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Machine Learning-Based Optimization with IoT of an Automated Composting System for Coffee Grounds †

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Abstract

Traditional composting requires months to mature and is often disrupted by uncontrolled environmental factors, such as insufficient heat generation during colder seasons. Therefore, we developed a smart, automated composting system that maintains a controlled environment with regulated heating, watering, mixing, and ventilation. Sensor feedback continuously drives the system toward optimal parameters. Coffee grounds were selected as feedstock because of the growing waste generated by increasing coffee consumption. The bin integrates IoT devices for real-time monitoring, and the collected data were analyzed using machine learning techniques, including principal component analysis, random forest, and decision tree algorithms, to predict compost maturity. The developed system reduced the maturation period to 12 days and produced compost of higher quality and safety compared with traditional methods. Optimal parameters were achieved, including soil temperature of 55–60 °C, moisture levels of 40–65%, and pH between 5.5 and 9.

Keywords: automated composting; coffee grounds; compost quality; sensors; IoT; machine learning

1. Introduction

The mismanagement of organic waste, intensified by global urbanization, contributes to environmental pollution and greenhouse gas emissions. Repurposing nutrient-rich waste streams offers a sustainable alternative [1]. Spent coffee grounds, a major by-product of global coffee consumption [2], represent a promising candidate for this approach. Composting can convert organic waste into nutrient-rich soil amendments, but traditional methods are slow and inconsistent, underscoring the need for innovative solutions that accelerate decomposition and standardize compost quality.

Automated composting systems have potential, though challenges remain. Illahi et al. [3] automated the mechanical and thermal processing of food waste, maintaining temperatures of 55 °C during pre-composting and 42 °C during maturity. However, their system suffered from moisture retention, recording borderline humidity levels of 32–43%. Addressing similar constraints, Adique et al. [4] achieved precise regulation, sustaining temperatures between 45 and 55 °C, moisture levels of 50–62%, and pH values of 5.5–9.0.

Recent automated composting systems rely on machine learning (ML). By applying principal component analysis (PCA), decision trees (DT), random forest (RF), and AdaBoost to banana waste, compost maturity within 10 days is predicted, identifying moisture and

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pH as primary drivers [5]. However, automated systems suffer from moisture retention and pH stabilization during thermophilic stages. Coffee grounds present additional biochemical challenges, including rapid pH crashes and evaporative dehydration, which stall biological activity in manual setups [6]. These limitations highlight the need for automated hardware to vary coffee ground ratios, coupled with an ML framework capable of auditing system performance and extracting optimization thresholds.

In this study, we developed an ML-based optimization system for an automated composting system that regulates key parameters to produce high-quality compost from coffee grounds [7]. The system integrates sensors and control mechanisms for interval monitoring and active regulation of soil moisture and temperature. PCA is applied to identify high-impact variables, whereas RF and DT algorithms predict compost maturity. System effectiveness is evaluated by comparing automated compost yields against traditional, uncontrolled manual composting.

By integrating hardware automation with data science, the system actively regulates moisture and temperature to prevent biological stall-outs that commonly occur in coffee waste decomposition. ML is used to audit using PCA, RF, and DT algorithms to optimize system stability. Designed for small- to medium-scale applications, the system provides households and commercial entities with an autonomous solution for converting volatile coffee by-products into pathogen-free fertilizer. System performance was evaluated across four coffee-to-carbon ratios (100%, 80:20, 70:30, and 50:50) under controlled indoor conditions to isolate hardware performance from environmental noise. System efficiency was compared with manual composting bins to validate the necessity of automation, while alternative waste management methods such as anaerobic digestion and vermicomposting were excluded from the scope.

2. Methodology

The developed system defines the inputs required to begin composting. Green material is placed in the automated bin, combined with brown material, and monitored by sensors. Once the process starts, sensors collect data continuously. We tested four weight ratios of coffee grounds to brown material: 100:0, 80:20, 70:30, and 50:50 [5]. A feedback loop adjusts conditions to reach optimal parameters, and data are transmitted wirelessly and stored in Excel files. The final compost is analyzed in both traditional and automated setups, with the germination index [8] calculated for each ratio.

