

AI-Based Bio-Waste Decomposer System

Ms. Nidhi Suhas¹, Ms. Nishchitha S², Ms. Sneha Patgar³, Ms. Yashwitha⁴, Ms. Deepthi⁵
^{1,2,3,4,5}*Department of Information Science and Engineering, Shree Devi Institute of Technology*

Abstract—The increasing generation of biodegradable waste has created a need for efficient and controlled decomposition methods that can reduce manual intervention and improve process management. Conventional bio-waste decomposition often depends on periodic monitoring and manual regulation of environmental conditions, which may result in inconsistent operating conditions. This paper presents an AI-Based Smart Bio-Waste Decomposer that integrates Internet of Things (IoT), sensor-based monitoring, machine learning, and automated actuation to facilitate controlled decomposition of organic waste. The implemented prototype employs temperature, humidity, and moisture sensors to acquire real-time environmental parameters from the decomposition chamber. An ESP32 microcontroller serves as the central processing unit, collecting sensor measurements and communicating the monitored information to an IoT-based dashboard. A Decision Tree machine-learning model analyzes the acquired parameters and determines the appropriate operating condition for the decomposition process. Based on the model output, actuators such as a stirring motor, aeration fan, heating element, and water pump can be controlled through a relay interface. The system consequently establishes a feedback-oriented framework in which environmental conditions are continuously monitored and corrective actions can be initiated when required. This integrated approach combines intelligent decision-making with automated process regulation and remote monitoring, providing a scalable foundation for smart biowaste management. The implemented prototype is intended to improve process consistency, reduce manual supervision, and support efficient utilization of biodegradable waste.

Index Terms—Bio-waste decomposition, Artificial Intelligence, Machine Learning, Decision Tree, Internet of Things, ESP32, Sensor Monitoring, Automated Composting.

I. INTRODUCTION

The rapid increase in the generation of biodegradable waste has intensified the need for efficient waste

management practices that can minimize environmental impact and improve resource recovery. Conventional waste management approaches often depend on manual collection, segregation, monitoring, and handling, which can limit operational efficiency. The integration of Internet of Things (IoT) technologies has introduced automated approaches for monitoring waste-related parameters and improving the management of waste-handling systems [2], [3], [5].

Recent developments in smart waste management have demonstrated the use of sensors and connected devices for realtime monitoring and automated decision-making. IoT-enabled systems can collect operational data continuously and transmit it to monitoring platforms, thereby reducing dependence on periodic manual inspection [6], [8], [10]. Machine learning has further expanded the capabilities of such systems by enabling data-driven analysis and intelligent decision-making. AI- and machine-learning-based approaches have been investigated for smart waste management, including automated waste classification and intelligent waste-handling systems [1], [4], [9].

Biodegradable waste requires appropriate environmental conditions for effective biological decomposition. Parameters such as temperature, relative humidity and waste moisture influence the environment condition within a decomposition system. Consequently, continuous monitoring of these parameters can provide useful information for regulating the decomposition environment. Existing IoT-based waste management research demonstrates the feasibility of combining sensing, communication, and automated control within wastemanagement applications [2], [3], [8].

However, a system designed specifically for automated bio-waste decomposition requires more

than simple parameter monitoring. The collected sensor information must be interpreted to determine the appropriate operating condition, followed by suitable control actions. Deep-learning and machine-learning approaches have already been explored in intelligent wastemanagement systems [4], [7], [9], providing a basis for incorporating computational intelligence into automated wasteprocessing applications.

This work proposes an AI-Based Smart Bio-Waste Decomposer that integrates sensor monitoring, an ESP32-based control unit, a Decision Tree machine-learning model, automated actuators, and an IoT monitoring interface. Temperature, humidity, and moisture measurements are acquired from the decomposition chamber and processed by the control system. The machine-learning component analyzes these parameters to determine the required operating condition, while relay-controlled actuators such as a stirring motor, aeration fan, heating element, and water pump provide environmental regulation. The monitored information can also be presented through an IoT dashboard for remote observation.

The proposed system therefore establishes an integrated Sense–Analyze–Decide–Control–Monitor framework for intelligent bio-waste decomposition. By combining IoT-based sensing with machine-learning-assisted control, the system aims to reduce manual supervision, maintain more consistent operating conditions, and provide a structured platform for automated biowaste processing.

