

Compost In: AI and Internet of Things to predict food waste at home and to check how good the compost is at a given time.

Abhijay Gupta

Abstract

The largest and most obscure section of food waste worldwide is food that people throw away in their homes. The UNEP Food Waste Index Report 2024 reported that in 2022, a total of 1.05 billion tonnes of food was wasted. This means one in five of food pieces that could be eaten by the people were not in use. Out of that total 631 million tonnes

came from homes. This is 79 kilograms annually per capita. That is much more than the restaurant or store food waste. In this study a new solution is proposed called CompostIn. CompostIn is a system that deals with food waste in an efficient way and not merely throwing it away. A prediction engine is the primary component of CompostIn.

This engine examines the purchase patterns. It discovers the consumption level of food by a household and thereafter accurately estimates household waste production that is going to be generated in the next few days. The second part of CompostIn is a bin with sensors. This container decomposes and reports a grade known as the Compost Health Index, which varies with time. The lid of the bin has a camera and a weight sensor. These instruments indicate what a home discards, giving the prediction engine the required information. The family is not requested to declare its waste. All the data is collected through image processing. Learning across households is done using learning, so no private information about each household's eating habits is collected. CompostIn was designed to stand out against the appliances that currently exist, but this study refers to those as dehydrators rather than composters. I consider this interesting since it provides an avenue to minimise food waste.

Keywords: *Artificial Intelligence, Food Waste Prediction, Smart Composting, Edge. Computer Vision, Compost Sensors, Compost Maturity, Federated Learning, IoT Sensors, Computing, Circular Economy.*

Date of Submission: 05-10-2026

Date of Acceptance: 16-10-2026

I. Introduction

Typically, food waste is regarded as a supply chain issue. With them, things go bad while they are transported. Unsold food is discarded by stores. This is not where the majority of food waste happens. According to the 2024 UNEP data, the main source is households. Sixty percent of total food waste is from households. Food service is responsible for 28 percent. Retail has 12 per cent to blame. Households are that part of the chain where no one really measures the waste. Nobody monitors the contents in a home kitchen bin.

The presentation of one of the findings in that report was what this study is about. Hence, there exists a connection between income and household food waste. The difference between high-income countries and middle-income countries is about 7 kilograms per person per year. The climate of the place plays a huge role. Food waste is larger in warmer countries. This is because they consume more food. They also have supply chain systems. In a nation such as India, where the climate is warm, it changes the way the problem is understood. Household food waste is not mainly due to carelessness. It relates to food that had been purchased previously and went out of date before anyone could consume it.

This is necessary as there are patterns of spoilage. A house that purchases a lot of coriander and gets rid of half of it every week is creating a signal. A predictable signal which can be easily forecasted. The spotting of patterns can be done by a system that steps in at the moment of purchase, instead of disposal, as by that time it's too late. There already exist two types of products that assist in this problem. Countertop waste is composed in machines after it has been made. They do not inform the user why the waste was made. Food tracking applications aid in planning. They do not know what they put in the bin, so they will never know whether their advice was followed. Neither completes the cycle between anticipation and result. Compost In

will fill that gap.

II. Research Problem

The four gaps give rise to this piece of work.

Firstly, there is no feedback to our prediction of waste and disposal. Current literature on the predictability of household waste is based on the use of self-reported diaries or surveys.

These are only limited studies; they are likely to be biased towards desirability. They are hardly close to real time. A learned prediction model, which is trained on what people state to have wasted, cannot be compensated for what they really have wasted.

Second, commercial smart composters are not predictive. In some cases, they do not compost at all. By simply considering the appliances separately, it becomes evident that they make things dry and grind rather than decomposing food with the help of microbes. They lessen the quantity by 80 per cent. They abandon dry organic mass in the same form, but this mass is biologically perishable and begins to form mould in a few days when put into soil. The microbial succession that composting requires will not be able to occur in a 16-20 hour cycle.

Third, research prototypes are only a representation of the raw data; they do not display what is meant by the sensor values. I believe that a family cannot do anything based on a reading of 640 parts, per million ammonia. What is lacking is how to reduce sensor data into a single interpretable indicator and a more mature estimate using science about how things disaggregate, rather than a simple timer.