The systematic flowchart (Figure 1) shows how the system controls its components. Coffee grounds are loaded into the bin, and once triggered, the composting process begins. Controls regulate conditions within target ranges [4]. For example, although the ambient temperature may be 30 °C, the system raises the pile temperature to 55–60 °C. If values fall outside these ranges, the feedback loop adjusts them until stability is achieved. When the parameters are met, the system evaluates compost maturity and quality using the germination index, which must reach 70 or higher [9].

The block diagram shows the composting process (Figure 2). Initial phase, coffee grounds and brown material are prepared in four ratios (100:0, 80:20, 70:30, and 50:50). Composting is carried out using both the traditional Hot Berkeley Method and the automated smart chamber system. PCA is used to identify the contribution of variables, and predictive algorithms, including DT and RF, are used to classify compost maturity and evaluate accuracy. Lastly, compost quality is assessed using the germination index across all ratios, allowing comparison between automated and traditional methods and ranking of performance [10].

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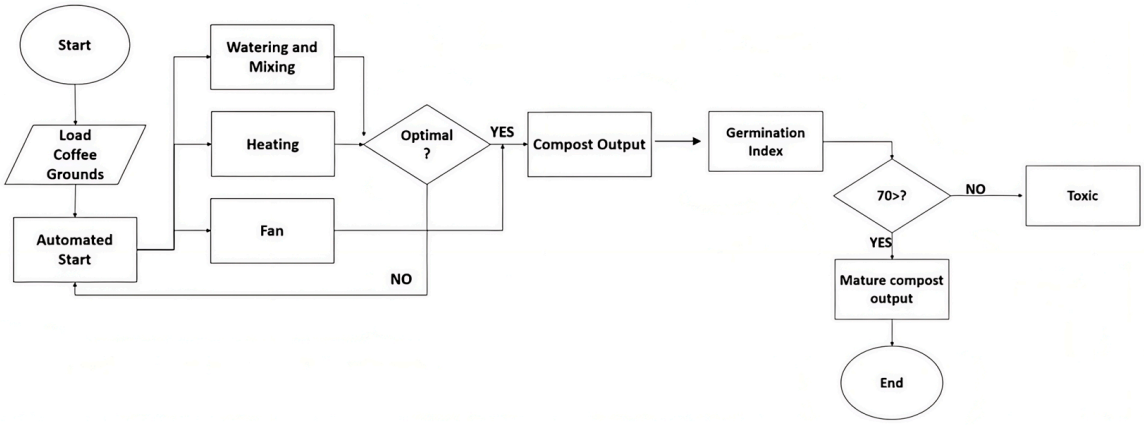


Figure 1. Systematic flowchart for the automated compost.

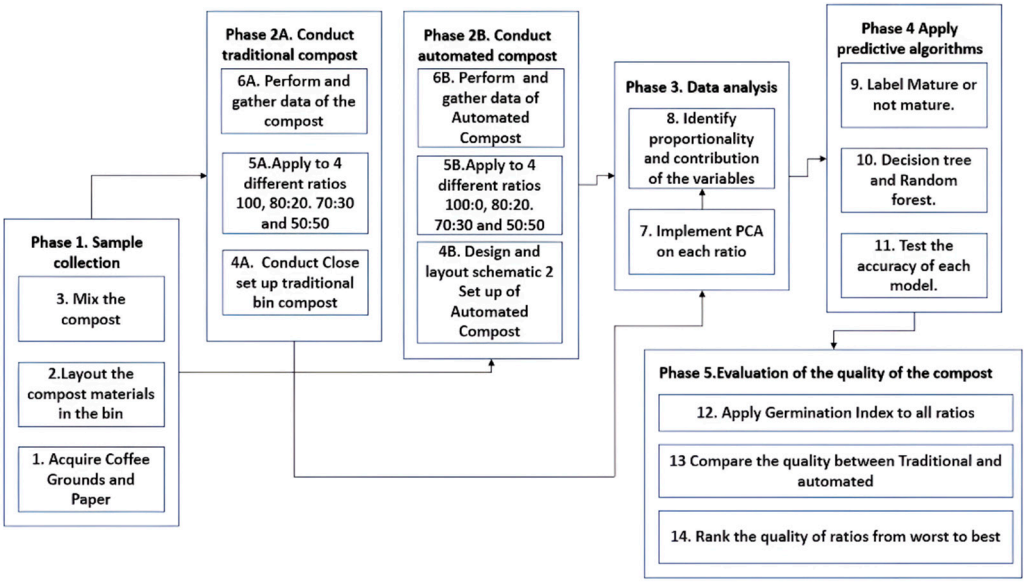


Figure 2. Block diagram for the automated compost.

