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# Revolutionizing Agro-Food Waste Management: Real-Time Solutions through IoT and Big Data Integration

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## Abstract

Globally, approximately one-third of the total food produced is wasted. The environmental effect of such wastage is the contribution to greenhouse gas emissions, and economically, money that could have been reinvested in the economy is lost. This research showcases the ability of IoT devices to gather data on wastage and management as they happen, as well as big data analytics in facilitating data acquisition for enhanced decision-making. The research proposal seeks to show how the use of these technologies can support waste minimization, efficiently utilize resources, and promote sustainability in the agro-food chain. Thus, a literature survey will be applied to outline the methodologies currently in use, the holes in current practice, and new ideas on how to incorporate IoT and big data in waste management. Furthermore, several case studies 'success stories' are highlighted to explain and quantify an actual application of these technologies in different sectors of the agro-food chain with tangible results in terms of reduction of the number of wastes and gains in efficiency. The application of Internet of Things (IoT) technologies and big data analytics for real-time handling of agro-food waste is a major problem in the agro-food sector. The conclusions highlight the positive effect of IoT and big data in tackling agro-food waste; at the same time, they give practical suggestions for the key players throughout the supply chain. Thus, our study gives insights into a shift in the management of agro-food waste through efficient technology and rallying policymakers, industry experts, and researchers to fully capture technological improvements for development.

## Keywords

Agro-Food, Big Data, IoT, Machine Learning, Waste Management

## 1. Introduction

The increasing concern with environmental protection and the economy has driven the agro-food industry to search for solution to waste facilitating. Because reducing food waste and its implications remains a critical issue to date, different approaches, including IoT and big data, can contribute to finding the best solution. These technologies can enhance real-time tracking and inform efficient waste management to enhance the agro-food industry (Irani et al., 2018). Through the analysis of IoT and processing of large amounts of data, the stakeholders are able to employ necessary technological changes to maximize the possible efficiency in the usage of resources and create a sustainable food system. The agro-food industry is among the biggest industries in the world economy, manufacturing most of the foods consumed today. However, it is also a significant source of waste, including nearly one-third of all food that is produced globally being thrown away each year. Such waste can be incurred at the production stage, processing stage, distribution and even the consumption stage (Hannan et al., 2015). The consequent environmental effects of agro-food wastes include increased emission of greenhouse gases, loss of biodiversity, and exhaustion of resources. The wastage of food is a major economic challenge, with food being wasted worth a figure of approximately $940 billion annually (UNEP, 2024).

Furthermore, the problems concerning agro-food waste are aggravated by barriers like climate change, population growth, and shifts in consumer preferences. However, the growth of the agro-food sector and the increase in the human population's demanding food are making a call for innovative strategies to reduce wastage and improve sustainability within the agro-food value chain (Wan et al., 2019). The following sections establish the rationale for waste minimization and waste management. The reduction of agro-food waste has many reasons. For that reason, it can be said that the topic reduces both the environmental impacts by decreasing the amount of waste that is dumped into the dumps and the greenhouse gas (GHG) emissions from food waste decomposition. Secondly, the reduction of waste has substantial economic benefits that can be realized at the producer, retail and consumer level (Henningsson et al., 2004). The adaptive pressure can be applied not only to the list of products but also to the use of water, energy and wage, which would increase the profitability of stakeholders and help create a more sustainable food chain. Besides, good waste management plans can improve food security by making it easier for more food to get to the consumer than if it is being wasted. This is especially needed in the parts of the world where hunger is well known and food shortage is a real problem. Thus, having applied new technologies for waste minimization, it is necessary to aim at wider sustainability objectives. Hence, there is a need to bring IoT technologies and big data analysis in an endeavor to offer a better way of tackling waste issues within the agro-food sector. Internet of things facilitates handling of several aspects of the supply chain, among them being temperature, humidity and stock quantity and quality. Picking this data collection allows for timely intervention that can help to stop product spoiling and hence a reduction in wastage is achieved. It encompasses the assessment of IoT device functions in real-time surveillance and big data processing strategies for obtaining valuable information, as well as novel model layouts to improve waste management (Sridhar et al., 2023; Rahaman et al., 2023). Lastly, this study aims to elaborate on how this integration of IoT and big data can be used to minimize agro-food waste and provide suggestions to the relevant actors in the agro-food industry. The Internet of Things is therefore supported by big data analytics, which offers the necessary tools for processing and analyzing large volumes of data from various sources (Das et al., 2019). By using such techniques as statistical analysis and pattern matching, the waste generators can get acquainted with the rates of the generation process and, thus, improve operations. For example, accurate demand forecasting based on data numbers can assist producers in changing their supply policies to meet consumers' needs closely so that overproduction and wastage can be reduced (Ahmadzadeh et al., 2023).

