

From Compost Intelligence to Farm Decisions: A Review of Explainable AI for Organic Manure Maturity and Management

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Abstract

Composting of animal manure and agricultural organic waste represents a significant strategy for nutrient recycling, soil improvement and sustainable waste management. However, an accurate evaluation of the compost maturity and quality is a challenging task due to the number of physical, chemical, biological and environmental factors involved in the process. Conventional approaches usually rely on laboratory analyses and individual maturity indicators which can often be time-consuming and difficult to integrate with practical decision support systems. Thus, recent studies have explored the use of machine learning (ML), artificial intelligence (AI), spectroscopy, the Internet of Things (IoT), and explainable artificial intelligence (XAI) to predict compost maturity, quality parameters and environmental emissions. This paper aims to review 20 studies published between 2020 and 2026 on manure composting, compost maturity prediction, spectroscopic monitoring, microbial additives, greenhouse-gas emissions, artificial intelligence, sensor-based systems and agricultural waste management. The reviewed literature revealed that Random Forest, Extra Trees, XGBoost, AdaBoost, ANN and adaptive neuro-fuzzy inference systems can deliver highly accurate prediction results under certain experimental conditions. Nevertheless, most of the studies suffer from small dataset size issues, heterogeneous data, lack of feedstock variety, controlled environment, limited external validation, inconsistent compost maturity definitions and limited comparison between different findings. While the recent advances in SHAP and LIME interpretation techniques facilitate better understanding of model behaviour, there is still a long way to go before such findings can be used to make actionable agricultural recommendations. The review identifies a research gap for an integrated, reproducible, and explainable decision-support framework that combines compost maturity prediction with interpretation and practical manure-management recommendations using publicly available data. The identified gaps motivate the proposed FarmMind framework for explainable organic-manure decision support.

Keywords: agricultural waste; compost maturity; decision support system; explainable AI; organic manure; SHAP

1 Introduction

Agricultural activities generate substantial quantities of animal manure, crop residues, and other organic wastes. Composting provides a biological pathway for converting these materials into more stable organic amendments that can potentially improve soil properties and support nutrient recycling. However, immature or improperly managed compost can create problems related to phytotoxicity, nutrient imbalance, pathogens, odor, and environmental emissions. So, reliable evaluation of compost maturity and quality is an important requirement for sustainable manure management.

Compost maturity is a complex property because it is influenced by several interacting physical, chemical, biological, and environmental parameters. Conventional approaches usually rely on laboratory analyses and individual maturity indicators, which can be time-consuming and difficult to integrate with practical decision support systems. Recent studies have therefore explored machine learning (ML), artificial intelligence (AI), spectroscopy, the Internet of Things (IoT), and explainable AI (XAI) to predict compost maturity, quality parameters, and environmental emissions. This paper reviews 20 studies published between 2020 and 2026 on manure composting, compost maturity prediction, spectroscopic monitoring, microbial additives, greenhouse-gas emissions, sensor-based systems, and agricultural waste management. The objectives are:

1. To review AI and ML methods used for compost maturity and quality prediction.
2. To identify commonly used maturity and process indicators.
3. To compare datasets, algorithms, and reported model performance.
4. To examine the use of explainable AI in compost-related prediction.
5. To identify recurring limitations and research gaps.
6. To establish the research opportunity addressed by the proposed FarmMind framework.

2 Review methodology

A structured literature analysis was carried out using 20 studies discussing compost maturity, manure composting, agricultural waste management, spectroscopy, microbial additives, greenhouse-gas emissions, AI, ML, IoT-based monitoring, and decision-support applications.

The studies were selected to represent different methodological categories, including experimental studies, ML-based prediction studies, spectroscopy research, sensor-based systems, and literature reviews. Each paper was analyzed according to the following attributes:

- publication year and source;
- compost or waste type;
- dataset characteristics;
- prediction target;
- ML or AI methodology;
- reported performance;
- limitations;
- identified research gap; and
- contribution and major findings.

The 20 studies were subsequently grouped into five major themes:

1. ML-based compost maturity and quality prediction;
2. spectroscopy and non-destructive maturity monitoring;
3. AI and sensor-based compost monitoring;
4. environmental emissions and sustainability; and
5. agricultural waste-management decision support.

3 Compost maturity and quality indicators

Compost maturity is a multidimensional characteristic rather than a single measurable property. The reviewed literature identifies several indicators that can be used independently or jointly.

3.1 Germination index

Germination index (GI) is one of the most frequently used biological indicators of compost maturity. It reflects the possible phytotoxic effect of compost extracts on seed germination and plant growth.