II. LITERATURE REVIEW

Recent research demonstrates an increasing integration of Artificial Intelligence (AI), Internet of Things (IoT), sensor networks, and automated control within waste-management systems. The reviewed studies provide a technological foundation for the proposed AI-Based Smart Bio-Waste Decomposer.

[1] Sahoo et al. presented an AI-driven bio-waste classification and bin-management system incorporating sensor fusion and IoT. The system employs multiple sensors for waste identification, bin-level monitoring, and automated management. Its architecture demonstrates how AI and IoT can be

combined to improve the handling of biodegradable and non-biodegradable waste.

[2] Aman, Sharma, and Gupta investigated IoT-based wastemanagement devices through a comprehensive analysis. Their work highlights the application of connected sensing and embedded technologies in waste-management systems. The study provides a broader technological perspective on IoT-enabled waste-management devices, although the work is primarily concerned with waste-management infrastructure rather than automated decomposition.

[3] Singh, Patel, and Verma explored sensor-enabled waste management for smart-city environments. Their work emphasizes the utilization of IoT and sensing technologies for monitoring waste-related operations. Such systems establish the importance of continuous data acquisition and communication in intelligent waste-management applications.

[4] Roy, Das, and Banerjee proposed an end-to-end architecture combining IoT and machine learning for smart waste management. The integration of sensing, communication, and computational intelligence indicates the potential of machinelearning techniques to transform conventional monitoring systems into data-driven management platforms.

[5] Gao, Li, and Dai investigated the design and implementation of an IoT-enabled smart-bin system for efficient waste management. The study demonstrates the practical implementation of sensors and connected hardware for monitoring waste conditions. Such prototype-oriented work provides a foundation for developing embedded wastemanagement systems.

[6] More, Thatte, and Rathi examined an IoT-based wastemanagement system oriented toward sustainable cities. The study emphasizes the role of connected devices in improving wastemanagement operations and supporting sustainable urban infrastructure. It demonstrates that IoT can facilitate continuous monitoring and information exchange between field devices and management systems.

[7] Prajapati and Banerjee investigated an IoT-integrated deeplearning approach for real-time solid-waste management. The work illustrates the use of deep-learning techniques alongside connected sensing infrastructure for intelligent wastemanagement applications. This demonstrates the increasing shift from simple monitoring toward computationally assisted decision-making. Related research has also demonstrated the integration of deep learning with smart-bin systems for real-time waste management.

[8] Li et al. proposed a smart dry- and wet-waste management system using IoT. The study focuses on automated waste handling and segregation through connected sensing and embedded hardware. This demonstrates the applicability of IoT technologies to different categories of waste-management operations.

[9] Huang, Davis, and Davis investigated an AI-driven smart-bin system using machine learning. The study represents the application of machine-learning techniques to wastemanagement processes, moving beyond conventional sensorbased monitoring toward intelligent data interpretation. This direction is relevant to the proposed system because the present work also uses machine learning to interpret environmental parameters and determine control actions.

[10] Wang investigated an IoT-based smart waste-management system designed for real-time monitoring. The study emphasizes continuous acquisition and transmission of waste-related information, demonstrating the importance of real-time monitoring in automated waste-management environments.

Research Gap

The reviewed literature establishes that IoT-based sensing, realtime monitoring, AI, and machine learning can significantly support intelligent waste-management systems. A systematic review of IoT-enabled waste-management research identified the use of diverse sensors, actuators, communication technologies, and data-processing approaches across smart-waste applications. However, much of the existing work concentrates on waste classification, bin-level monitoring, collection optimization, and segregation, rather than directly regulating the

biological decomposition environment. This creates an opportunity for a system that combines environmental sensing with machinelearning-based decision-making and automatic actuation specifically for bio-waste decomposition.

The proposed AI-Based Smart Bio-Waste Decomposer addresses this area by integrating temperature, humidity, and moisture sensing; ESP32-based data acquisition; Decision Tree-based analysis; automated stirring, aeration, heating, and moisture regulation; and IoT-based monitoring within a unified framework.