Therefore, this study seeks to analyze how IoT interconnects with big data in real-time agro-food waste management. It will also feature a literature review of currently available data regarding new methodologies and gaps that warrant innovations, and the study will show examples of the application of these technologies in different agro-food sectors.

## 2. Literature Review

As a result, the paper systematically outlines the research findings and methods concerning agro-food waste management, with special reference to the IoT and big data solutions. This section will highlight the current research activities about agro-food waste management, big data analysis practices, and how machine learning has been used to reduce wastage (Caruso et al., 2019). At the same time, it will define the gaps in the existing research and suggest the necessity of the implementation of innovative ideas.

### 2.1. Agro-Food Waste Management Today

The approaches used in agro-food waste management were previously rudimentary at best, involving little more than the use of paper and pencil and even simple monitoring methods that could not cope with the modern supply chain challenges (**Table 1**). Some of the existing treatments include composting, anaerobic digestion, and food redistribution but these techniques do not follow the current procedure of being efficient and effective (Pereira et al., 2024). Modern research has revealed that somehow, incorporating technology into waste management can boost its performance. For example, organisations have recently installed more complex tracking systems that use IoT gadgets to track waste collection in real-time to enable timely action.

### 2.2. IoT Applications in Agro-Food Waste Management

The use of IoT in managing agro-food waste has been considered in the past

Table 1. Key methods of agro-food waste management—composting, anaerobic digestion, food redistribution, incineration.

| Method | Description | Advantages | Challenges | Reference |
|---|---|---|---|---|
| Composting | Biological decomposition of organic waste into nutrient-rich soil amendment. | Reduces landfill waste; produces useful compost. | Time-consuming; requires proper management. | Pereira et al. (2024) |
| Anaerobic Digestion | Microbial decomposition of organic matter in oxygen-free conditions to produce biogas and digestate. | Generates renewable energy; reduces greenhouse gas emissions. | High initial setup cost; technical expertise needed. | Smith et al. (2022) |
| Food Redistribution | Redirecting surplus edible food to people in need. | Addresses food insecurity; reduces waste. | Requires logistics and coordination. | Irani et al. (2018) |
| Incineration | Burning waste to generate energy or reduce waste volume. | Decreases landfill dependency; energy recovery. | Releases harmful emissions; not suitable for all types of waste. | Pereira et al. (2024) |
| Landfilling | Disposal of waste in designated landfill sites. | Low cost; easy to implement. | Contributes to environmental pollution; limited capacity. | Sharma et al. (2022) |

few years. Smart sensors and RFID tags as some of the IoT devices are used to monitor different attributes of foods in order to determine qualities and wastage levels (Sharma et al., 2022). Scholars suggest that these technologies can assist in minimization of spoilage by tracking and recording temperature and humidity in storage and transportation. In addition, IoT systems can enhance efficient tracking of stocks available and their time lifespan thus reducing unnecessary production.

### 2.3. Big Data in Agro-Food Waste Management

They point out that big data analytics are fundamental for turning raw data from IoT devices into valuable information. Stakeholders can review a vast amount of data and find out the general tendencies concerning waste generation based on this analysis (Rejeb et al., 2021). Literature review has revealed that big data can facilitate demand forecasting, the optimization of supply chain and the right utilization of resources. For instance, predictive analytics can be used to change the planting calendar with dates showing the history and markets to discourage overproduction (**Figure 1**).

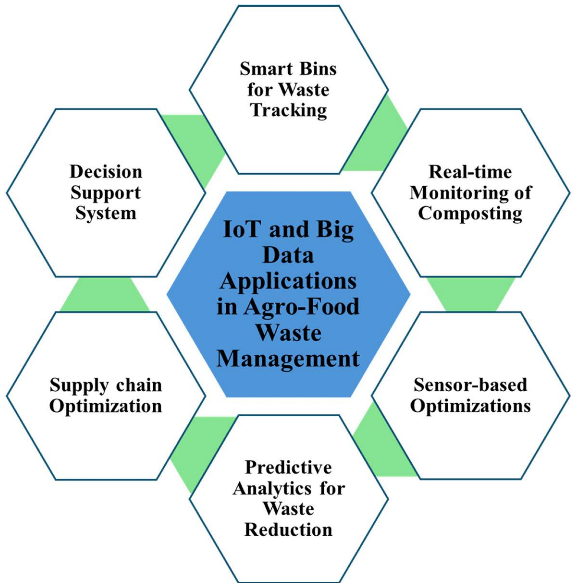


**Figure 1.** Showing the applications of IOT and Big Data in agro-food waste management.

## 2.4. Machine Learning Trees to Tackle Waste Management

Advanced methods of artificial intelligence analysis are viewed as valuable approaches to reducing food losses in the agro-food chain. Several models have been created to categorize waste types; forecast future waste generation; and assess supply chain operational efficiency. Scholars underline the ability of ML models to predict the causes of food waste and give suggestions on how it can be prevented (Munir et al., 2023). Also, machine learning reduces the work of finding appropriate data representation and depiction and helps to automate control decision-making in IoT systems (**Figure 2**).