Shi et al. [18] showed that ML models can predict GI using variables of manure composting, and the RF, and Extra Trees algorithms have achieved $R^2 > 0.90$ due to the selection of duration, TN, and EC as important predictors.

Karimi et al. [9] also introduced maturity-related predictors in the composts and vermicomposts of cattle and sheep manures and have achieved a classification accuracy up to 0.98 with the application of RF and AdaBoost algorithms.

Abdi et al. [2] reported an R^2 equal to 0.992 for GI prediction using the ANFIS algorithm in an in-vessel composting system. These studies demonstrate the nonlinear nature of the relationships between compost process variables and maturity.

3.2 C/N ratio

The Carbon-to-Nitrogen ratio is a valuable indicator for assessing organic-matter decomposition and the proportion of nutrients. Dehghan et al. [5] explored several ensemble models for predicting the C/N ratio of municipal organic waste. Extra Trees achieved a testing R^2 of 0.97, though the study suffered from the limited regional data set and a possible optimism from interpolation and random data splitting.

Abdi et al. [2] similarly predicted C/N using ANN and ANFIS and reported an ANFIS R^2 of 0.994.

3.3 pH and electrical conductivity

pH and EC are typical chemical indicators associated with compost stability and phytotoxicity. In this regard, Abdi et al. [2] reported an R^2 equal to 0.999 for both EC and pH using the ANFIS tool. These results indicate that nonlinear models can be suitable for capturing the relationship between the composting process and these two chemical maturity indicators.

At the same time, the consideration of different indicators and maturity definitions in different studies limits the possibility of comparisons. Indeed, such complications were also reported in the spectroscopy literature [15].

3.4 Temperature, moisture, and process duration

Temperature, moisture, and composting duration are important process variables because they influence microbial activity, decomposition rate, oxygen availability, and nutrient transformation.

The importance of composting duration was demonstrated by Shi et al. [18], where duration was among the key predictors of GI. Sensor-based research has extended this concept by collecting temperature, moisture, CO₂, and NH₃ measurements for continuous prediction [10], [11].

4 Machine learning-based compost prediction

4.1 Tree-based ensemble models

Tree-based ensemble methods are among the most frequently used ML models in the reviewed studies.

Shi et al. [18] compared RF, Extra Trees, XGBoost, GBDT, BPNN, and MLP for manure compost maturity prediction. RF and Extra Trees achieved $R^2 > 0.90$ for GI prediction.

Karimi et al. [9] compared RF, Logistic Regression, Decision Tree, Naive Bayes, KNN, SVM, and AdaBoost for cattle and sheep manure compost maturity. RF and AdaBoost achieved classification accuracy of up to 0.98.

Dehghan et al. [5] evaluated AdaBoost, RF, Extra Trees, Decision Tree, CatBoost, and SHAP for C/N prediction. Extra Trees achieved a testing R^2 of 0.97.

These studies suggest that ensemble models are effective for structured compost datasets because they can capture nonlinear interactions between multiple input variables.

4.2 Neural networks and fuzzy models

ANN and ANFIS have also demonstrated strong predictive capability. Abdi et al. [2] used an in-vessel composting system with biochar and reported ANFIS R^2 values of 0.999 for EC and pH, 0.994 for C/N, and 0.992 for GI.

However, the controlled in-vessel environment limits direct generalization to full-scale composting systems. Therefore, high prediction accuracy should be interpreted together with dataset size, experimental conditions, and validation strategy.

4.3 Regression and instance-based models

Lyberatos and Lyberatos [13] compared Decision Tree, Linear Regression, XGBoost, and KNN regression using 88 composting batches. KNN obtained the lowest reported test MSE of 120.841 and MAE of 7.943.

This result demonstrates that a simpler model can outperform more complex models for a particular dataset. Consequently, systematic model comparison is important instead of assuming that the most advanced algorithm will always produce the best result.

5 Spectroscopy-based compost monitoring

Spectroscopic approaches provide a potential nondestructive method for monitoring organic-matter transformation.

Abaker et al. [1] used UV and fluorescence spectroscopy with PLS regression for composting-process monitoring and maturity prediction. Prediction errors were approximately 9.4–12% for solid organic matter and 4.2–7% for water-extracted organic matter.

Perez-San Martín et al. [15] reviewed UV-Vis, infrared, fluorescence, and ^{13}C NMR spectroscopy and reported that differences in measurement conditions and maturity definitions remain major barriers to model transferability.