III. METHODOLOGY

The implemented AI-Based Smart Bio-Waste Decomposer integrates sensor-based data acquisition, machine learning, embedded control, and IoT monitoring to regulate the environmental conditions associated with bio-waste decomposition. The implemented prototype follows a closedloop architecture in which the decomposition environment is continuously sensed, analyzed, and regulated according to the obtained measurements. The overall methodology consists of biowaste containment, sensor-based monitoring, data acquisition, preprocessing, machine-learning-based decision-making, automated actuation, and remote monitoring.

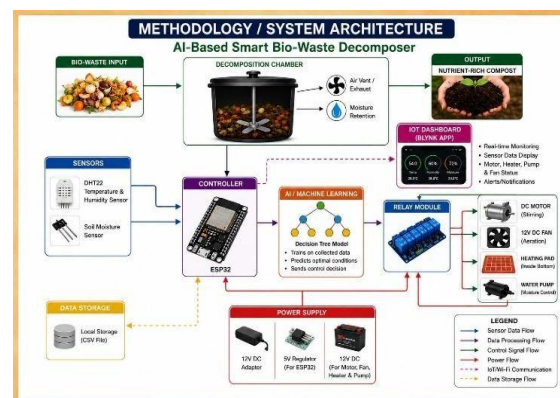


Fig 1.1: System Architecture

A. Prototype Architecture

A functional prototype was developed using an ESP32 microcontroller as the central control unit. A DHT22 sensor was employed to acquire temperature and relative humidity measurements, while a capacitive moisture sensor was used to monitor the moisture condition of the bio-waste. The acquired sensor values

are processed by the ESP32 and supplied to the machine-learning component for determining the corresponding operating condition.

A Decision Tree Classifier was incorporated as the machinelearning model. Temperature, humidity, and moisture constitute the principal input features used by the model. Based on the resulting classification, the ESP32 generates control commands for the connected actuators. A four-channel relay module interfaces the microcontroller with the stirring motor, aeration fan, heating element, and water pump. The system is additionally integrated with the Blynk IoT platform to facilitate remote visualization of sensor measurements and actuator status.

B. Sensor-Based Data Acquisition

The decomposition chamber contains the bio-waste under controlled operating conditions. The DHT22 sensor continuously measures the temperature and relative humidity within the chamber, whereas the capacitive moisture sensor provides the moisture measurement of the waste material. These parameters are important inputs for assessing the prevailing decomposition environment.

The ESP32 periodically acquires the sensor measurements and organizes them into structured data records. Each record contains the measured temperature, humidity, and moisture values together with the corresponding operating or actuator condition. The collected observations form the basis for subsequent data processing and machine-learning operations.

C. Data Preprocessing

The acquired sensor data are subjected to preprocessing before being utilized by the machine-learning model. The collected records are examined for missing, invalid, or inconsistent observations. The sensor measurements are converted into a suitable numerical format and organized according to their respective input features and target variable.

The feature matrix is represented as:

$$X = [T, H, M]$$

where (T) denotes temperature, (H) denotes humidity, and (M) denotes moisture. The target variable represents the operating condition or actuator state

associated with the corresponding sensor measurements.

The processed dataset is subsequently divided into appropriate subsets for model development and evaluation.

D. Decision Tree-Based Machine Learning

A Decision Tree Classifier is utilized to establish a relationship between the measured environmental parameters and the required operating condition. Decision Trees perform classification by constructing a sequence of feature-based decision rules that progressively separates the input data into different classes. During training, the model receives temperature, humidity, and moisture as input features and learns the corresponding target classes from the prepared dataset. The trained model can subsequently classify newly acquired sensor observations and generate an appropriate control decision.

The general process is represented as:

$$(T, H, M) \rightarrow \text{Decision Tree} \rightarrow \text{Operating}$$

The interpretable structure of the Decision Tree also allows the generated decision rules to be examined and related to the environmental conditions observed within the decomposition chamber.

E. Automated Actuation

The output generated by the machine-learning model is processed by the ESP32 to determine the required actuator response. The four-channel relay module provides switching control for the major actuating components of the prototype.