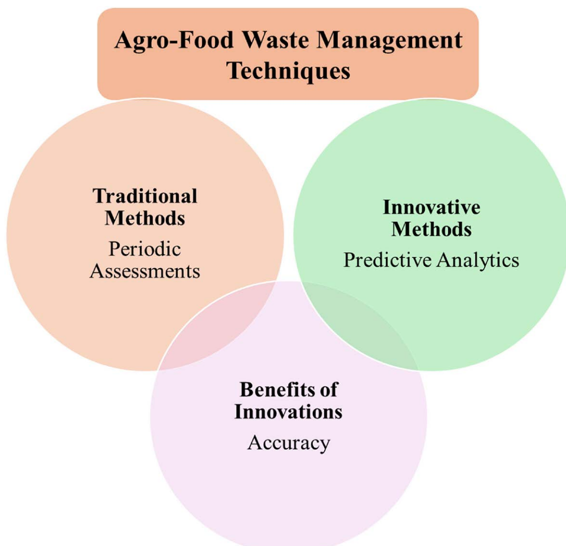


**Figure 2.** Traditional and innovative techniques of agro-food waste management.

## 3. Current Research Gaps

However, there are still some gaps present in the current research in the field of technology for agro-food waste management. Most of the research work targets individual IoT or big data applications or implementation with little research on combined use or interaction between the two. In addition, there are not enough systematic schemes that can include such technologies together with machine learning for the integrated approach to waste management (Rahaman et al., 2023). These gaps suggest a potential for future research to propose new models to take full advantage of IoT and big data analytics to minimize agro-food waste. The present literature review aims at providing an appreciation of the current state of research on agro-food waste management and the opportunities for leveraging IoT and big data. In the subsequent sections, the materials and methods used in this research to pursue these innovations are presented. Agro-food waste management is a critical area of study due to its significant environmental, economic, and social impacts. Despite advancements in this field, several research gaps persist, hindering the development of effective and sustainable waste management strategies. This article identifies and discusses these key gaps.

Recent studies emphasize the importance of integrating circular economy (CE) principles into agro-food supply chains to enhance sustainability and resource efficiency. However, there is a lack of comprehensive research on practical applications and the long-term impacts of CE practices in this sector. Further investigation is needed to develop actionable insights and recommendations for policymakers and practitioners (Cahyadi et al., 2024). The valorization of agri-food waste into value-added products is a promising approach to waste management. Nonetheless, challenges such as heterogeneous waste composition, technological limitations, and economic feasibility hinder its widespread adoption. Addressing these challenges requires a multidisciplinary research approach to develop efficient and scalable valorization processes (Zhang & Zhang, 2024). Moreover, the adoption of smart technologies, including big data analytics, artificial intelligence, and the Internet of Things, has the potential to revolutionize agro-food waste management. However, their application remains limited, particularly in developing regions. Research focusing on the implementation of these technologies in diverse contexts is essential to enhance waste management practices globally (Zhang & Zhang, 2024). Effective agro-food waste management requires the involvement of various stakeholders, including farmers, policymakers, and consumers. Current research often overlooks the importance of stakeholder engagement and the socio-economic factors influencing waste management practices. Future studies should adopt a holistic approach, incorporating stakeholder perspectives to develop inclusive and sustainable solutions (Berenguer et al., 2023).

## 4. Big Data in Agro-Food Waste Minimization

This section provides an overview of the different materials and methods used to undertake this research on the use of IoT and big data technologies in the real-time management of agro-food waste (Trevisan & Formentini, 2023). It will pay special attention to the methods of data acquisition and data processing and analysis to support proper waste minimization.

### 4.1. Data Collection and Sources

To reduce waste in the agro-food chain, many data sources are collected and used; satellite information for crop assessment, data from IoT devices, data which belongs to supply chains, and others. These features allow the achievement of the multiple goals set for the system, including the acquirement of data on different stages of the agro-food supply chain—from production to consumption (Belaud et al., 2019). IoT sensors are used to monitor the environmental conditions in and around the devices and their operational parameters, which create conditions for waste generation. Mining is the process of extracting valuable resources from the Earth or analyzing large datasets to uncover patterns and insights. Mining helps the farmers to determine the appropriate time for harvesting by analyzing crop health and growth patterns on the farms through satellite imagery, which reveals regions of crop failure or diseases that cause waste (**Figure 3**).