Fourth, the concept of privacy is discussed as a policy statement, but not one of its features. Any system that traces your food and the garbage your family discards is intrinsically intrusive. A reliable system must not permit decipherable images or shopping information to venture out of the house. This is the system that needs to be designed so that it is limited at the outset.

III. Research Objectives

The primary objective is to develop a system, which will bridge a home to curb food wastages by predicting what will be thrown away and composting any leftovers with monitoring. There are four objectives that follow. The initial goal is a machine learning model that has two stages. Domestic food waste is identified in the future by household and quantity by predicting the volume and type of food waste. It also labels discarded items as they are thrown out, providing ground truth labels that will correct the prediction. The second goal is to design a sensor stack and a phase-sensitive Compost Health Index. There is a description of this index, which estimates maturity not on elapsed time alone, but on decay based on carbon dioxide respiration. The third objective (privacy-preserving architecture) is a privacy-preserving architecture that integrates on-device inference with learning. This implies that the data on behaviour will not be stored anywhere in a form that could be recognised.

The fourth is to establish the measure of success that is calibrated with resultant publications of indeterminate fantasies. This enables the proposal to be experimented with and possibly falsified, not suggested.

IV. Literature Review

Forecasting: Random forests, gradient-boosted trees and shallow neural networks can anticipate correct waste quantities accurately, when we consider previous consumption data. However, this study is nearly entirely a retrospective study since models have been trained once on a fixed set of information and do not get updated with domestic knowledge.

Time-series models are suitable to fit this problem because domestic waste is highly expected to peak after shopping, when there is a festival. This was demonstrated in Alsalem (2025) food waste domain. In that paper, an LSTM model distilled out timing patterns, which were then added to enhance the support vector machines, random forests and logistic regression. A combination of these achieved 99 per cent accuracy over Brooklyn food waste data. Yet there is a caveat: the outcome is a classification benchmark of a sample, not real-time prediction of each household, which is more difficult and not yet solved. The goals in Section 8 reflect that.

Kinaesthetic sense and sense-making: Bejarano-Meza and colleagues (2026) offer a peer-reviewed

study. In this study, Bejarano-Meza and colleagues built a solar-powered model which utilised a DHT22 sensor on ESP32 composter, a form of carbon sensor named MQ-135 sensor. This measured carbon dioxide along with a separate four-in-one sensor which detected oxygen, carbon monoxide, hydrogen sulphide and methane. Bejarano-Meza and colleagues reported that optimum temperatures were thermophilic, with a temperature of between 56.7 and 59.2 degrees Celsius. Bejarano-Meza and his colleagues observed that the highest level of carbon dioxide was found to be 3840 ppm on day twelve and then fell to 900 ppm by day forty-five. Another study by BejarandoMeza and others also concluded that the time required to compost in the solar-powered ESP32 composter was reduced by half, by taking between forty-five and ninety days to complete composting as opposed to ninety days on the system. Two main conclusions emerged. First, aerobic composting is a time-consuming process that, when optimised, will take weeks. Second, mass decrease of seventy to eighty per cent through a twenty -four hour cycle cannot be compared to composting development as it only indicates dehydration. The MQ-135 sensor alone cannot detect methane; it is sensitive to nitrogen oxides, carbon dioxide, alcohol and benzene, and smoke. As methane is an indicator of failure, a special methane channel needs to be included to the solar-powered ESP32 composter.

Behavioural precedent: This method of itemised feedback of waste is particularly common in South Korea, and has proved to be successful. It actually functions the way it works. The magnitude of the change is often made big. The weight based RFID disposal system in South Korea began in Seoul during its 2013, which reduced waste by 7.3 percent.

Approximately 14 per cent per annum. In a study conducted in 2024, Lee and colleagues discovered that national food waste increased by 16 per cent from 2013 to 2019, showing a real success of the country in diverting and recycling waste, not as a way of preventing its production. The feedback system in the study is both. Disregarded, enhancing the illusion of size.

Federated learning: An overview of 86 papers on learning (201924) on food research topics (crop disease monitoring, quality assessment, fraud detection and supply chain security) by Fendor and colleagues (2025) concluded that this method is viable in this context and is applied. In cases where it is impossible to regard data sensitivity and collaboration by other means is impossible.