The stirring motor facilitates mixing of the bio-waste, while the aeration fan promotes air circulation within the chamber. The heating element is used for temperature regulation, and the water pump supplies moisture when moisture adjustment is required. Accordingly, the control mechanism establishes a relationship between the sensed environmental condition and the corresponding physical response of the prototype. This enables the system to regulate the decomposition environment with reduced dependence on continuous manual intervention.

F. IoT-Based Monitoring

The ESP32 communicates with the Blynk IoT platform through a wireless network. The platform provides a monitoring interface through which the

measured temperature, humidity, moisture, and actuator status can be observed remotely.

The IoT layer therefore complements the local control mechanism by providing visibility into the operating state of the prototype. The recorded information can also support subsequent analysis of the decomposition process and evaluation of the system's operational behaviour.

G. Closed-Loop Control Process

The implemented prototype operates through a continuous feedback mechanism. Initially, bio-waste is introduced into the decomposition chamber. The sensors acquire the prevailing environmental conditions and transmit the measurements to the ESP32. The acquired values are processed and supplied to the trained Decision Tree model. The model determines the corresponding operating condition, after which the ESP32 activates or deactivates the appropriate actuator through the relay module.

The resulting changes in the chamber environment are subsequently detected by the sensors, generating updated measurements for the next decision cycle. The complete process can therefore be represented as:

Bio-Waste → Sensing → ESP32 → Data Processing → Decision

Tree → Control Decision → Relay → Actuators → Feedback

This continuous Sense–Analyze–Decide–Control–Monitor cycle forms the core methodology of the developed AI-Based Smart Bio-Waste Decomposer. The integration of sensing, machine learning, automated actuation, and IoT monitoring provides a unified framework for intelligent regulation of the bio-waste decomposition environment [2], [4], [7], [8], [10].

IV. IMPLEMENTATION

The proposed AI-Based Smart Bio-Waste Decomposer was implemented as a functional prototype integrating embedded hardware, sensor-based data acquisition, machine learning, automated actuation, and IoT-based monitoring. The implementation was divided into hardware development, software development, dataset

preparation, machine-learning model development, actuator control, and IoT integration.

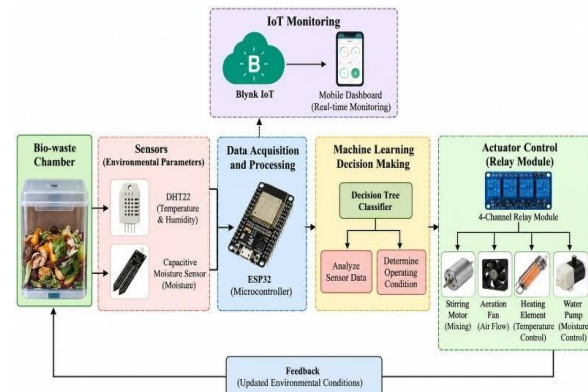


Fig 1.2: Work Flow

A. Hardware Implementation

The prototype was developed using an ESP32 microcontroller as the primary processing and control unit. The ESP32 receives environmental measurements from the sensors and generates control signals for the actuators.

The implemented hardware components include:

- ESP32 development board
- DHT22 temperature and humidity sensor
- Capacitive moisture sensor
- Four-channel relay module
- DC geared motor with stirring mechanism
- DC aeration fan
- Heating element
- Water pump
- Water reservoir
- Bio-waste decomposition chamber
- External power supply for the actuators

The DHT22 sensor is connected to a digital GPIO of the ESP32, while the capacitive moisture sensor is connected to an analog input. The relay module receives control signals from the ESP32 and switches the corresponding actuators according to the generated control commands.

B. Embedded Software Implementation

The ESP32 firmware was developed using the Arduino IDE. The program initializes the sensors, establishes

communication with the relay module, acquires environmental measurements, and executes the control logic.

The sensor readings are periodically collected and transmitted through the serial interface for verification and debugging. The embedded program also manages the ON/OFF states of the connected actuators.

The basic control sequence implemented in the ESP32 is:

Initialize → Read Sensors → Process Data → Determine Condition → Control Actuator → Repeat

This continuous execution enables the prototype to respond to changing conditions within the decomposition chamber.

