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Review

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

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Abstract: Food waste reduction, as a major application area of the Internet of Things (IoT) and big data technologies, has become one of the most pressing issues. In recent years, there has been an unprecedented increase in food waste, which has had a negative impact on economic growth in many countries. Food waste has also caused serious environmental problems. Agricultural production, post-harvest handling, and storage, as well as food processing, distribution, and consumption, can all lead to food wastage. This wastage is primarily caused by inefficiencies in the food supply chain and a lack of information at each stage of the food cycle. In order to minimize such effects, the Internet of Things, big data-based systems, and various management models are used to reduce food waste in food supply chains. This paper provides a comprehensive review of IoT and big data-based food waste management models, algorithms, and technologies with the aim of improving resource efficiency and highlights the key challenges and opportunities for future research.

Keywords: IoT sensors; food waste reduction; big data; communication technologies; supply chain

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1. Introduction

Food waste has been recognized as a serious issue, and significant efforts have been made worldwide to address the challenges and to reduce food waste. Simultaneously, there have been tremendous developments in the IoT sensor and big data technologies. These technological developments can transform the ordinary supply chains into smart supply chains, which can be adopted for reducing food waste using big data analysis approaches, appropriate models, and algorithms. There is broad literature for food waste control [1–9]. A smart supply chain uses information and communication technologies (ICT) to improve citizen welfare by providing better services through sharing information with the stakeholders. One of the most crucial aspects of a smart supply chain is the IoT infrastructure. Through various types of sensors, data can be sent to be analyzed to reduce food wastage. IoT applications are employed for a variety of purposes, for example, monitoring the environment inside homes [10] or in food processing factories [11].

The importance of Food Wastage Reduction (FWR) is related to the loss of all the natural resources in the supply chain, including expenditures related to the use of land, water supply, and energy consumption. Additionally, with respect to importance of sustainable agriculture, production, and supply chain, FWR will have major impacts on the economy, the environment, and society. It is critical to investigate how food wastage affects each of the three aspects. Yildirim et al. [12] discusses the economic impacts of FWR. To explain and better understand the determinants of food waste across the supply chain, Chalak et al. [13] closely examines the sectors of Hospitality, Restaurants, and Canteens/Cafeterias (HORECA), as well as the food retail and wholesale sectors. Data from 33 developed countries were analyzed by means of a regression model to identify the macroeconomic factors contributing to the generation of food waste. The challenges and opportunities for enhancing the emerging bioeconomy are explored in Morone et al. [14]. Additionally, Salemdeeb et al. [15] address the environmental aspects of using food waste. On the other hand, Scherhaufer et al. [16] explore the environmental effects of FWR which is an increasingly significant issue in smart cities. Sustainability is an extremely crucial issue that should be taken into consideration. The importance of sustainable food waste management is discussed by Mak et al. [17]. FWR models are widely discussed by Ananno et al. [18]. This literature supports the motivation for study on FWR based on IoT and big data technologies to control its negative environmental, social, and economic aspects.

Mak et al. [17] developed an IoT-based real-time FWR system for use in the office. They proposed a model in which an IoT-mounted weighbridge measures food wastage in office premises and reports it via a mobile device to the employees. Breakfast, lunch, dinner, and snacks are all considered as part of the measurement and can provide insight into how employees can reduce the amount of food lost at work. However, this proposed system does not discuss how various types of foods might be prevented from being wasted using this approach. Jayalakshmi et al. [19] implemented a novel approach for FWR through IoT-based smart garbage and waste collection bins. The embedded systems are used for measuring and recycling food waste to create social awareness and reduce food waste. In the present paper, a disposal system is presented that reduces the amount of food waste by reducing the total number of trips by garbage vehicles. In addition, it increases the overall cost associated with garbage collection. Gull et al. [20] used an Arduino Uno microcontroller to detect gas emissions from different food items, i.e., meat, rice, and bread. As explained in the paper, the MQ4 sensor detects the CH_4 gas, while the MQ135 sensor detects CO_2 and NH_3 in this system. A strain gauge load cell sensor and a converter as a weight sensor are used to measure the weight of the food being wasted. To ensure the accuracy and efficiency of the proposed system, the sensors are calibrated. Data is collected on cooked, uncooked, and rotten food items. A machine learning algorithm is used to predict food items based on gas emissions to make this a smart system. The decision tree algorithm is used for training and testing purposes. In this way, 70 instances of each food item are contained in the dataset. According to the rule set, this system is implemented to measure food wastage and to predict food items. When a specific food item is detected, data is gathered on how much of that food item is wasted in one day. This system had an accuracy of 92.65 percent. As a result, the system reduces the amount of food that is wasted at home and restaurants by providing a daily report of food wastage in their computer system. The application of IoT to FWR systems is also examined by Gayathri et al. and Luthra et al. [21,22], where [21] use RFID sensors as a key tool to monitor food waste for each individual in accordance with the proposed model, while [22] describe the application of IoT-based technologies to agricultural supply chain management in developing countries.

Thus, IoT and big data-based systems are finding more and more successful applications in FWR. However, based on an analysis of the literature, there is a paucity of a review that comprehensively analyzes the published literature, brings out the strong points of applications of IoT and Big Data technologies, and highlights neglected areas that might need more efforts from future researchers. This paper fills this void with a focus on food waste reduction. In this paper, we try to review different layers of IoT and big data infrastructure that merge together with the aim of reducing food wastage in the supply chain. This article provides a broad understanding of the patterns of prior studies in terms of the following aspects:

1. Reducing food waste with IoT and big data-based systems.
2. Machine learning algorithms that are used for FWR.
3. Various types of sensors and technologies that are used to reduce the amount of food wastage and improve food quality.
4. The challenges and opportunities related to using IoT and big data analysis for reducing food wastage in the supply chain.