The gap: No prediction, downstream, point-of-disposal verification (computer vision) and downstream. The quality-monitoring system of compost in any system has been reported in the literature or, within the consumer network, a privacy-preserving architecture. A combination such as this is the input of this study.

V. Proposed Methodology

The system that is proposed is made up of two halves, which constantly correct each other with the assistance of an app.

Stage one: Stage of Garbage Prediction: The purchase per-category time series and consumption are modelled using an LSTM. The patterns that are explained by these models are as follows:

Repeat over weekly and seasonal patterns. The system that contains the LSTM has a part in it which is a gradient-boosted regressor. This regressor takes advantage of tabular data which the LSTM does not process, such as household size, historical waste rates per category or calendar data such as holidays or travel. Combined, these elements forecast the probability of every item in the household will be destroyed in the three to seven days. The data is inputted into the system through receipt capture using on-device optical character recognition, pantry check-ins, along with optional linkages to systems.

Stage 2: Stage of Disposal Classification. The bin lid possesses a camera module and a load cell attached. When one throws something away, a trained MobileNetV3-Small model finds the weight of an object and its weight is recorded in the load cell. It is what makes CompostIn

better than other approaches. It provides the ground truth labels that one requires in the step. It will not require the user to do anything additional. This is unlike steps in self-reporting that weaken. CompostIn, a household waste study, does not need any user input. If an item has a confidence value, which is less than the threshold it is not considered wrong. Rather, it leads to a single-tap correction queue.

Stage three: Looping it Back to You. The difference between the stage one prediction and the stage two observation comes in handy in two aspects. It acts as a training indicator, which assists and enhances predictions and also provides an indicator for providing recommendations. For example: when the prediction says that a particular item will be used but the camera shows it being discarded, the system can make a

suggestion, such as advising the user to use half of a herb that has been thrown away for three weeks. This method is different to the guidance that households should cut waste, which numerous individuals have discovered difficult to follow.

Stage four: Privacy Architecture. This information concerns buying and disposal, which makes it sensitive in nature. Image inference occurs entirely on the device. Frames are not stored. Once they are classified they are discarded. Each household learns using its data and only transmits encrypted information to the server. The server combines these changes using averaging. Then it comes up with a quality shared model. Households can choose not to join the federation at all and instead run a model locally. It is noteworthy that updates about weights are never conveyed in such a manner that they can be accessed.

Gradient inversion attacks have demonstrated the ability to hack approaches to secure aggregation, and differential privacy is now considered an essential part of the system.

Rather than an optional extra.

VI. Designing the Composting Bin

The composting core is designed to be low-cost that easily gets hold of materials. A DHT22 is used to measure the temperature and humidity of the headspace. Then, a capacitive soil moisture probe is marked over an one due to the fact that resistive types are lost to rust in a moist, slightly acidic environment of the interiors of a compost bin. Acidity is monitored by a pH probe with a signal conditioning board. An MQ-135 is used to monitor ammonia, carbon dioxide and volatile organic compounds, and a methane sensor on account of the reasons in Section 4. A servo motor-powered aeration vent automatically opens in response to readings of gas, moisture or oxygen which indicate the formation of pockets, but a small heating device maintains the pile within the cold range in hot weather. The heater is aimed at promoting activity and not to dry out the contents, which is the difference between this design and the commercial competitors that it faces.

The essential item the bin offers is the Compost Health Index, which can be specified as follows:

$$CHI = 100 \times (0.30 \cdot S_{temp} + 0.30 \cdot S_{moisture} + 0.15 \cdot S_{pH} + 0.25 \cdot S_{gas}) \times A$$

The -score S of each parameter has a range of zero to one is at one when the parameter lies in the healthy band of the parameter and drops off when it is out of the band. Moisture level is maintained at 50-60 and pH at 6.5-8.0. An early drop to 5.0 or 5.5 is also naturally an element of the process and is not judged. The two common concepts of the cause of lack of success in household-scale piles are both temperature and moisture both. This occurs most commonly because they are the two variables that can be addressed by hardware hardware i.e. the heating element and the aeration vent respectively.

