donors and food banks can identify any items that may be spoiled or contaminated and remove them from their inventories.

AI-powered distribution can promote sustainability by ensuring that donations are distributed efficiently and reducing food waste. In addition, AI applications to food systems can potentially divert food from landfills, thereby reducing the environmental impact of food production and waste.

The magnitude and complexity of the challenge of food insecurity require sophisticated interventions to improve food access, availability, and stability. Moreover, at minimum, six of the Sustainable Development Goals are centred around food sustainability [107].

Digital technologies and AI applications, including predictive analytics, can remove many challenges faced by the food supply chain [104]. Food banks are an important channel through which food insecurity can be reduced. Food banks can be defined as non-profit organisations that distribute food freely to people without charging them a price to improve access to food and reduce hunger [108]. Factors that drive individuals to use food banks include loss of income and employment, lack of financial stability due to household unemployment, a delay in cash transfers to individuals receiving state social support, and sanctions [109]. A study by Bertmann et al. [110] showed that food banks and pantries supported food access and improved food and vegetable intake for the most vulnerable class of the population. Charitable organisations have also jumped on the bandwagon and partnered with healthcare systems in some countries in a bid to assist and support individuals experiencing food-related issues including limited access, affordability, and instability [111]. AI presents an opportunity to match food donors with food banks and charitable food systems. The following aspects of AI can be optimised to allocate resources and help reduce food waste and connect donors with food banks and other organisations involved in the distribution of food to the most at-risk individuals:

Natural language processing (NLP) can be used to enable the interaction between computer programs and food donors, food banks, and beneficiaries. Donors can describe the type and quantity of food they want to donate, and the AI system can match their donations with the needs of food banks and other organisations. Moreover, NLP can assist in determining the nutritional quality of food at the food banks and the recipes possible from the donated food [112].

Machine learning (ML) algorithms can be used to analyse large datasets on food donations, locations, population size, frequency of donation by food donors, and patterns in food distribution by food banks and other charitable organisations. This information will help make supply and demand forecasts as well as identify areas or regions with the largest number of individuals affected by food insecurity. Furthermore, ML could establish dietary patterns in the affected individuals who are recipients of the food [113,114]. Based on the ML algorithms applied, efficient and effective distribution locations, quantities, and strategies can then be put in place

Computer vision can be leveraged to identify and categorise food items visually. This will improve the process of matching donors with recipient organisations and individuals. Moreover, computer vision can assist in recognizing food, establishing quantities, and accurately sensing and measuring key parameters that determine the safety of the food donated as well as its quality [115]. For example, computer vision technology can identify perishable items that need to be distributed quickly and identify food items that food banks commonly request.

Geographic information systems (GISs) can be used to map hotspots of food insecurity and the locations of food banks and food donors. They can also be used to analyse data on food distribution patterns to optimise the allocation of resources [116].

4.2. Examples of AI-Powered Food Redistribution Systems

Having established the fact that there is an upsurge in food waste in many countries, it is pertinent, therefore, to generate innovative solutions to tackle this waste.

Demand for quick, reasonably priced, and easily accessible food alternatives has changed as a result of shifting customer preferences, which have transformed the food and beverage sector. Utilizing AI and machine learning (ML) technologies help the food sector manage food waste, scale up processing, and remain competitive in a changing market context.

A quick and effective heuristic prediction technique, such as big data analysis (BDA), is required for forecasting hazards, risk assessment, and prevention connected to food safety. The food processing lines benefit from automation, and a sizable quantity of data is gathered, saved, processed, and utilised for risk assessments in addition to helping to strengthen the food supply chain [117].

BDA and related technologies improve the functionality of the Internet of Things (IoT) for supply chain monitoring and food safety to address food security challenges. Using RFID-based transparency to carry out rights and rules is essential for guaranteeing food security and redistribution. Also, substantial data are produced at an unprecedented rate using modern digitalisation for optimal choices to address the growing issues with agricultural output, investigate the complicated agrarian potential, and keep an eye on machinery performance [118].

4.3. Connection between GIS and AI

Artificial intelligence (AI) has grown quickly in recent years and has matched or even exceeded human competence in certain activities including text translation, reading comprehension, and image recognition. AI is the ability of a machine to perform a task that typically requires a certain degree of human intelligence. This is made possible using several engines, one of which is machine learning. It uses algorithms powered with data to learn from data and share the information needed. Deep learning is a novel approach to machine learning that uses neural networks created with computers that are similar to and inspired by the human brain to identify and tackle issues and forecast outcomes [119].

New opportunities are emerging as a result of the confluence of AI and GIS. A series of technologies known as AI GIS integrates artificial intelligence (AI) with GIS functions such as spatial data processing and analysis algorithms. In recent years, AI GIS has increasingly taken centre stage in geoscience investigation and implementation [120].