C. Dataset Preparation

A structured dataset is required for training the machine-learning component. The principal input attributes consist of temperature, humidity, and moisture, while the corresponding target represents the required operating condition or actuator state.

The dataset is handled using Python and Pandas. Data preprocessing includes checking the collected observations, organizing the feature columns, handling unsuitable records, and preparing the target variable for supervised learning.

For the implemented Decision Tree model, the feature set is represented as:

$X = [\text{Temperature, Humidity, Moisture}]$

and the target variable is represented as:

$Y = \text{Operating Condition}$

The prepared data are subsequently supplied to the machinelearning algorithm for training.

D. Machine-Learning Implementation

The machine-learning component was implemented using Python and Scikit-learn. A Decision Tree Classifier was selected to classify the operating condition from the environmental parameters.

The implementation follows these steps:

1. Import the required Python libraries.
2. Load the prepared dataset.
3. Select temperature, humidity, and moisture as input features.
4. Define the target variable.
5. Divide the available data into training and testing subsets.
6. Initialize the Decision Tree Classifier.
7. Train the model using the training data.
8. Evaluate the trained model using the testing data.
9. Generate decision rules from the trained tree.
10. Use the resulting classification as the basis for actuator control.

A simplified representation of the machine-learning pipeline is:

Dataset → Preprocessing → Feature Selection → Train/Test Split
→ Decision Tree Training → Prediction → Evaluation

E. Actuator Implementation

The physical control layer was implemented using a four-channel relay module. Each relay channel is assigned to a specific actuator:

Relay Channel	Actuator	Function
CH1	Stirring motor	Mixing of bio-waste
CH2	Aeration fan	Air circulation
CH3	Heating element	Temperature regulation
CH4	Water pump	Moisture regulation

The ESP32 generates the control signals for the relay channels. The relays electrically switch the higher-power actuator circuits while keeping the control signals separate from the actuator power supply.

F. IoT Implementation

The prototype incorporates Blynk IoT for remote monitoring. The ESP32 communicates sensor

information to the Blynk platform through Wi-Fi. The dashboard can display:

- Temperature
- Humidity
- Moisture
- Stirring motor status
- Fan status
- Heating status
- Pump status
- Overall operating condition

This provides a convenient interface for observing the prototype without requiring direct access to the decomposition chamber.

G. Prototype Operation

During operation, bio-waste is introduced into the chamber and the sensors begin acquiring environmental measurements. The ESP32 receives the sensor readings and forwards the relevant parameters to the processing and machine-learning layer. The Decision Tree model determines the corresponding operating condition, and the ESP32 applies the resulting control decision to the appropriate actuator through the relay module. The altered environmental conditions are subsequently detected by the sensors, creating a continuous feedback cycle. This enables the prototype to dynamically respond to variations in the decomposition environment.

H. Software and Development Tools

The implementation utilizes the following software technologies:

Tool/Technology	Purpose
Arduino IDE	ESP32 programming
C/C++	Embedded firmware development
Python	Dataset processing and ML development
Pandas	Dataset manipulation
Scikit-learn	Decision Tree implementation
OpenPyXL	Excel dataset handling
Blynk IoT	Remote monitoring
ESP32 Wi-Fi	Wireless communication

The implemented prototype therefore combines embedded control, machine learning, automated actuation, and IoT monitoring into a single system for intelligent bio-waste decomposition.

V. RESULT AND DISCUSSION

The developed AI-Based Smart Bio-Waste Decomposer was evaluated at the prototype level to examine the functioning of its sensing, processing, actuation, and IoT monitoring components. The implemented architecture integrates environmental sensing with embedded processing and machine-learning-based decisionmaking, extending the monitoring-oriented approaches reported in previous IoT-based waste-management studies [2], [3], [5], [10].

The DHT22 sensor was integrated with the ESP32 to acquire temperature and relative humidity, while the capacitive moisture sensor was used to monitor the moisture condition of the biowaste. These parameters provide the primary environmental inputs for the machine-learning component. Continuous acquisition of such parameters is consistent with sensor-enabled waste-management approaches reported in the literature [3], [6], [8].