Although spectroscopy can provide rich chemical information, its practical deployment may require specialized instruments and calibration. The literature therefore indicates a need for transferable models and standardized spectral libraries.

6 Sensor-based monitoring and explainable AI

6.1 IoT-based compost monitoring

Recent research has combined IoT sensing with ML to enable continuous compost monitoring.

Khandakar et al. [10] proposed a sensor-based and interpretable ML approach using IoT sensors, XGBoost, CatBoost, five-fold cross-validation, LIME, and SHAP. Both XGBoost and CatBoost achieved $R^2 = 0.9912$, while XGBoost achieved an MAE of 1.1845.

Lazrak et al. [11] proposed a connected bioreactor framework integrating IoT monitoring, XGBoost, SVM, and RF for maturity and quality dynamics. Temperature, moisture, CO₂, and NH₃ measurements were used as inputs.

These systems demonstrate the feasibility of real-time compost monitoring. However, their dependence on controlled environments and sensing infrastructure introduces hardware, calibration, and deployment challenges.

6.2 Explainable artificial intelligence

Prediction accuracy alone is insufficient when an agricultural decision must be justified. Explainable AI provides methods for identifying the variables contributing to model predictions.

SHAP can provide global and local feature contributions, while LIME can provide local approximations of individual model decisions. Khandakar et al. [10] incorporated both LIME and SHAP into their sensor-based compost prediction framework.

Li et al. [12] used XGBoost with SHAP, partial dependence plots, force plots, and other analytical methods to investigate environmental and microbial drivers of CO₂-equivalent emissions. The model achieved $R^2 = 0.9863$ with environmental and microbial features.

Although these studies improve interpretability, explainability is still primarily used to identify influential variables rather than to generate farmer-oriented management recommendations.

7 Environmental emissions and sustainability

Manure and compost management can influence emissions of ammonia and greenhouse gases.

Scotto di Perta et al. [17] investigated biochar as a floating cover for manure storage. The controlled experiment reported a 78% reduction in cumulative NH₃ emissions and a 33% reduction in CH₄ emissions. However, the laboratory-scale design limits certainty about field-scale performance.

Li et al. [12] investigated environmental and microbial drivers of CO₂-equivalent emissions using XGBoost and XAI. The study used only 45 samples from one mixed composting system, which limits generalization.

Goswami et al. [8] reviewed greenhouse-gas mitigation strategies in poultry farming, covering manure management, composting, biochar, AI, and IoT. The broad review identified opportunities for in-

tegrated farm-to-compost systems but did not provide experimental validation of an integrated decision-support framework.

Dankwa et al. [4] reviewed methods for measuring greenhouse-gas emissions from composting and reported that heterogeneous measurement protocols and limited spatial coverage restrict comparability between studies.

These findings indicate that maturity prediction and environmental impact assessment are closely related but are often treated as separate research problems.

8 Agricultural waste management and decision support

AI has also been investigated at the broader waste-management level.

Fang et al. [6] reviewed AI applications in smart waste management, including sorting, logistics, monitoring, recovery, and waste-to-energy. However, heterogeneous applications and evaluation metrics make direct comparison difficult.

Oueld Lhaj et al. [14] reviewed 120 studies from 26 countries concerning agricultural waste management and composting impacts on soil health. The review highlighted the need to optimize compost composition, composting duration, monitoring, and site-specific application.

Rastogi et al. [16] reviewed microbial additives for solid-waste composting and identified the need for predictive rules that can select appropriate inoculants according to feedstock and operating conditions.

Szulc et al. [19] reviewed biological and physical processing pathways for organic waste and identified the need for decision models integrating processing performance, contamination, economics, and end use.

Cervelli et al. [3] used GIS, kernel density, spatial modelling, and probabilistic multi-criteria analysis for livestock manure management in the Sele Plain, Italy. The study identified suitable locations for manure treatment and spreading, but its single regional case limits generalization.

Goldan et al. [7] reviewed manure compost as a soil amendment and summarized agronomic benefits and environmental risks. However, the review did not provide a harmonized quantitative dataset or predictive model.

These studies demonstrate that manure management requires more than prediction of an individual compost parameter. A practical system should connect input characteristics, maturity assessment, environmental considerations, explanation, and final use.

9 Comparative analysis of the reviewed literature

Table 1 summarizes the major characteristics of the 20 reviewed studies.

Table 1. Comparative analysis of the 20 reviewed studies.