Data were collected to compare datasets and demonstrate the prototype's functionality. Traditional composting was also documented to track its behavior against the controlled automated system. The Hot Berkeley Method Composting is used as the benchmark for manual composting [11]. Cucumber seed germination tests were conducted to determine compost maturity and quality.

3. Results and Discussion

Automated composting outperformed traditional manual composting in both operational efficiency and product quality. The automated system achieved optimal stabilization within 3 days, whereas manual composting required significantly longer to reach partial maturity. Germination tests indicated that manual compost retained residual phytotoxins due to insufficient heating. In contrast, automated composting produced non-phytotoxic material, with the 70:30 coffee grounds-to-carbon ratio yielding the highest germination index. Physical analysis confirmed that this 70:30 ratio provided superior decomposition, texture, and structural characteristics (Figure 3). This accelerated physical breakdown in the automated system is attributed to the controlled, mechanized regulation of aeration and moisture, which prevents the formation of anaerobic pockets that typically stall traditional composting.

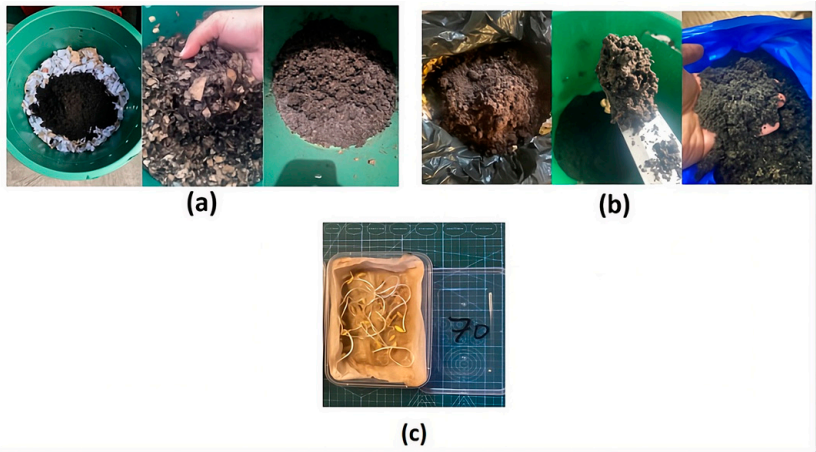


Figure 3. Physical characteristics and seed germination testing of composting mixtures: (**a**) 70:30 traditional compost showing incomplete decomposition; (**b**) 70:30 automated compost displaying dark, uniform texture; (**c**) seed germination assay using 70:30 automated compost extract.

Seed germination assays evaluated phytotoxicity by comparing root lengths from compost extracts against control samples. The 70:30 automated compost achieved the highest germination index of 210.29, confirming complete maturity and safety for agricultural use (Table 1). A germination index of this magnitude indicates that the 70:30 ratio provides the optimal balance for thermophilic microorganisms to rapidly metabolize plant-inhibiting organic acids. Manual composting batches consistently failed to sustain thermophilic conditions, with temperatures peaking only between 31.9 and 42.3 °C. These samples experienced severe evaporative dehydration, with moisture levels falling below 23%, which led to premature biological stagnation. In contrast, the automated system maintained stable environmental parameters, achieving moisture levels above 52% and sustaining thermophilic temperatures between 59.9 and 85.5 °C. These ranges are critical for effective pathogen reduction. Thus, automated composting consistently achieved the required parameter thresholds, while traditional methods struggled to sustain them. By preventing moisture loss and heating up the compost, the automated system allowed microbial metabolism to remain highly active, thereby generating the essential heat required to reach these pathogen-killing temperatures. Among the tested ratios, the 70:30 ratio composting showed the most effective, producing a dark, soil-like compost with an earthy odor that indicated high quality. Because of these improved physical characteristics, the dataset from the 70:30 batch was selected for training and evaluation in the machine learning models.

Table 1. Germination index results.

Parameter	Control (Distilled Water)	70:30 Compost Extract
Germination Count	15	14
Mean Root Length (cm)	45.33	102.14
Final Germination Index (GI)		210.29%

An RF classification model predicted compost maturity using data from automated batches (Table 2). Traditional batches were excluded due to incomplete biological progression. Soil temperature was omitted from input features to prevent data leakage caused by external heating elements. Relying solely on moisture and pH forced the model to evaluate physical stabilization directly. The model achieved high predictive accuracies ranging from 91.41% to 96.58% (Table 3).