This is a phase-sensitive index. Composting is a succession and not a steady state: the heap warms until it gets to a hot thermophilic stage of 45 to 65 degrees Celsius, and then cools down and matures. Any fixed optimum would only be punitive of a maturing pile because it had cooled, so the temperature goal band would move with the stage that the pile was at. Term A is an override that can override the whole score regardless of the other terms. The existence of greater than threshold of methane or below 5 per cent oxygen indicates that the pile has turned anaerobic and is generating the same greenhouse gas that the system is designed to stop, and no favourable temperature and pH readings should be allowed to hide that.

The maturity rate will be calculated using the rate at which the carbon dioxide will be set off by a countdown timer. One of the decomposing piles is breathing very hard, whereas the stabilised pile is breathing very little. Consequently, there is a direct relation between the compost and the finished pile, which differs in the declining curve that is a direct physical degree of the compost's approach to completion. This technique is equipped with a standard recommended in Section 4.

VII. System Architecture

There are three layers in the architecture. Purchase is collected in the Data Acquisition Layer, and pantry information regarding the application, disposal information regarding the camera and load cell and data (environmental) regarding the temperature, moisture, pH, gas and methane sensors are the composting core. The Edge Processing Layer, which is running on either the bin or a household hub, activates the forecasting, the vision classifier and the Compost Health Index.

It calculates local federated model updates. The User Interaction Layer delivers the waste forecasts, the compost health and maturity dashboard and itemised recommendations in the application. A MQTT is communicated with the use of Wi-Fi telemetry protocol. The default is that raw sensor data is stored locally, and derived weight adjustments and features are stored externally and are encrypted.

VIII. Expected Results

The targets that will be tested in a pilot of 10-20 households would be against bin and no-forecast control conditions. They have been presented as hypotheses and not alleged results.

Measure	Target
Accuracy of the forecasts	The mean absolute error should be less than 20 percent of the actual mass per category per week after eight weeks.
Classification of items	F1 of 0.85 or higher on a held-out food waste image set
Maturity time to compost	45 days or less, versus about 90 days unmonitored
Thermophilic ability	Active at 45 to 65 degrees Celsius
Anaerobic event rate	Methane above percentage at least 5 percent of observed hours
Mass decrease cycle	40-60 percent wet mass decrease per full aerobic cycle
Behaviour change	Reduction of three items or more in number that are wasted in three or more consecutive weeks

This study qualitatively leaves behind the figure that is often quoted in this field on the anticipated magnitude of waste reduction. A previous draft of this proposal claimed a cut of 20 percent to 40 percent with South Korea as evidence. When analyzing the data behind this number, that number was implausible: Seoul gained 7.3 percent in the year and over 14 percent overall whereas the growth of national generation increased during the same time. A testable hypothesis of CompostIQ can then be the reduction by mass of 10 to 20 percent over three months as in the spoilage- categories of fresh produce, dairy and leftovers and not distributed uniformly.

The contention that we may with some justification forecast more than Seoul had attained is a mechanistic and not a rhetorical one. The quantity is conveyed in a disposal fee only after the waste has happened. CompostIQ recognizes the recurring item and interferes at the level of purchase decision at which point the waste is actually decided. The rationale behind the need to be cautious is that this mechanism itself has never been experimentally tested and that feedback-driven interventions are often attenuated by a loss of novelty. The pilot is there to refute the hypothesis rather than prove it.

IX. Environmental Impact

The organic waste generated by the house that is deposited in the landfill decomposes anaerobically and releases a greater amount of methane with a strong short-term warming potential than carbon dioxide. It is estimated that the overall loss and waste of food in the chain accounts for five per cent of the world's yearly emissions of greenhouse gases. This is almost half the percentage that is due to aviation. Conversion of organics to actual aerobic compost leads to the generation of mainly carbon dioxide. This route is stabilized to emissions of organic material and is impeded. A soil amendment is produced, eliminating the necessity to use artificial fertiliser.

The environmental leverage, however, is prevention rather than treatment. Growing transportation and consumption of refrigerated and unrefrigerated food that is never eaten consumes all the water, land, fertiliser, and energy that are contained in it. All of which cannot be restored by composting.

CompostIn is thus structured in such a way that the preventive half of the loop bears the proportion of its environmental case. With composting performing the truly irreducible portion of peels, trimmings and inedible portions. Any system that composted successfully and could not keep out anything would be an amelioration; the converse, a large one.