This paper is structured as follows: Section 1 is an introduction and discusses the motivation and describes the relevant literature. Section 2 discusses research in IoT and big data analytics for FWR. The next sections explain the three layers of the FWR system. In Section 3, FWR based on IoT and Big Data analytics in Smart Supply Chain for the sensing and measurement layer is discussed. In Section 4, the service layer and big data analysis approaches for FWR are discussed, and a review of articles for understanding the models and algorithms is presented. Section 5 provides an investigation into the application of Machine Learning Techniques in reducing food loss. Section 6 introduces wireless technologies to reduce food waste. Section 7 provides a review of the challenges and opportunities related to an IoT-based FWR system. Finally, Section 8 concludes the paper. A list of acronyms used throughout the paper is presented in Table 1.

Table 1. List of acronyms and corresponding definitions.

Acronyms	Definitions
IoT	Internet of Things
FWR	Food Waste Reduction
MEMS	Microelectromechanical Systems
RF	Radio Frequency
BLE	Bluetooth Low Energy
WLAN	Wireless Local Area Network
ANN	Artificial Neural Network
SVM	Support Vector Machine
RFID	Radio Frequency Identification
GMM	Gaussian Mixture Model
KNN	K-Nearest Neighbourhood
WSN	Wireless Sensor Network
ML	Machine Learning
AI	Artificial Intelligence

2. IoT and Big Data

IoT technology through ICT infrastructure and smart devices combines to gather huge amounts of data in real-time, which is commonly known as big data. The big data generated by IoT devices will be stored in the big data storage system and will be used for analysis. The relationship between big data analytics and IoT is explained by Marjani et al. [23] by taking into account the architecture, opportunities, and open research challenges. Furthermore, this paper also covers big IoT data analytic types, methods, and technologies for big data mining. Additionally, the IoT architecture in relation to big data analytics is studied. IoT devices are connected to the network and the data is then stored in the cloud and then analyzed. In our paper, we enhanced the topic to IoT applications in smart food supply chains. In this section, IoT and big data are briefly discussed, and the relationship between IoT and big data analytics is explained in more detail.

2.1. IoT

According to Marjani et al. [23] and Al Nuaimiet al. [24], IoT offers a platform for sensors and devices to communicate seamlessly within a smart environment and enables information sharing across platforms in a convenient manner. Smart cities have seen a recent adoption of IoT. This is due to interest in intelligent systems, such as smart offices, smart retail, smart agriculture, smart water, smart transportation, smart healthcare, and smart energy. By using different types of sensors based on their application and communication technology, IoT is used in smart supply chains to reduce food wastage.

Figure 1, inspired by Jagtap et al. [25], illustrates IoT as a platform for FWR in a smart supply chain. As is illustrated, the four layers of sensing, application, network, and service form an IoT system, which is indicated for FWR applications.

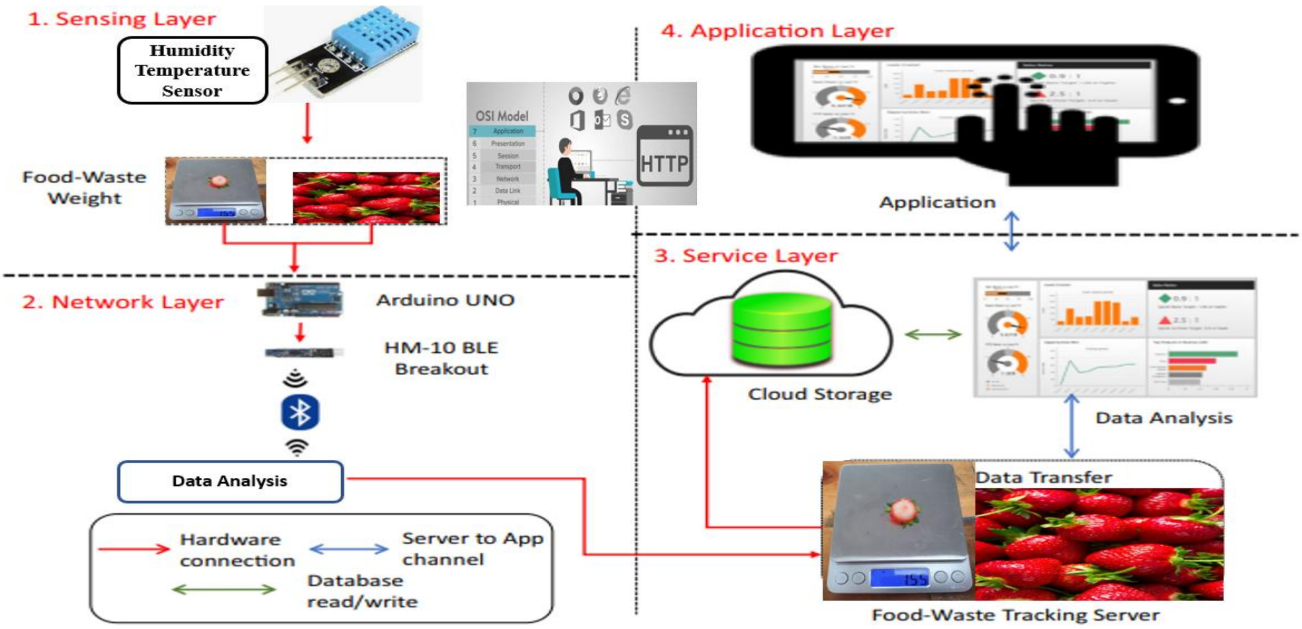

Figure 1. IoT platform for FWR [23].