Artificial intelligence (AI) for GIS is the use of AI to enhance the intelligence of GIS programs with techniques including AI attribute collecting, AI survey and the mapping process, AI cartography, and AI interaction. On the other hand, GIS for AI is the ability of GIS to enable AI by utilising its geographical visualisation and spatial analytic skills to systematically analyse and extract data in response to AI recognition discoveries. In order to automate procedures, enhance predictive modelling, and obtain competitive advantages, the food industry, as well as other sectors and businesses are systematically utilising artificial intelligence (AI), particularly machine learning, and using location data as a unifying link [120].

Manufacturers utilise AI solutions to streamline supply chains, automate inspections and quality control, plan predictive maintenance, and spot any unforeseen events before they stop production. On the other hand, suppliers use machine learning and location intelligence for choosing a store, customer assistance, pricing formulating, supply chain maximisation, location-based advertising, and creating individualised consumer experiences. Even government organisations use georeferenced drone and satellite images to automate fieldwork, simulate growth scenarios, estimate agricultural yields, and continuously check crop health [121].

Not all soils can be utilised for agriculture, and not all crops can be effectively grown under particular soil conditions because various crops have varied nutritional requirements and different soils have distinct physico-chemical properties. For this reason, researchers think it is critical to map the appropriateness of terrain [122]. As a result, land suitability studies are required to ensure an effective and sustainable supply of food from these limited natural resources [123]. The integration of GIS and AI models and analytic methodologies has therefore enabled the development of a variety of high-quality decision-making systems that carry out complicated treatments involving several factors [122].

5. Discussion

The use of artificial intelligence (AI) for supporting circular economy initiatives and waste management has shown promising results. AI technologies have the potential to identify opportunities for waste reduction and recycling, which are essential components of the circular economy. By analysing new data from various sources, AI algorithms can generate real-time results and adapt as necessary, providing governments with precise information for effective decision-making.

In the context of solid waste management (SWM), AI can enhance the effectiveness, security, and quality of production processes. It enables automation, boosting efficiency and scalability while reducing costs. The application of AI algorithms in SWM optimisation has been growing globally, indicating its value for addressing complex problems in waste management, social security, safety, health, climate, energy, facilities, and transportation.

Furthermore, AI can support data collection for sustainable goals, particularly in the manufacturing industry. It can analyse data related to processes and products, allowing for improved monitoring and decision-making. The integration of AI in waste management processes, such as collection, transportation, sorting, and recycling, has the potential to optimise these processes and improve resource efficiency.

The benefits of AI-supported circular economy initiatives are numerous. AI can help extract as much value as possible from resources, improving energy efficiency and extending the usable life of products and components. By reducing waste and increasing resource efficiency, AI can contribute to the achievement of environmental, social, and economic sustainability goals.

In the domain of food production and supply chains, AI plays a crucial role in optimising various stages of the process. Using an analysis of data on weather patterns, crop yields, and consumer demand, AI can provide insights into optimising pre- and post-harvest food production and supply chains. This enables more precise agriculture practices, leading to higher yields and less waste in the supply chain.

AI applications in agriculture, food processing, and transportation are diverse. They include image-based analysis for estimating crop age, physical field processing with AI for improved drying and energy consumption, data mining for intelligent fisheries management, and AI-assisted food safety monitoring systems.

The potential benefits of AI optimisation in the food sector are significant. AI can help reduce food waste by identifying areas of waste and enabling real-time decision-making and process optimisation. By leveraging AI and big data, risks can be managed at all stages of production and supply chains, preventing costly food recalls and enhancing food quality and safety.

However, it is important to critically evaluate the implementation of AI in these contexts. While AI has the potential to bring numerous benefits, challenges and concerns exist. These include issues of sustainability, government regulations, food security, traceability, algorithmic bias, and external disruptions. The readiness of agri-tech firms and the choice of AI models also play a role in the success of AI applications. Despite these challenges, AI is expected to become the standard for monitoring food quality and safety in production and supply chains.

Overall, the results of using AI in circular economy initiatives and food production and supply chains are promising. AI has the potential to improve efficiency, reduce waste, and enhance sustainability in various sectors. However, careful consideration of ecological and economic factors is necessary to ensure that the benefits of AI outweigh the associated infrastructure requirements.

6. Conclusions

Food waste is a significant global issue with far-reaching economic, social, and environmental impacts. Fortunately, the circular economy approach provides a promising solution to this challenge by promoting waste reduction and increasing resource efficiency. In recent years, the use of artificial intelligence (AI) in the food industry has gained traction to address food waste and enhance circular economy initiatives. AI can be utilised to monitor and optimise food production and supply chains, redistribute excess food to those in need, and support waste reduction and recycling efforts. By leveraging AI technologies, we can maximise resource efficiency, minimise environmental impact, and create a more sustainable and equitable food system. The potential benefits of AI-supported circular economy initiatives are numerous, including improved energy efficiency, extended product lifespan, and enhanced decision-making processes. Continued investment and research in AI technologies are crucial to unlocking the full potential of the circular economy and reducing food waste on a global scale.

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