Information is collected from the logistics and distribution channels to determine where and when the products are moving, what stocks are available, and when they are set to expire so that wrong decisions on stock production are averted.

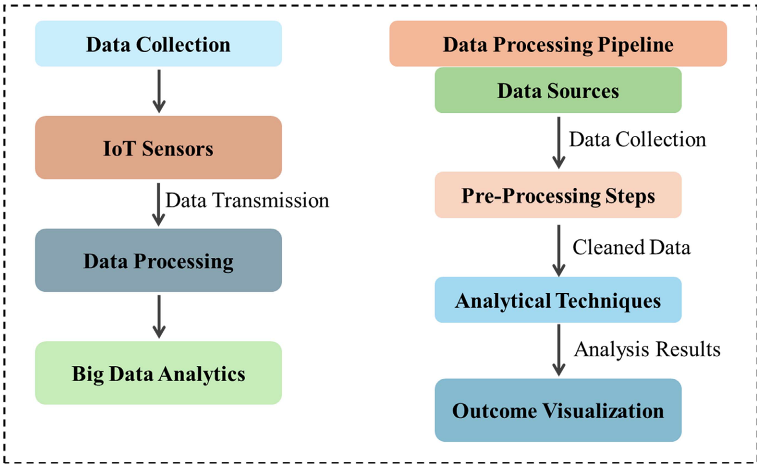


**Figure 3.** IoT and Big Data streamline agro-food waste management from data collection to visualization.

### 4.2. Data Processing Techniques

The data collected also goes through several pre-processing stages to make it useful for subsequent analysis. These steps include

**Cleaning**—This is because data accuracy is important in any dataset, and so cleaning it to reduce improper entries is important. This may be done to rectify wrong records, or AVs that may have been omitted or complied with in different formats.

**Filtering—**It is always helpful to choose what pieces of information contribute to waste analysis to highlight the most influential factors. For example, one can remove noise, or non-relevant data can help improve the meaning of the insights that can be gathered from this data.

**Feature Extraction—**Important factors that define waste generation should be clearly described and defined for the analysis (Arshadi et al., 2016). It may involve obtaining characteristics like the fluctuations of the market demand, the seasonal characteristics, or such environmental parameters as related to the high throughput of wastes.

### 4.3. Big Data Analytics Approaches

Using processed data, several analytical techniques are used for the analysis of waste trend determination. Statistical methods including regression analysis, clustering, and time series are used to analyze the data and make forecasts on future waste generation. The extension of machine learning algorithms in the end also increases the efficiency of finding varied patterns in the data.

Descriptive for the interactions between different variables such as temperature with spoiling rates, regression is useful in scaling the impact of one factor on waste (Oruganti et al., 2023). This technique simply clusters observations with the aim of finding patterns of waste generation in other related contexts, such as the type of product or geographical region. Clustering can then be used to identify what products are likely to suffer from waste in the given circumstances. This method of waste generation prediction involves the use of historical data over time, in which the foreseen waste generation is analyzed with reference to the existing season and market forces. It enables the stakeholders involved to make appropriate changes to the production calendar actively (**Table 2**).

**Table 2.** Case Studies for farm management, inventory tracking, and food processing optimization.

| Case Study | Implementation | Limitations | References |
|---|---|---|---|
| **Food Processing Plant Optimization** | IoT sensors for environmental monitoring, big data storage, and machine learning predictive analytics to optimize the production calendar. | - High setup costs, reliance on technology, and skilled personnel.<br>- Optimization and scalability remain challenges. | Tummers et al. (2021) |
| **Retail Chain Inventory Management** | Machine learning models integrated with IoT-enabled smart shelves for demand forecasting, considering factors like seasons, social events, and weather. | - High implementation costs and reliance on accurate data for predictions.<br>- Incorporating external factors like weather<br>- Specialized skills pose additional challenges. | Sridhar et al. (2021) |

Continued

| | | | |
|---|---|---|---|
| **Farm Management System** | IoT soil moisture sensors combined with machine learning algorithms and weather forecasts for optimized irrigation management. | - -High initial cost and maintenance of soil moisture sensors and machine learning systems.<br>- Dependence on accurate weather forecasts and data integrity poses risks to system reliability.<br>- Scalability to diverse crops and climates remains uncertain, and specialized skills are required. | Tummers et al. (2021) |

#### 4.3.1. Case Study 1—Food Processing Plant Optimization

A food processing plant that was especially in fruit and vegetable processing required a big data analytics solution to enhance its production calendar and minimize wastage. Before the adoption of this system, this plant used to experience cases of spoilage since there was wrong stocking, and since the demand for some foods fluctuated, the plant used to experience a lot of wastage.