2.2. Big Data

The massive data generation by sensors, devices, social media, healthcare applications, temperature sensors, and various other software applications and digital devices that continuously generate large amounts of structured, unstructured, or semi-structured data results in big data. Mak et al. [17] describe big data technologies as an upcoming generation of technologies and architectures. These technologies aim to take the value out of a massive volume of data in a variety of formats. This is done by enabling high-velocity capture, discovery, and analysis. In the studies conducted by Kambatla et al. [26] and Gantz et al. [27], trends and approaches for big data analysis are discussed. There are various characteristics of big data, such as veracity, value, variability, and complexity. These characteristics include the volume or size of data, variety or different sources of data, and velocity or speed of data creation, which are studied by Gani et al. [28] and Paul et al. [29]. Big data analytics is the process of examining large data sets that contain a variety of data types to reveal unseen patterns.

Data analytics consists of estimating hidden correlations, customer preferences, and other useful business information [30]. Having a clear understanding of data is the most significant objective of big data analytics, which helps food production companies to make efficient decisions. Big data analytics require technologies and tools that can transform a large amount of data into a more understandable data format for analytical processes. There are algorithms and tools that are used for the purpose of data analysis. Tools like these are used to identify patterns in data over time and visualize them as tables and graphs. Therefore, the performance of current algorithms for data analysis is a challenging issue that should be taken into consideration [31]. There are various tools and platforms that are in use for the purpose of data analysis; however, the most critical approach is to process huge data sets within a reasonable amount of processing time [32,33]. The data can be collected through various sources including online food quality databases, smartphones and handheld devices, social media, and satellite imagery. There are different types of data analytics, which are explained as follows:

- Real-time analytics (RTA)

Real-time analysis is typically performed on data gathered from sensors. Clearly, data changes constantly in this scenario, so rapid data analytics techniques are required to get an analytical result. It consists of two architectures: parallel processing clusters and memory-based computing platforms, which are detailed by Pfaffl et al. [34] The applications and challenges of big data analysis are discussed in [35]. A description of RTA architecture in the sustainable industry 4, the fourth stage of an industrial revolution, is provided by Novak et al. [36].

- Off-line analytics (OLA)

Off-line analysis is used when a quick response is not required [37]. For example, many Internet enterprises use Hadoop-driven offline analytics as explained in Zahid et al. [38]. There are other approaches for big data analytics such as memory-level analytics, business intelligence analysis, and massive analysis, which are defined based on the size of data in comparison with the allocated memory based on the application, which is explained in Refs. [39,40], respectively. The relationship between IoT and big data analytics is explained in Figure 2.

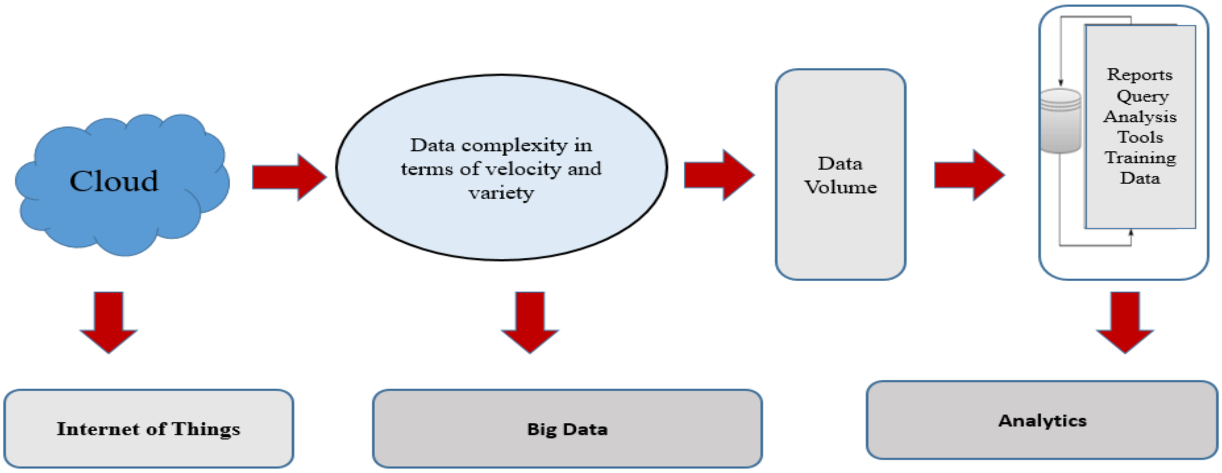

Figure 2. Relationship between IoT and big data analysis [23].

Nguyen et al. [41] present a state-of-the-art literature review on big data analysis for supply chain management. Arora et al. [42] provide an overview of big data analysis methods and procedures. Additionally, a comparison between various big data analysis techniques is provided as well. This is further explained in the following sections with more focus on FWR in the supply chain.

3. FWR Based on IOT and Big Data Analytics in Smart Supply-Chains: Sensing and Measurement Layer

In the work by Anagnostopoulos et al. [43], a visual tree for waste management is developed. It can be further developed to reduce food waste. Figure 3 illustrates how to classify the technologies that reduce food wastage. Anagnostopoulos et al. [43] review the literature related IoT-based technologies for reducing food waste in different layers of sensing and measurement, processing, and data transmission. As illustrated in Figure 3, there are various technologies that are used for the purpose of minimizing food waste. In the following sections, we examine these technologies and discuss the challenges. The term ‘smart’ refers to the process of checking the quality of food based on sensing and data analysis approaches, which will be discussed in more detail later. Here, we review the sensor technologies and introduce various types of sensors and their applications to better understand the measurement and data collection process in advanced IoT-based systems that aim to minimize food waste. Sehrawat et al. [44] review various types of IoT sensors. Table 2 provides a definition of these sensors and their applications in the food supply chain.