No.	Study	Year	Methods / Focus	Main Result	Major Limitation
1	Shi et al.	2025	RF, Extra Trees, XGBoost, GBDT, BPNN, MLP	RF and Extra Trees achieved $R^2 > 0.90$ for GI	Heterogeneous literature-derived data; 184 complete observations; limited generalizability

No.	Study	Year	Methods / Focus	Main Result	Major Limitation
2	Goldan et al.	2023	Manure compost review	Synthesized agronomic benefits and environmental risks	No harmonized quantitative dataset or predictive model
3	Lyberatos and Lyberatos	2025	DT, LR, XGBoost, KNN	KNN: test MSE 120.841; MAE 7.943	Small dataset and limited operational diversity
4	Abaker et al.	2025	UV/fluorescence spectroscopy, PLS	Prediction error 4.2–12% depending on material	Condition-specific models required
5	Karimi et al.	2025	RF, LR, DT, NB, KNN, SVM, AdaBoost	Accuracy up to 0.98	Replicate averaging may obscure batch-level uncertainty
6	Cervelli et al.	2021	GIS, spatial modelling, multi-criteria analysis	Identified suitable manure-treatment and spreading areas	Single regional case study and planning assumptions
7	Scotto di Pertà et al.	2020	Controlled storage experiment	NH ₃ reduction 78%; CH ₄ reduction 33%	Small laboratory study; uncertain field-scale transferability
8	Oueld Lhaj et al.	2025	Literature review and bibliographic analysis	Reviewed 120 articles from 26 countries	Heterogeneous review-level evidence
9	Fang et al.	2023	AI waste-management review	Sorting accuracy reported between 72.8–99.95%	Heterogeneous applications and metrics
10	Perez-San Martín et al.	2023	Spectroscopy review	Reviewed UV-Vis, IR, fluorescence, NMR	Different methods and maturity definitions
11	Khandakar et al.	2025	IoT, XGBoost, CatBoost, SHAP, LIME	R ² = 0.9912 for XGBoost and CatBoost	Very small dataset and limited independent-data separation
12	Xie et al.	2025	Composting, nutrient analysis, sequencing, FTIR	GI up to 94.79% for peanut-straw compost	Single experimental setting and limited feedstock set
13	Abdi et al.	2023	ANN and ANFIS	ANFIS: R ² = 0.999 for EC/pH; 0.994 C/N; 0.992 GI	Controlled in-vessel system limits full-scale generalization
14	Li et al.	2026	XGBoost, SHAP, PDP, microbial features	R ² = 0.9863 for CO ₂ -equivalent emissions	Only 45 samples from one system
15	Goswami et al.	2026	GHG mitigation review	Synthesized farm-level mitigation pathways	Broad review; no specific experimental validation
16	Dehghan et al.	2025	AdaBoost, RF, ET, DT, CatBoost, SHAP	Extra Trees testing R ² = 0.97	Small regional dataset; possible optimistic random split
17	Rastogi et al.	2020	Microbial-additive review	Synthesized microbial effects on composting	Heterogeneous evidence and limited standardized comparisons
18	Dankwa et al.	2026	GHG measurement review	Compared static/dynamic chambers and other methods	Heterogeneous protocols and limited spatial coverage

No.	Study	Year	Methods / Focus	Main Result	Major Limitation
19	Szulc et al.	2021	Organic-waste processing review	Compared biological and physical processing routes	Limited quantitative model comparison
20	Lazrak et al.	2025	IoT, XGBoost, SVM, RF, bioreactor	Predicted maturity and quality dynamics	Controlled bioreactor setting; further real-world validation required

10 Research gaps

The analysis of the 20 studies reveals several recurring research gaps.

10.1 Small and limited datasets

Dataset size is one of the most significant limitations. Shi et al. [18] used 184 complete observations, Li et al. [12] used 45 samples, and Lyberatos and Lyberatos [13] used 88 composting batches. Small datasets can restrict model generalization and increase the risk of overfitting.

10.2 Heterogeneous data

Several studies rely on heterogeneous evidence or literature-derived datasets. Shi et al. [18] explicitly identified heterogeneous literature-derived data as a limitation. Reviews by Goldan et al. [7], Oued Lhaj et al. [14], Rastogi et al. [16], and Szulc et al. [19] also demonstrate that composting studies differ in feedstocks, experimental procedures, and application conditions.

10.3 Limited external validation

A recurring limitation is the absence of independent validation across farms, feedstocks, climates, seasons, or composting scales. This issue is particularly visible in experimental and sensor-based studies [1], [9], [10], [2], [11].