**Background**—To add, the plant employed in the processing of fruits and vegetables is more than fifty tons per day, of which approximately fifteen percent are chucked as waste because of spoilage. This translated to about 7.5 tons of waste daily, which in a year translated to over $1 million in losses (Koroteev et al., 2022).

**Implementation**—They had IoT sensors put up across the stored and processed commodities to allow for continuous tracking of environmental conditions. Information received from these sensors was physically stored in a cloud based big data storage structure where machine learning based models were implemented for predictive analysis.

**Results**—The control plant (specific facility or operational unit within the organization where the cold chain system was implemented and monitored to assess its impact on spoilage rates, cost savings, and workflow efficiency) also recorded a decline in spoilage rate in the first six months from 7.5 tons per day to 5.25 tons because of the application of the cold chain system. This reduction not only proved to be an annual cost saving of an estimated $300,000 but also proved quite effective for the overall workflow efficiency of the company as it provided much required flexibility to perfectly match the production strategies to the market targets.

**Key Metrics:** Waste Reduction—From 15% to 10.5% of total output; Cost Savings—Estimated $300,000 per year; Operational Efficiency—Improved production scheduling and reduced labor costs by approximately 10%.

#### 4.3.2. Case Study 2—Retail Chain Inventory Management

One very large grocery store chain put into action a big data plenty predictive analytics and system to better control inventory and decrease spoilage in its outlets.

**Background**—Although the chain had been managing over 1000 stores all across the United States, the organization found its average food waste percentage of 8% across its perishable food categories, resulting in a yearly loss of about $600 million.

**Implementation**—Machine learning models were created based on historical sales data in conjunction with real-time data from IoT-enabled smart shelves to make better predictions of demand patterns by the retail chain. Some of these models included external factors such as changes in seasons, social events and even the weather (Sridhar et al., 2021).

**Results**—For perishable foods sub-sector, reduced food wastage by a quarter within the first year of applying the theory to the retail chain. It translated to about $150 million in cost savings per year. Also, the gains made in the inventory through purchases inventory management caused stock replenishment activities to minimize stockouts by 20 percent.

**Key Metrics**—Waste Reduction—From 8% to 6%; Cost Savings—Approximately $150 million annually; Stockout Reduction—Improved from a rate of 15% to 12%.

#### 4.3.3. Case Study 3—Farm Management System

A case of a large-scale farm implementing the farm management IoT Big Data Solution to reduce water wastage and draught on crops through right irrigation.

**Background**—The farm was overseeing more than two thousand acres of crop production that were recording high losses because of poor water management and control; fresh crop failures were costing the farm about $200,000 per year.

**Implementation**—In this case, the farm had placed soil moisture sensors that relayed the condition of the soils to the farm at different fields. This data was used along with the seven-day forecasts on the weather patterns to come up with machine learning algorithms that helped in the prediction of the irrigation patterns based on the moisture levels of the soil (Tummers et al., 2021).

**Results**—When this system was established on the farm for one growing season, this farm claimed that they experienced a decrease in crop damage by about 40% due to water content. From this improvement, they estimated that their yield would be boosted by approximately $80,000 per year.

**Key Metrics**—Crop Loss Reduction—$200,000 annually, which is reduced to $120,000 annually; Yield Increase—Potential increase in annual revenue of about $80,000.

The conclusions drawn from the case studies highlight how big data analytics and machine learning can create real added value in agro-food logistic systems and processes. Through real-time data and data-driven prediction, organizations are able to shave off wastage while improving operations, profitability and effectiveness. (**Table 3**)

### 4.4. Types of Models

There are several machine learning programs that address specific issues linked to agro-food waste. They are models which are used to classify types of waste for

Table 3. Machine learning approaches waste minimization with limitations.