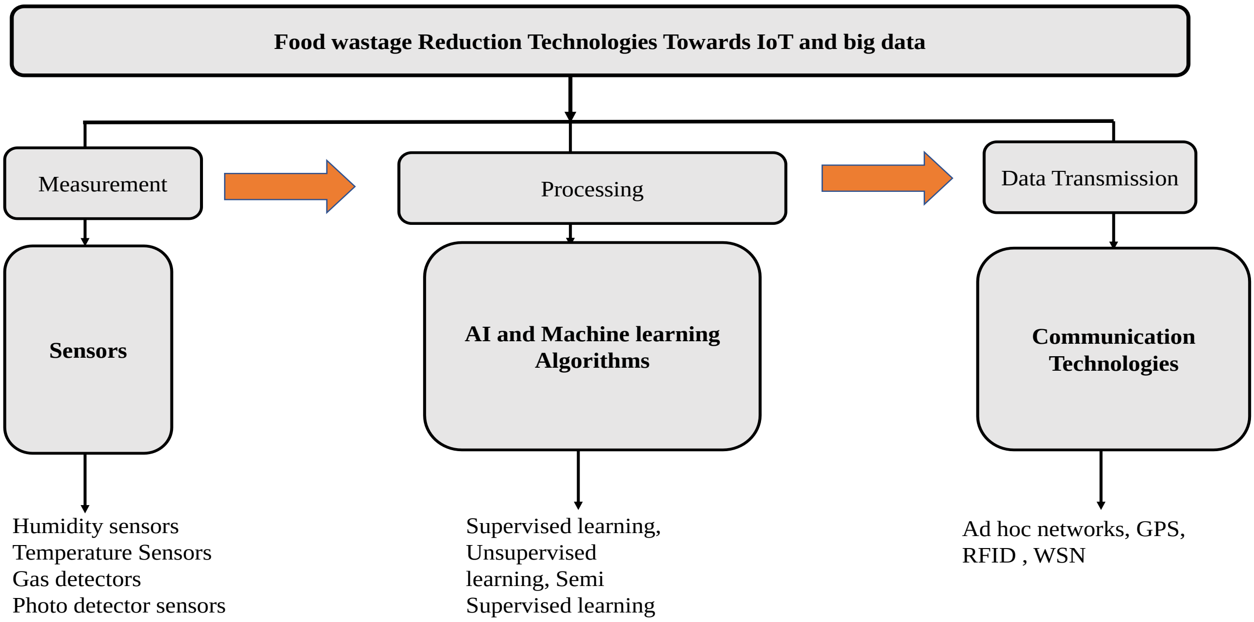

Figure 3. Ingredients of smart food waste reduction technology based on IoT and Big data analysis.

Table 2. Categorisation of the sensors for FWR and the applied technology.

Sensor Type	Technology	Application	Reference	Year
Proximity Sensor	The position of any nearby object is detected without any physical contact by emitting electromagnetic radiation such as infrared and looking for any variation in the return signal	Multi-application, depending on the type. There are various types such as inductive, capacitive, ultrasonic, photoelectric, and magnetic. Mostly used in applications demanding security and efficiency. Main applications of FWR are cutting number of items, measuring the amount of rotation for positioning of objects, and measuring movement direction.	[20,44,45]	2019, 2020, 2021
Position and occupancy sensors	Detection of the presence of human or objects in a particular area by sensing the air, temperature, humidity, light, and motion of a nearby object	Security and safety purposes, smart agriculture, smart FWR	[46,47]	2017
Motion and Velocity sensors	Motion sensors detect all kinds of physical movements in the environment and the velocity sensors calculates the rate of change in position measurement at known intervals in linear or angular manner	Smart city applications for intelligent vehicle monitoring, for example, acceleration detection of the boxes of food in the trucks for food protection during transmission	[48,49]	2015, 2016
Temperature sensors	Measurement of heat energy	FWR and smart farm	[50,51]	2016, 2018
Pressure sensor	Measurement the amount of force and convert it to signal	Smart FWR, smart refrigerator	[52]	2018

Table 2. *Cont.*

Sensor Type	Technology	Application	Reference	Year
Chemical sensors	Conversion of a chemical or physical property of a specific analyte into a measurable signal that its magnitude is normally proportional to the concertation of the analyte.	FWR and smart agriculture	[53]	2020
Optical sensors	Light intensity measurement	Food industry, FWR For instance, assessment of wine grape phenolic maturity based on berry fluorescence	[54,55]	2021, 2008