The ESP32 successfully functions as the central processing and control unit of the prototype. It receives the sensor measurements and provides control signals to the relay interface. The fourchannel relay architecture enables the proposed system to interface with the stirring motor, aeration fan, heating element, and water pump. This combination of sensing, embedded processing, and actuator control is aligned with the development of automated IoT-based waste-management systems described in previous studies [2], [4], [5].

The Decision Tree classifier provides a structured mechanism for interpreting temperature, humidity, and moisture measurements and associating them with an operating condition. Unlike a monitoring-only arrangement, the machine-learning layer enables the acquired sensor information to contribute to controloriented decision-making. The application of machine-learning and deep-learning techniques to

intelligent waste-management systems has also been investigated in earlier studies [4], [7], [9].

The prototype further incorporates Blynk IoT to provide remote observation of the monitored parameters and actuator states. The IoT interface allows information obtained from the ESP32 to be presented through a monitoring dashboard, thereby reducing the need for continuous physical inspection of the prototype. Realtime monitoring and connected waste-management architectures have been explored in previous IoT-based systems [3], [6], [10].

The implemented system consequently establishes an integrated Sense–Analyze–Decide–Control–Monitor cycle. Sensor measurements are acquired from the decomposition chamber, processed by the control system, analyzed through the machinelearning layer, and associated with the required control response. The resulting environmental changes can then be observed through subsequent sensor measurements. This feedbackoriented architecture extends conventional sensor-based waste monitoring toward automated environmental regulation.

At the current prototype stage, quantitative performance values such as Decision Tree accuracy, decomposition-time reduction, energy consumption, and percentage mass reduction should be determined through systematic experimental trials. These values are not stated here because they must be obtained from measurements performed on the developed prototype rather than estimated or assumed.

Overall, the prototype demonstrates the technical feasibility of integrating ESP32-based sensing, Decision Tree classification, relay-based actuator control, and IoT monitoring within a biowaste decomposition system. The developed architecture provides a foundation for further experimental evaluation using a larger dataset and extended operating trials.

VI. CONCLUSION

The developed AI-Based Smart Bio-Waste Decomposer integrates sensor-based monitoring, embedded processing, machine learning, automated actuation, and IoT connectivity into a unified bio-

waste management framework. The implemented prototype employs an ESP32 microcontroller to acquire temperature, humidity, and moisture measurements from the decomposition chamber and uses these parameters as inputs for Decision Tree-based analysis. The resulting operating condition is associated with the control of the connected actuators through a relay interface.

The integration of IoT monitoring further enables remote observation of sensor parameters and actuator status through the Blynk platform. The developed Sense–Analyze–Decide–Control–Monitor framework provides a structured approach for reducing manual supervision and regulating the decomposition environment. The integration of sensing, intelligent decisionmaking, and automated control is consistent with the direction of previous IoT- and AI-enabled waste-management research [2], [4], [7], [9].

The prototype establishes the feasibility of applying machinelearning-assisted control to bio-waste decomposition. However, comprehensive experimental evaluation is required to quantify model performance, decomposition efficiency, energy consumption, and long-term operational reliability. Such evaluation will provide the basis for further optimization and scaling of the developed system.

VII. FUTURE SCOPE

The developed AI-Based Smart Bio-Waste Decomposer can be further enhanced through extended experimentation, improved sensing, and advanced machine-learning techniques. Future development can focus on collecting a larger dataset from prolonged prototype operation to improve the reliability of the Decision Tree model and enable more comprehensive evaluation of its classification performance.

Additional environmental parameters such as pH, oxygen concentration, carbon dioxide concentration, and bio-waste mass can be incorporated to obtain a more detailed representation of the decomposition environment. The inclusion of these parameters can provide additional information for analyzing the biological process and refining the control decisions.

The machine-learning layer can also be extended by evaluating alternative algorithms and comparing their performance with the implemented Decision Tree approach. Automated actuator scheduling can be optimized to minimize unnecessary operation of the stirring motor, fan, heating element, and water pump, thereby improving resource utilization.

The prototype can subsequently be scaled to accommodate larger quantities of biodegradable waste. Long-duration experimental trials can be conducted to evaluate decomposition duration, mass reduction, energy consumption, moisture stability, and overall process consistency. Integration of improved sensor calibration, data storage, and advanced IoT analytics can further enhance the reliability and scalability of the system.

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