| Model | Application | Advantages | Limitations | References |
|---|---|---|---|---|
| **Regression Models** | Estimate waste amounts under specific conditions (e.g., temperature, humidity). | Simple to implement; effective for quantitative predictions. | May oversimplify relationships; sensitive to outliers. | Liu et al. (2017) |
| **Clustering Analysis** | Categorize waste patterns to identify influential factors (e.g., product type, geographical region). | Identifies hidden patterns; works well for large datasets. | Results can be hard to interpret; depends on the chosen number of clusters. | Ahmadzadeh et al. (2023) |
| **Ensemble Methods** | Combine predictions from multiple models to improve accuracy and stability. | High accuracy; reduces overfitting. | Computationally expensive; harder to interpret. | Lakhouit et al. (2023) |
| **Decision Trees** | Classify waste types based on spoilage factors or environmental conditions. | Easy to interpret; handles both categorical and numerical data. | Prone to overfitting; may not generalize well. | Munir et al. (2023) |
| **Support Vector Machines (SVM)** | Predict which products are susceptible to waste under given conditions. | Effective for high-dimensional data; robust to overfitting. | Computationally intensive; challenging with large datasets. | Liu et al. (2017) |

instance depending on its source, content or spoilage factors (Kumar & Singh, 2024). However, other forms of machine learning such as classification methods such as decision trees and support vector machines can predict which products are susceptible to being wasted given the past record and conditions of the environment (Bhuiyan et al., 2023). Regression Models are used to estimate the amounts of waste produced under conditions such as changing temperatures and humidity in the storage environment. Methods such as linear regression as well as significantly more advanced models like random forest can express the regularity of the input variables to the waste output which can help to collect the necessary inventory information and make decisions among the stakeholders (Rahaman et al., 2023; Islam et al., 2024). Moreover, clustering analysis is used to help categorize similar waste patterns so that relevant factors causing waste can be determined. Methods such as the k-means clustering or hierarchical clustering provide a way to identify which product or process is most susceptible to waste with subsequent steps to organize an intervention (Bhuiyan et al., 2023).

The idea behind Ensemble Methods is to train multiple models so that when used together, we get better predictions with better accuracy and stability. Also, somewhat related to mixing the values received from different models, bagging and boosting can improve the performance of individual models and can offer a more inclusive outlook into waste dynamics (Lakhouit et al., 2023).

### 4.5. Model Architecture and Design

Hence, each of the models is constructed with a special architecture to deal with the problem under consideration. Closely related to the deep learning models, it is necessary to determine the number of layers and neurons. A well-designed neuron circuit diagram might contain a number of hidden neurons that help to recognize the high-level dependencies in the data while the neurons in each sequential layer capture more detailed dependencies. Metrics about individual learning rates, participation rates, and regularization during training contain sensitive information about such learning models (Liu et al., 2017). To choose model parameters we can use a grid search or random search which can help across hyperparameters in order to get the best performance of a given data set. Feature engineering is the method of defining, changing, or developing new attributes required by a model to be optimized. Feature engineering is demonstrative of the procedures that can mean improving the potential of a model to forecast waste, especially using domain knowledge of the agro-food processes. Techniques like k-fold cross validation also make it possible to guarantee that the algorithm performs well on new datasets. Overfitting is prevented through this approach because the performance of the model is checked through another portion of the training data (Rajvanshi et al., 2023).

## 4.6. Training Process

**The training process involves**

Using three sets of data—training, validation, and a test set—is crucial to properly judging the prowess of a given model. The training set is then used to build the model, and the validation set is used to tune the parameters of the model, and the test set is used to test the model. In the case of cross-validation, the idea is to get some level of confidence in the model by assessing it on different subsets of data. This makes it easy to detect early signs of over and under-fitting during the training process, and it can be effectively used by designers. To identify effective models, measures like accuracy, precision-recall, F1-score, and AUC will be useful in providing a complete account of the performance of the models (Golbraikh et al., 2003). These have the effects of enabling the stakeholders to evaluate how accurate the constructed model is in predicting waste and the ability to reduce waste in the future. Some tools that help understand the relative importance of certain features when it comes to the output are SHAP (SHapley Additive exPlanations) values or LIME (Local Interpretable Model-Agnostic Explanations).

## 4.7. Results and Findings

The results section will discuss the comparison between the various models in the aspect of how well and how effectively they can estimate and reduce different forms of agro-food waste. It will also make possible conclusions about one model or the other that was most efficient under certain circumstances. Specific differences between multiple machine learning models will be discussed by specifying their accuracy, speed, and applicability for various contexts in the agro-food sector (Montecinos et al., 2018). A summary of the strengths and weaknesses of various approaches will be discussed in this work. The findings will therefore present two aspects, these are: which of the features was more relevant for forecasting waste generation? For instance, some environmental conditions or operational practices may develop into influential factors determining the rates of waste. They shall also be jointly accompanied by implications in relation to organizational stakeholders in the agro-food supply network, including guidelines on how dwelling and deploying machine learning solutions they are likely to encounter are best affected. This portion of the paper broadens the presentation of machine learning systems for reducing agro-food waste and highlights the significance of building solid structures in addition to considering the practical application of already developed models in the current setting (Aït-Kaddour et al., 2024).