- Proximity Sensors: The proximity sensors are intended to detect a nearby object using electromagnetic radiation such as infrared by detecting variations in the return signal. There are various types of these sensors, such as inductive, capacitive, ultrasonic, photoelectric, and magnetic [44]. These sensors are widely used in the food industry and in FWR systems [20].
- Position Sensors: The position sensor senses the motion of an object in a certain area to detect its presence. It can be used in smart agriculture and in IoT-based FWR systems [46]. There are also motion sensors that can be considered in this category that are designed to sense all kinds of kinetic movements of an object, as described by Ref. [56]. Ndraha et al. [57] apply various types of sensors including position sensors for the improvement of cold chain performance and improper handling.
- Occupancy Sensors: These sensors are used for the remote monitoring of variables such as temperature, humidity, light, and air [47].
- Motion or Kinetic Sensors: The sensor detects all kinetic and physical movement in the environment [56] and could be used in a truck to detect possible movement of fruit boxes to provide needed information to estimate the rate of food deterioration in a certain period for better decision-making.
- Velocity Sensors: The velocity sensors calculate the rate of position variation, which might be linear along a straight line or angular related to device rotation speed at known intervals [48]. These sensors can be used in crates to determine the variation of food position during food transfer. This will enable us to monitor the parameters that can affect food quality and make the appropriate decisions.
- Temperature sensors: Temperature sensors are widely used for the monitoring of environmental conditions of the surroundings [50]. This type of sensor is also widely used in FWR systems and more, especially for smart agriculture to enable farmers to increase their overall yield and product quality by getting real-time data on their land [51].
- Pressure Sensors: Pressure sensors sense the amount of force and convert it into signals. Sensors of this type can be used to measure the amount of pressure in boxes of food and send the data to the server for decision-making to avoid food waste caused by excessive pressure in boxes during transport. The sensor triggers a notification to the user as soon as the applied pressure is below a certain value that affects the quality of the food [52,58].
- Chemical Sensors: These types of sensors sense any chemical reaction and can be used for reducing food wastage in smart agriculture [53].
- Optical Sensors: Optical sensors are a broad class of devices for detecting light intensity. Optical sensors are suitable for IoT applications related to the environment. Therefore, they can be used for food quality control applications, in the food industry [55], and in smart agriculture [54].

4. Processing the Aggregated Data: Service Layer

There is a broad range of literature on the application of Machine Learning (ML) for IoT big data analytics [59,60]. Data from the sensors need to be processed; this section reviews the algorithms that are mostly used in IoT-based food quality monitoring systems.

4.1. ML and Predictive Models

ML methodologies consist of a learning process with the objective of learning or experiencing trained data with the aim of performing a task. The data in ML might be nominal, binary, or numeric. The performance of the ML models is measured by a metric using various statistical and mathematical models. The trained model can be used to predict or cluster new examples. Figure 4 illustrates the ML approach.

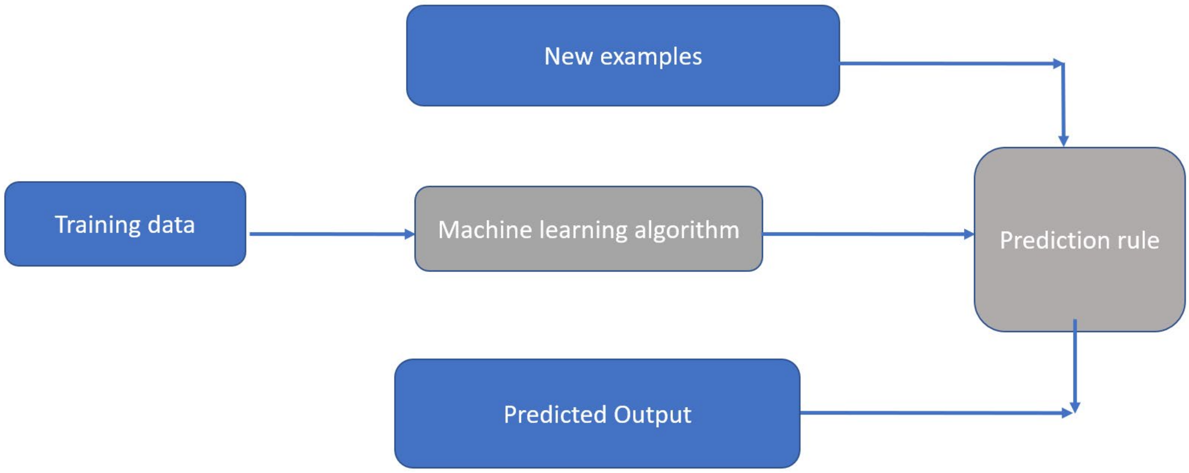

Figure 4. Illustration of ML approach.

In ML algorithms, the learning process might be divided into supervised or unsupervised based on various types of learning models such as classification, regression, clustering, and dimensionality reduction. In the supervised setting, the trained model is applied to predict the missing outputs and labels for the test data. On the other hand, in unsupervised learning, there is no distinction between training and test sets, and the data is unlabeled. The input data is trained with the goal of discovering hidden patterns. Our objective in this section is to review ML-based predictive models that are mostly used for data analysis approaches in agriculture 4, which focuses on precision agriculture based on IoT technologies and big data analysis. Liakos et al. [61] explore various machine learning algorithms for agricultural production.

In predictive models, solving the problem of finding a function that maps a vector of specific length to an output variable to estimate some unknown model parameters is called a regression problem. There are various types of regression models that are used for solving regression problems, such as linear regression models, tree-based models including regression trees, bootstrap aggregated trees, random forests, gradient boosting, and regularization techniques [62]. Data dimensionality reduction (DR) is applied in both supervised and unsupervised learning types, with the aim of providing a lower-dimensional representation of data to simplify computation. Principal component analysis, partial least squares regression, and linear discriminant analysis are some of the most common DR algorithms, as discussed in Refs. [63–65]. All these techniques are widely used for analyzing data in agriculture 4 for decision-making applications.

4.2. Learning Models

The presentation of the learning models in ML is limited to the works presented in this review.