Table 2. Summary of composting batches.

Batch Ratio	Max Temp (°C)	Avg Moisture (%)	Final pH	Final Status
100% Coffee (M)	42.3	22.3	5.8	Stalled
100% Coffee (A)	85.5	52.8	5.4	Matured
80:20 Mix (M)	36.9	16.7	5.2	Stalled
80:20 Mix (A)	61.2	62.3	6.1	Highly Mature
70:30 Mix (M)	31.9	18.2	6.2	Stalled
70:30 Mix (A)	59.9	89.3	5.1	Matured
50:50 Mix (M)	34.6	19.5	5.7	Stalled
50:50 Mix (A)	60.5	58.8	5.4	Matured

Table 3. RF results.

Random Forest	100%	80:20 Mix	70:30 Mix	50:50 Mix
Predictive Accuracy	95.93%	96.58%	91.41%	94.32%
Weighted F1-Score	95.95%	96.58%	91.17%	94.32%

To analyze the multivariate interactions within the composting environment, principal component analysis (PCA) was employed to reduce dataset dimensionality and identify correlations among soil moisture, temperature, and pH. As illustrated in the PCA biplots, PC1 and PC2 collectively accounted for 76.4% of the total variance, with moisture and pH showing a strong positive correlation (Figure 4). These findings underscore moisture content as the principal driver of compost activity; as moisture is maintained, pH naturally stabilizes because microorganisms can efficiently consume organic acids. A DT algorithm showed threshold values for distinct maturity phases using Gini impurity. Aligning with the feature importance results, the root node split on soil moisture at an operational threshold of 71.80%. This learned threshold provides direct control logic for programming microcontroller actuators to maintain optimal moisture levels automatically.

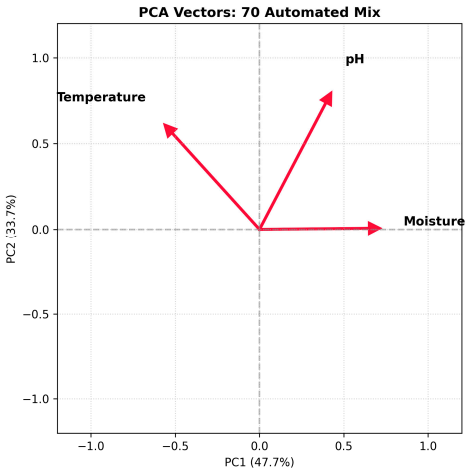


Figure 4. PCA results.

4. Conclusions and Recommendations

The study aimed to provide an improvement regarding composting that benefits plants and agriculture in general by integrating machine learning and a controlled environment into a single automated bin. Researchers compared automated and traditional composting to determine which method produces higher-quality compost capable of improving soil

strength. Different ratios of coffee grounds and brown material, specifically 100:0, 80:20, 70:30, and 50:50, were tested in both systems under an enclosed area, comparing traditional manual practices against an automated setup using a fan, heating element, mixing blades, and water pump. Germination index (GI) testing using cucumber seeds was used to determine which compost ratio had the highest GI and best quality.

The results from GI indicated that automated compost, specifically the 70:30 ratio, gave the best quality. Researchers concluded that automated composting was much more effective than traditional composting, providing more accurate data and faster decomposition of the material. The researchers used ML models (PCA, Decision Tree models, and Random Forest) to determine the variables that most significantly impact compost quality and the decomposition process, resulting in a predictive framework for compost maturity and for auditing data.

This is significant for agriculture and waste management as it promotes composting that recycles organic waste effectively. With the increase in agricultural production, the amount of waste increases proportionally. Thus, the elaboration of methods for rapidly obtaining high-quality compost contributes to overcoming these difficulties while increasing efficiency and benefits for producers. Nevertheless, the study scope is strictly limited to small-to-medium-scale composting applications and does not explore alternative methodologies such as vermicomposting or anaerobic digestion.

Regarding recommendations, the researcher suggested that the design be horizontal to determine whether it makes the mixing process more convenient. To advance the system, MySQL is recommended for real-time maturity notifications. Lastly, the use of different machine learning models should be considered.

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