## 5. Innovations in Agro-Food Waste Management

### 5.1. Technological Advancements

Novel developments in both the field of BDAS and machine learning have created new possibilities for improving agro-food waste management. Improvements like remote control of monitoring systems by IoT have also evolved to a level where changes can be managed in real time. New technologies enabled by tiny, sophisticated sensors for temperature and humidity, as well as gas emission, spoilage, and many other parameters, changed the approach to waste management (El-Ramady et al., 2022). These sensors produce detailed information that can help to develop intervention schedules. Cloud computing, when integrated with IoT and BDAS provides the means of storing and processing a large quantum of data that arises from the agro-food processes. This also promotes solutions that can easily be scaled up and be accessed anywhere and standards ensure that the stakeholders can make proper decisions upon getting real time information. Featuring the ability to provide indisputable trails of merchandizer's movement, blockchain can increase competence in waste control in the food chain. This technology can show areas that need improvement so that proper changes can be made. Competence in the manufacturing of AI algorithms to analyze big data sets and decision support systems is gradually being used in different fields (Procentese et al., 2019). Such developments provide the possibility to control the equipment's condition without its failure, efficient deliveries, as well as better demand estimation leading to minimized wastage.

### 5.2. New Model Approaches

In this research, new model configurations are proposed to utilize both real time IoT data streams and past data. They have become useful tools to improve prediction and organizational effectiveness within waste management systems. Hybrid models can consider more patterns in generation data in comparison with the best regression and classification models, since the last ones combine different types of machine learning algorithms, for instance, regression and classification models integrated into one ensemble model (Kotsiantis et al., 2006). This approach improves the reliability of the predictions. It is a strategic necessity to integrate models that can be adjusted to respond to changing conditions in real-time into the waste management sphere. These models rely on real-time data input from IoT technologies to refine estimation in real-time operational conditions, resulting in enhanced waste estimation. IoT systems need to be integrated with machine learning solutions that give a broader picture of the agro-food supply chain (Das, 2019). This integrative approach helps in making good decisions since more than one factor influencing generation of waste is considered.

### 5.3. Interconnection of IoT and Real-Time Data

IoT is used to collect data that serves as the foundation for machine learning by feeding real-time data. The following section will also describe how it is possible to catch real-time data feeds from sensors and fit them into analytical structures that make possible dynamic decision-making. Applying data fusion procedures makes it possible to include data from various sources (for example, IoT, weather conditions, customers' demand) into a single analytical system (Joshi et al., 2022). This rich set of data improves the reliability of machine learning forecasts of waste production. It also allows stakeholders to address new issues when they are identified by analyzing data from the stream as it happens. For example, when there is a high temperature within storage facilities as obtained from the sensors, the appropriate corrective measures must be taken to avoid spoilt food. The integration of feedback on IoT systems and machine learning models guarantees continual optimization and criminal intentions of individuals they will detect, and as new data is collected, the model is trained further to improve its accuracy.

### 5.4. Potential for Automation

An exploration of how the adoption of IoT and machine learning could lead to a future where the actual reduction of waste could be at least partly automated will be made. Automate the process so that changes can easily occur in real time and lead to better resource allocation as supported by the predictive analytic tools. When machine learning is applied to IoT data sources, organizations can create decision-making systems that are capable of processing data in real-time when it comes to things such as inventory control, production planning or logistics (Aziz et al., 2023; Rahaman et al., 2023). For instance, the automation of a specific process could entail changing order quantities depending on a predicted, necessary demand rate, calculated from previous sales trends. Automation is not limited only to changes in operations; it includes predictions for maintenance and preservation of food machinery as well. In observing performance data of equipment, an organization is likely to identify some failures before they happen hence reducing on time wasted. Introducing bins that incorporate sensors that determine their fill levels will make collection time for waste disposal services efficient (Engler, 2004). This eradicates the time-wasting as well as the cost-incensing exercise of making many trips to the compound to remove the waste just in case it has overflowed. These advancements are important innovations to properly address the current wastage practices, mostly within the agro-food sector, to demonstrate that technology can promote improvements, promote sustainability efforts, and promote a reduction of wastage within supply chain networks.