(1) Regression: The regression approach is based on supervised learning with the objective of providing the prediction of an output variable according to the input known variables. There are various types of regression problems that are studied in the literature, such as linear and logistic regression [66,67], stepwise regression [68], ordinary least squares regression [69], multivariate adaptive regression spline [70], multiple linear regression [71], cubist [72], and locally estimated scatter plot smoothing [73].
(2) Clustering: Clustering is widely used as an unsupervised learning approach for group clustering of data. Some examples of this approach include K-means [74], a hierarchical technique [75], and an expectation maximization technique [76].
(3) Bayesian Models: The type of Bayesian model belongs to the supervised learning category, and it can be used for solving regression or classification problems. The Bayesian model is a kind of probabilistic graphical model. There are various types of this algorithm, including Naive Bayes [77], Gaussian Naive Bayes [78], multinomial Naive Bayes [79], Bayesian network [80], and Bayesian belief network [81].
(4) Instance-Based Models: Instance-driven models (IBM) are memory-based models that learn by comparing new examples with instances in the training database. This algorithm generates predictions based on specific instances. This type of algorithm faces a disadvantage because the complexity grows with the data. Examples of these learning algorithms are k-nearest neighbor [82], locally weighted learning [83], and learning vector quantization [84].
(5) Decision Trees: According to the definition provided in [85], decision trees are classification or regression models formulated in a tree-like architecture. With these tree-based algorithms, the dataset is progressively organized into smaller homogeneous subsets or sub-populations. In tree-based algorithms, the leaf nodes represent the final decision or prediction taken after following the path from the root to the leaf which is expressed as a classification rule. The most common learning algorithms in this category consist of the classification and regression trees [86] and the chi-square automatic interaction detector [87].
(6) Artificial Neural Networks: ANNs are inspired by human brain functionality. It is mostly used for solving problems in pattern recognition, cognition, and decision-making. In ANN several nodes are arranged in multilayers consisting of an input layer that feeds the data into the system, some hidden layers for doing the process of learning, and an output layer where the decision is given. ANNs have basically supervised models that are used for solving regression and classification problems. Deep ANN is a new area of ML research that applies multiple levels of abstraction to solve computational models that are composed of multiple processing layers. DNNs are simply ANN with multiple hidden layers between the input and output layers and can be either supervised, partially supervised or even unsupervised. A convolutional neural network (CNN) is a common DL model where the feature maps' extraction is performed by convolutions in the image domain. There is a wide range of algorithms that are commonly used for ANN and DNN. Table 3 provides a review of these algorithms.
(7) Support Vector Machines: SVM is basically a binary classifier that is used for data classification. A kernel trick can be implemented to upgrade traditional SVMs through the transformation of the original feature space into a feature space of a higher dimension. This algorithm is widely used in IoT-based food reduction algorithms. Table 4 reviews the functionality of this algorithm alongside other ML algorithms for reducing food wastage using advanced IoT technologies.

Table 3. Categorization of artificial neural network algorithms.

ANN Algorithm	Deep ANN Algorithm	Paper	Year
Radial basis function networks	——-	[88]	1996
Convolutional Neural Network	✓	[89]	2017

Table 3. *Cont.*

ANN Algorithm	Deep ANN Algorithm	Paper	Year
Perception Algorithms	——	[90]	2002
Back Propagation Algorithms	——	[91,92]	1998, 2021
Resilient Back Propagation Algorithm	——	[93,94]	1996, 2021
Deep Boltzmann Machine	✓	[95]	2019
Counter Propagation Algorithms	——	[96]	2008
Adaptive Neuro Fuzzy Inference Systems	——	[97]	2020
Generalized Regression Neural Network Algorithms	——	[98]	2010
Deep Belief Network	✓	[99]	2015
Hopfield Networks	——	[100]	2020
Multilayer perception Algorithms	——	[101]	2005
Auto-encoders	✓	[102]	2020
Extreme Learning Machines	——	[103]	2011

5. Application of Machine Learning Algorithms for FWR: Application Layer

IoT-based food waste reduction has benefited from technological advancements, particularly by incorporating industrial advances into a sustainable agriculture production system. Each year millions of tons of food are wasted around the globe. This negatively affects the economy of the country. Machine learning's adaptability, promotion, and reduced costs help in assessing the complicated link between the input and output of agricultural systems by utilizing analytical approaches [104]. Applications of machine learning and artificial intelligence in reducing food wastage have been studied in the literature, which is represented in Table 4.

Table 4. Application of ML and AI algorithms for FWR based on IoT technologies.

ML Algorithm	Functionality	Paper	Year
SVM	Automatic count of coffee fruits on a coffee branch	[105]	2017
ANN	Method for the accurate analysis for agricultural yield predictions	[106]	2016
Regression, SVM	Estimation of monthly mean reference evapotranspiration arid and semi-arid- regions	[107]	2017
Bayesian Models	Detection of Cherry branches with full foliage	[108]	2016
Deep Learning	Identification and classification of three legume species: soybean, and white and red bean	[109]	2016
ANN	Estimation of daily evapotranspiration for two scenarios	[110]	2017

As is explained in Table 4, Machine Learning algorithms such as SVM, ANN, Regression, and Bayesian models are used for FWR in different stages of production to enhance the quality of food products. In Ramos et al. [105] SVM is used to classify the ripe, overripe, and unripe coffee fruits. In Kung et al. [106] ANN is used for agricultural yield prediction. Mehdizadeh et al. [107] and Amatya et al. [108] use multivariate adaptive regression and Bayesian models for the estimation of the monthly mean and detection of cherry branches respectively. In order to provide high-quality food for consumers after prediction, appropriate communication is needed for the transportation of the information after sensing the temperature or other vital parameters such as environmental humidity that can significantly have an impact on the quality of the produced food for proper decision-making purposes to transfer the food to the closet customer.

With respect to the importance of communication technologies for FWR, communication technologies in the food supply chain are explained in the next section.

6. Wireless Communication Technologies for FWR in Smart Supply Chains: Network Layer

In this section, an overview of the various wireless communication technologies is presented. Different technologies are compared in terms of data transmission range and power consumption. By following this section an understanding of various wireless communication technologies will be provided to be considered based on the application requirements and the trade-off between transmission range and battery consumption. There are a variety of wireless communication technologies, such as RFID, GPS, narrowband (NB-IoT), long-range (LoRa), and ZigBee, which can be used for IoT applications to transfer measurements to reduce food waste. A comparison between different wireless communication technologies with energy harvesting capabilities for FWR is provided by Sadowski et al. [111]. Table 5 provides a comparison between wireless communication technologies based on data rate, cost, and transmission range. A categorization of wireless communication technologies and their application in FWR is explained as follows:

Table 5. A comparison between different Wireless communication technologies [111].