Consequently, reported high R^2 values should not automatically be interpreted as evidence of broad real-world applicability.

10.4 Feedstock and condition specificity

Many models are developed for a particular feedstock or experimental condition. Spectroscopic models can require condition-specific calibration [1]. Plant-derived waste research may also involve a limited number of feedstocks [20]. Controlled in-vessel and bioreactor studies further restrict generalization [2], [11].

10.5 Different maturity definitions

Maturity is assessed using GI, C/N, EC, pH, nutrient characteristics, spectroscopic indicators, microbial characteristics, or combinations of these variables. The lack of a consistent definition makes comparison between studies difficult [15].

10.6 Prediction of individual parameters

Many ML studies focus on one primary target such as GI, C/N, EC, pH, or greenhouse-gas emissions. Although these predictions are valuable, they do not necessarily provide an integrated assessment of manure readiness for agricultural use.

10.7 Limited explainable decision support

SHAP and LIME are increasingly used to interpret ML models [10], [12], [5]. Nevertheless, the explanations are usually presented as feature importance or local contribution plots. There is comparatively limited work on transforming those explanations into actionable manure-management recommendations.

10.8 Hardware dependency

Recent real-time approaches use IoT sensors and connected bioreactors [10], [11]. Although these systems enable continuous monitoring, they require sensor infrastructure, calibration, maintenance, and deployment resources.

10.9 Lack of integrated decision frameworks

The reviewed literature contains individual solutions for ML prediction, spectroscopy, environmental emissions, microbial analysis, GIS, IoT monitoring, and waste management. However, these capabilities are rarely combined into one reproducible and explainable software-based framework.

11 Research opportunity: FarmMind

Based on the identified gaps, an opportunity exists for an integrated explainable decision-support framework for organic manure management.

The proposed framework, FarmMind, is intended to investigate the use of machine learning for manure maturity/readiness assessment using a publicly available dataset. Rather than proposing ML prediction as a new concept, FarmMind focuses on integrating model comparison, explainability, and decision support.

The conceptual workflow is described below.

The proposed framework follows a systematic workflow in which a public dataset is first preprocessed to handle missing values and inconsistencies. Relevant features are then engineered and provided to machine learning models for prediction. SHAP is subsequently used to explain the model predictions by identifying the contribution of individual features. Finally, the prediction and explanation results are used to generate appropriate recommendations.

Candidate models can include Decision Tree, Random Forest, Extra Trees, Gradient Boosting, and XGBoost. Their performance can be compared using metrics such as R², MAE, RMSE, and, where appropriate, classification accuracy, precision, recall, and F1-score.

The best-performing model can subsequently be interpreted using SHAP. Instead of presenting only the numerical prediction, the framework can identify the variables that contribute positively or negatively to the prediction.

The final decision-support layer can convert model outputs into understandable categories such as:

- predicted manure maturity/readiness;
- quality category;
- influential factors;
- factors requiring attention; and
- application or further-processing recommendation.

This structure addresses the gap between ML prediction and practical decision support.

12 Research questions

Based on the literature gaps, the following research questions are proposed:

1. Which ML algorithm provides the most reliable prediction of manure maturity/readiness using the selected public dataset?
2. Which input features have the greatest influence on manure maturity prediction?
3. Can SHAP-based explanations improve the interpretability of the selected ML model?
4. How can model predictions and explanations be transformed into an actionable manure-management decision-support output?

13 Expected contributions

The proposed research is expected to contribute:

1. A reproducible public-dataset-based ML methodology for organic manure maturity/readiness prediction.
2. A comparative evaluation of multiple ML algorithms on a common dataset.
3. SHAP-based interpretation of the selected prediction model.
4. An integrated decision-support layer that converts predictions into understandable manure-management recommendations.
5. A software-oriented framework that does not require dedicated sensing hardware for its core prediction functionality.

14 Conclusions

This review examined 20 studies on ML-based compost maturity and quality prediction, spectroscopy, sensor-based monitoring, and emissions. Tree-based ensembles, ANN, and ANFIS perform well under controlled conditions, but small datasets, narrow feedstock coverage, inconsistent maturity definitions, and limited external validation restrict how far these results can be trusted in practice.

Explainable AI is still used mainly to rank influential variables rather than to guide farmers. Farm-Mind is therefore proposed as a reproducible, software-based framework that links public-data prediction, SHAP explanation, and manure-management recommendations. Future work should validate such a framework across feedstocks, farms, and scales and move toward a common definition of compost maturity.

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