## 6. Challenges and Future Perspectives

The discussion section of the paper sums up the results that have been obtained in the previous sections of the work, discussing the role of big data and machine learning in minimizing the problem of agro-food waste (Ahmadzadeh et al., 2023). Moreover, it will demonstrate how such technologies can reorient current practices, discuss major differences between such technologies and conventional approaches, and consider sustainability and economic concerns. The coupling of big data analytics and machine learning in the agro-food waste management approach has been observed to have great possibilities for changing existing practices. Disposal of waste can therefore be checked through close monitoring of data from the IoT devices, which reveal trends in waste generation, and hints at possible solutions which can then be applied immediately through the IoT devices (Wang et al., 2024). For example, it can predict demand patterns better than traditional measures such that producers can control their production amount and reduce wastage. Additionally, algorithms can determine if supply chains have some problems that should be fixed and provide ideas on routes and inventory management that would minimize waste the most at each step. However, some drawbacks are still recognizable in the present research framework. This is an important consideration since many organizations may not have access to the required big datasets that must feed into machine learning. Second, there is also a rise in privacy and security issues when there are increased numbers of IoT devices in the agro-food industry (Islam et al., 2024; Ahmad Tarmizi et al., 2020). As for future research perspectives, its main subject should be the question of the improvement of the unified guidelines for the exchange of data and adherence to corresponding rules and regulations in the field of privacy protection (Rahaman et al., 2024).

Moreover, conventional methods of waste management involve monitoring and preventing waste by reacting to it, and they require manual intervention. The use of big data and machine learning is a more systematic and, largely, data-based approach as compared to the heuristics-based method (Hannan et al., 2015). For example, while traditional approaches may include checking stock periodically, IoT technology makes it possible to monitor the levels constantly and take appropriate actions whenever the risk of waste is observed. Besides, this transition from the reactive to the proactive approach does contribute to the improvement of the flow of organizational processes as well as to the development of a culture of constant improvement (Islam et al., 2024; Bhuiyan et al., 2023). The results complement the recent discourse on the roles of big data and machine learning in contributing to other sustainable development objectives. The minimization of agro-food waste leads to a decreased impact on the environment with direct implications on enhanced control of the emissions of greenhouse gases related to the production and disposal of foods. In economic positivity, the reduction of waste means the reduction of losses among producers and retailers (Wan et al., 2019). For example, reduced overhead costs such as losses under treasury through proper inventory management or decreased transportation costs through proper management of logistics are effects of organizational efficiency. These economic benefits also explain why agro-food businesses could continue to advance their use of new technologies. Countries like the United Kingdom, China, and the Netherlands are at the forefront of IoT and big data analytics in agro-food waste management. The UK focuses on integrating IoT for sustainability and traceability (Fischer & Lyon, 2021), while China leverages digital technologies for cross-border food supply chains (Li et al., 2023). The Netherlands employs IoT for real-time monitoring, enhancing precision agriculture and waste reduction (Bijl et al., 2024).

Furthermore, Agro-food waste management plays a vital role in addressing environmental, economic, and social challenges. Despite progress, significant research gaps persist, including inadequate integration of circular economy principles, which limits sustainability advancements (Cahyadi et al., 2024). Challenges in waste valorization, such as technological and economic constraints, hinder the efficient conversion of waste into value-added products (Zhang & Zhang, 2024). Limited application of smart technologies, including AI and IoT, restricts optimization in developing regions (Zhang & Zhang, 2024; Islam et al., 2024). Additionally, insufficient stakeholder engagement highlights the need for inclusive approaches that incorporate diverse socio-economic perspectives (Berenguer et al., 2023). So, there is still a research gap regarding model accuracy, specifically for related contexts within and across the agro-food chains. Since waste generation might be distinctive given product type and could be affected by diverse factors such as climatic conditions, consumer preferences, etc., it may be important to develop models with a view of distinct scenarios.

## 7. Conclusion

The successful implementation of big data analytics and the use of machine learning technology in agriculture will be a revolution in managing food wastage, which has become a major problem for the food industry all over the world. This study emphasizes the possibilities that the technologies bear for improving operational performances, managing resources optimally and making a positive impact on sustainable development. The results presented support the relevance of data-derived solutions to traditional waste management methodologies, as well as illustrate how predictive analytics can improve inventory management and lower wastage rates. In addition, the discussion focuses on the reduction in wasted food and beverages and related advantages that holders of the products would have more financial profitability. With this change being observed in the agro-food sector, policymakers, businessmen, and even researchers are expedited in encouraging the use of such technologies. This study demonstrates how real-time data from IoT devices, along with more sophisticated analysis, provide suitable tools for key stakeholders to make decisions to minimize wastage at all levels of the supply chain. Therefore, there are enormous opportunities for increasing industrial efforts to reduce waste and improve sustainability by investing in more efficient infrastructures, supporting data sharing, and funding more research into applications of machine learning in specific fields. In the long run, adopting such developments will not only transform the waste management industry but also enhance the operations of the food industry regarding sustainability and economic returns.

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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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