Wireless Communication Technology	Data Rate	Range	Cost
Wi-Fi	100 MBps	10–40 m	Moderate
Bluetooth	1 MBps	10–30 m	Low
Bluetooth Low energy, and Zigbee	100 KBps	100 m	Low
RFID	1 KBps	1–9 m	Very Low
Cellular 5G/LTE/3G	1 MBps–100 MBps	1–10 km	High
LPWAN	150 KBps	1–20 km	Moderate-Low

(1) Low Power Wide Area Networks: LPWANs are widely used in IoT applications. For large-scale IoT networks, small, inexpensive batteries that last for years are used for long-range communication. The main application of these technologies is in the industry and commercial sectors. As LPWANs can connect all types of IoT sensors, they can be used for IoT applications in the food industry. With this technology, countless applications can be achieved, such as asset tracking, environmental monitoring, and facility management. Regarding the characteristics of LPWANs, only small blocks of data can be transferred at a low rate. Therefore, this technology is better suited for low bandwidth and not time-sensitive applications. It should be noted that selecting the most appropriate wireless technology for IoT use cases specified in the food supply chain requires an accurate assessment of bandwidth, QoS, security, power consumption, and network management. Here, in the rest of this section, other types of wireless technologies that can be applied in the food supply chain are explained.

(2) Cellular (3G/4G/5G): Different generations of mobile communication technologies and cellular networks offer reliable broadband communication that supports various voice calls and video streaming applications that are good for monitoring food quality, however, these technologies impose very high operational costs and power requirements that should be considered for their applications. Although cellular networks are not viable for the majority of IoT applications powered by battery-operated sensor networks, they fit well in specific use cases such as connected cars or for management applications in transportation and logistics. In the case of tracking trucks carrying food, the technology can be applied by relying on cellular connectivity, which is ubiquitous and high-speed. IoT applications in the food supply chain can be used with the next-generation 5G network with its high-speed mobility and low latency.

It can support real-time video surveillance for food quality control, real-time mobile delivery of measured parameters such as humidity and temperature, as well as relevant datasets for connecting several time-sensitive automation applications in the food supply chain that focus on food quality.

(3) Zigbee and Other Mesh Protocols: Zigbee is a short-range, low-power, wireless standard that is also referred to as IEEE 802.15.4. This wireless communication technology is commonly deployed in a mesh topology to extend coverage by relaying sensor data over multiple sensor nodes and therefore it is very useful for IoT-based technologies in the food supply chain. Compared to LPWAN, Zigbee provides higher data rates and much less power efficiency due to mesh configuration. As this technology is most suited for medium-range IoT applications with an even distribution of nodes in close proximity, it is suitable for monitoring the humidity and temperature in fridges and freezers to send an alarm in critical situations. Zigbee is a perfect complement to Wi-Fi for various IoT applications to monitor food quality and transfer measured data for further processing. This technology provides several remote monitoring solutions for applications for reducing food wastage.

(4) Bluetooth and Bluetooth Low Energy (BLE): Bluetooth technologies are defined in the category of Wireless Personal Area Networks (WPANS) a short-range communication technology that is originally intended for point-to-point or point-to-multipoint (up to seven slave nodes) data exchange devices. BLE devices are typically used in smartphones that serve as a hub for transferring data to the cloud. In today's world, BLE is widely used to transfer data from humidity, temperature, and acceleration sensors directly to the smartphone app to be analyzed and visualized. The BLE devices are widely used in retail contexts to provide versatile indoor localization features for in-store navigation and content delivery.

(5) Wi-Fi: Wi-Fi has a critical role in providing high throughput data transfer, however, in the IoT space, its major limitations in coverage, scalability, and high-power consumption make this technology less prevalent. Therefore, it is often not a feasible solution for large networks of battery-operated IoT sensors, especially in industrial IoT applications. As the coverage is almost good in comparison with other wireless technologies, Wi-Fi can be applied in IoT applications for food quality control purposes.

(6) RFID: It uses radio waves to transmit small amounts of data from an RFID tag to a reader within a very short distance. This technology is widely used for indoor data transfer in food quality monitoring applications. Additionally, RFID has facilitated a revolution in retail applications and logistics. To optimize supply chain management, RFID tags can be attached to food bags to track parameters such as acceleration, humidity, and temperature. Some of the applications of RFID in the retail sector consist of smart shelves, smart fridges, smart bags, and so on.

7. IoT-Based Food Wastage Reduction Challenges and Opportunities

7.1. Challenges

Although data analysis tools are used to monitor food quality features, there are several challenges that should be taken into consideration. In Ali et al.'s work [3], various risks in the food industry are analyzed. Additionally, Jin et al. [112] provide a review of big data in food quality monitoring. Some of the challenges in food safety are studied by Wang et al. [113]. Based on the literature review conducted in this study, a number of key challenges are identified and listed below:

- Data Quality: Research on Big Data Analytics in food quality control using cloud computing technology has its own relevant challenges related to data quality, scalability, availability, and integrity.
- Lack of Standardization: These can be related to using different management systems by users and can be considered the biggest challenges related to the generated data.
- Lack of Communication Protocols: Bouzembrak et al. [114] explain that this can be considered one of the main issues that affect the data transmission quality, as it may

cause delays, or some parts of the measured data might be missed due to a lack of reliable communication protocols.