The proposal is in line with the United Nations Sustainable Development Goal 12.3 to cut global food waste per person by half by 2030 and Goal 11 on cities and Goal 13, on climate action, communities.

X. Future Challenges

A number of limitations cannot be designed out. Are mentioned here instead of not having them. The prediction model takes weeks of household-specific data before its predictions become reliable, and seeding new households with the shared federated model can shorten this time but still does not do away with it. The vision classifier will treat items like vegetable trimmings easily but will find composite leftovers and regional dishes difficult to treat and therefore must have a confidence threshold with manual adjustment as opposed to optional. Gas and pH sensors drift and need to be recalibrated and the inside of a warm wet compost bin is just about the worst possible operating environment of such devices so this is a real ownership cost that needs to be faithfully reflected in any commercialisation plan. The extra hardware also puts the unit out of the bill of materials of a monitor competing with appliances already on the market at or close to 500 US dollars, and whether households will pay a premium out of prevention which they cannot see in advance is a market issue which this research cannot answer. Lastly, interventions based on feedback often wear out their welcome with time. A three-month pilot is able to perceive an effect without proving that the effect is lasting.

It might be possible to reduce the time to start by integrating with the retailer receipt interfaces in the future, generalise the concept to community-level compost sharing within apartment complexes and modify the system to accommodate an institutional kitchen in a school, hostel and canteen, where the volumes of waste and the regularity of patterns would justify the cost of the sensor much more easily than a single household and where the forecast would inform an actual procurement decision.

XI. Conclusion

The already existing gadgets which are solutions to food waste in the home hydrate it and refer to that as composting. The paper that can indeed forecast wastage lacks a method of learning the correctness of its forecasts, but with no physical component. Composting results related to it are stable and of low-friction. CompostIn will suppose that there is only one problem, which is the feedback loop. This means a bin predicts the materials that are about to be wasted by a given household. It will automatically determine whether the prediction was correct. It learns when it is not true to the prediction and is, in fact, achieving the actual success; then composting is successful.

The addition of capability to the design was not the most valuable component of preparing this research. It was checking its own figures, and finding that some of the figures were borrowed by the very machines they offer faults, and correcting them accordingly.

What is needed next, then, is not more conceptual refinements but a little pilot study in which these bins are put to the test in real kitchens so as to see which of the targets in Section 8 pass the test of practice.

References

- [1]. United Nations Environment Programme and WRAP. The 2024 Food Waste Index Report: Think Eat Save. Nairobi: UNEP, March 2024.
- [2]. Bejarano-Meza, M. E., Ramos Soncco, J. A., Vilca Quispe, M. L., and Chanove Manrique, A. M. Performance testing of a smart composting system based on the Internet of Things with photovoltaic solar energy to produce natural substrate out of domestic waste. *Environmental Technology and Innovation* 43 (2026): 105030.
- [3]. Alsalem, K. Enhanced food waste classification with LSTM and ensemble classifiers. *Discover Sustainability* 6 (2025): 443.
- [4]. Fendor, Z., van der Velden, B. H. M., Wang, X., Carnoli, A. J., Mutlu, O., and Hürriyetoğlu, A. Federation in food research. *Journal of Agriculture and Food Research* 23 (2025): 102238.
- [5]. Lee, E., Shurson, G., Oh, S-H., and Jang, J.-C. The management of food waste recycling a sustainable future: A case study of South Korea. *Sustainability* 16, no. 2 (2024): 854.
- [6]. McMahan, H. B., Moore, E., Ramage, D., Hampson, S., and Agüera y Arcas, B. The deep network learning with decentralized data using communication-efficient communication. *Proceedings of AISTATS, PMLR* 54 (2017): 1273–1282.
- [7]. Development Asia, Asian Development Bank. Reducing Waste using a Fee-Based System. Seoul volume- and weight-based food waste fee case study, 2019.
- [8]. Hanwei Electronics. MQ-4 Gas Sensor and MQ-135 Data sheets.
- [9]. Technical reviews of Lomi, Vitamix FoodCycler and Mill countertop food waste appliances, 20222026, on their mechanism of dehydration versus composting and the stability of their output.