- Security and Data Protection: Several issues are associated with IoT security in food quality control, such as inadequate hardware and software security. Additionally, IoT nodes that are not supported with enough security protocols can be a vulnerable point for the security of the entire IoT system along the food supply chain.
- Battery: The energy consumption issues related to the use of batteries also pose significant challenges to the success of IoT-based technologies for FWR.

According to Amer et al. [115], the challenges of using IoT in the food supply chain can be divided into technical, financial, social, operational, educational, and governmental.

The technical challenges contain hardware-related technical skills. It can also refer to network structure, and big data management and analytics capabilities. The financial challenges mostly refer to operation and management costs. There are also social challenges related to cooperation among supply chain players as well as integration and coordination of information among supply chain partners. The operational challenges are mostly in line with administrating supply chain IoT networks, data security, and industry operating IoT standards.

In addition, mobile-based applications can, in some cases, negatively contribute to the food waste phenomena [116–118].

7.2. Opportunities

IoT technologies will give companies many opportunities to reduce food waste. In this context, we cite the ongoing REAMIT project (https://www.reamit.eu/, accessed on 1 December 2022), which was founded by Interreg Northwest Europe. REAMIT provides several IoT-based food monitoring and control opportunities with the aim of FWR in food companies that are summarized as follows:

- Networking and Collaborations: These provided access to a network in North-West Europe with wide expertise and provided an opportunity for participation in future collaboration initiatives.
- Quality Assurance: Continuously monitor food quality and signal any potential loss in quality.
- Decision support and decision-making: Using big data analytics and artificial intelligence to provide rapid decision support for food logistics.
- Sensor Technology: Providing at the forefront of sensor (traditional and advanced) technologies for monitoring food quality and big data technology developments
- Data-Driven Decision-Making: Making the right decision for food quality based on carefully analyzing real-time data.

With the development of IoT monitoring systems, two main advantages will be achieved. In the first place, notifications can provide fresh information for the companies and suppliers to prevent food wastage, and in the second place, there are environmental benefits such as reducing carbon footprints that arise from IoT and big data analysis being combined with the overall aim of reducing food wastage in smart supply chains with IoT based infrastructure that can run FWR programs. In line with motivations and challenges for food companies in using IoT sensors for the purpose of FWR, Ramanathan et al. [119] provide insight and a roadmap for the future.

Figure 5 visualizes REAMIT approaches:

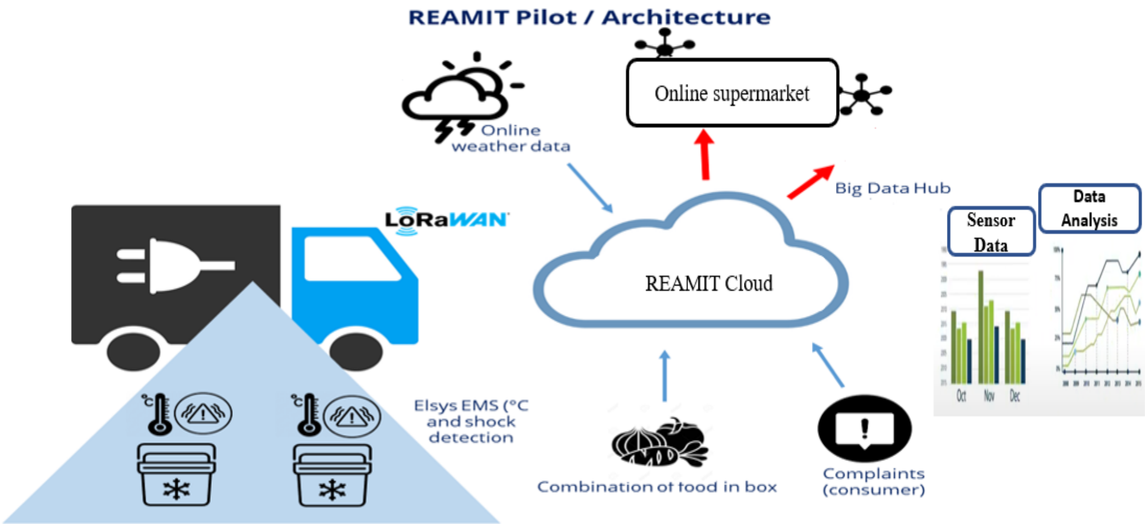

Figure 5. REAMIT approaches visualization.

8. Conclusions

The main objective of this review paper is to combine the most pertinent aspects of IoT with the main goal of reducing food wastage in food supply chains. This paper has provided a comprehensive review of the use of various IoT and Big Data technologies. It discusses how to reduce food waste from farm to fork along the food supply chains by integrating different technologies to create an IoT system. This paper reviews sensors, ML algorithms, and wireless data transmission technologies, which are the key components of IoT systems. It focuses on their applications for monitoring food quality and reducing wastage. The findings contribute to understanding how the IoT sensors and big data technologies can be used to reduce food waste. The paper also raises awareness of the challenges and opportunities faced by researchers and practitioners when implementing IoT-based systems for food waste reduction. Based on the review, this paper has identified a list of the most researched and least researched areas in terms of the application of IoT and big data technologies for reducing food waste. It finds that FWR is widely reviewed in terms of big data analysis; however, further investigation on the methods, approaches, and sensor types that can be applied to specific kinds of food is needed. For instance, for vegetables, what kind of sensor is optimal to use to reduce their wastage? What types of sensor data (e.g., odor, color, temperature) are most effective to indicate the freshness of vegetables? This research can be further expanded to other food categories such as meat, cooked foods, frozen foods, fish, fruits, etc. This study is intended for future research in this area.

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