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Design and Development of a Smart Circular System Based on IoT and Edge Computing for MBG Food Waste Management

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ABSTRACT (10 PT)

Food waste management represents one of the major challenges in Indonesia, which ranks as the second-largest food waste producer in the world (Syafaat & Syafaat, 2023). The MBG (Free Nutritious Meal) program has the potential to generate organic waste on a large scale that requires systematic handling. This research designs and develops a smart circular system based on the Internet of Things (IoT) and edge computing to manage MBG food waste efficiently and sustainably. The developed system integrates sensors for detecting the type and volume of waste, microcontrollers as edge processing units, and a cloud platform for real-time monitoring and data analysis. Through a circular economy approach, this system not only reduces waste but also converts food waste into valuable resources through bioconversion processes using maggots. Testing results demonstrate that the system is capable of classifying waste with high accuracy and providing rapid responses due to edge processing, aligning with previous research findings that achieved classification accuracy of up to 93.97%. This system is expected to serve as an integrated solution for MBG food waste management that supports environmental and economic sustainability.

INTRODUCTION (Capital, bold, Times new romance 11 pt)

The increasing population in urban areas has significantly contributed to the continuous rise in food waste production. According to data from the Ministry of Environment and Forestry, in 2020, food waste constituted the largest type of waste in Indonesia, reaching 40 percent of the total waste generated by communities across 199 regencies and cities (Kompas, 2022). Indonesia ranks among the top three countries with the largest food waste production globally, alongside Saudi Arabia and the United Arab Emirates, with each Indonesian citizen discarding food worth an average of Rp 2.1 million per year (Kompas, 2022).

Research conducted by the National Development Planning Agency (Bappenas) indicates that the potential economic losses due to food loss and food waste in Indonesia during the 2000-2019 period reached Rp 213 trillion to Rp 551 trillion per year, with the total value of wasted food across 199 regencies and cities reaching Rp 330.71 trillion per year, equivalent to one-sixth of the state revenue in 2021 (Kompas, 2022). This figure aligns with the findings of Syafaat and Syafaat (2023), who reported economic losses reaching Rp 1,011,743,415 per year due to unmanaged food waste at the restaurant level.

The adverse effects of food waste, predominantly composed of organic waste, can lead to environmental pollution due to the production of hazardous biogas such as methane (CH_4) and carbon dioxide (CO_2), which contribute to global warming (Syafaat & Syafaat, 2023). Research by Daas et al. (2025) confirms that approximately 562 million tons of waste are burned openly each year, particularly in Asia, significantly contributing to air pollution and greenhouse gas emissions. Other studies also demonstrate that improperly managed organic waste can generate methane gas emissions that contribute to climate change (Fitriana et al., 2025; Sharma et al., 2025).

Meanwhile, the Free Nutritious Meal Program (MBG), launched by the Indonesian Government in January 2025, is a national program aimed at building a healthy, intelligent, and productive generation toward Indonesia Emas 2045 (JICA, 2025). This program will be gradually expanded to serve approximately 80 million beneficiaries, including pregnant women, toddlers, and school children from early childhood education to senior high school, including madrasahs and Islamic boarding schools (JICA, 2025). Nutrition Fulfillment Service Units (SPPG) have been established in various regions as implementing units for this program (Pemerintah Kabupaten Maluku Tengah, 2025; Polres Asahan, 2026). With such a massive operational scale, the MBG program has the potential to generate significant volumes of food waste, originating from unconsumed food leftovers, packaging, and production process waste (ANTARA News, 2025). The Head of the National Nutrition Agency (BGN), Dadan Hindayana, stated that food waste from the MBG program must be managed through a circular economy approach, where waste should not be discarded at schools but must be transported to SPPG for processing (RRI, 2026). Without proper management, this waste will add to the burden of final disposal sites and pollute the environment (Syafaat & Syafaat, 2023).

On the other hand, the circular economy offers a new paradigm in waste management, where waste is viewed not as the end of a product's life cycle but as a resource that can be reused (Gomes et al., 2024). This approach aligns with the concept of zero waste, which is increasingly popular among researchers and policymakers (Sari & Wijaya, 2025). Bioconversion technology using maggots (Black Soldier Fly larvae or Hermetia illucens) has proven effective in rapidly decomposing organic waste and producing economically valuable products such as animal feed and compost (Syafaat & Syafaat, 2023; Dewi & Hidayat, 2024). Recent research shows that BSF can convert 15-25 kg of organic waste into 2-4 kg of maggot biomass, which can then be processed into fish and poultry feed with high protein content (Rahayu et al., 2025).

The development of Internet of Things (IoT) technology and edge computing opens up significant opportunities for creating intelligent and automated waste management systems. Previous research has demonstrated that IoT-based systems are capable of monitoring and managing waste in real-time (Penelitian Telkom University, 2025). Automated waste sorting systems based on IoT, utilizing microcontrollers and various sensors such as metal sensors, proximity sensors, and ultrasonic sensors, have been successfully developed to separate organic and non-organic waste (Nurhakim & Septianti, 2024; Patel et al., 2025).

Edge computing, which processes data near the data source (edge devices) rather than sending it to the cloud, offers advantages such as low latency, rapid response, and bandwidth efficiency (Gomes et al., 2024). In the context of waste management, edge computing enables systems to make real-time decisions without depending on stable internet connections (Sari & Wijaya, 2025; Sharma et al., 2025). Research in smart waste management also indicates that integrating IoT with artificial intelligence (AI) can improve waste classification accuracy to over 90 percent (Li et al., 2025; Zhang et al., 2025). Against this backdrop, this research aims to design and develop a smart circular system based on IoT and edge computing for MBG food waste management, encompassing automatic identification and classification of food waste using sensors and edge computing, real-time monitoring of waste capacity and conditions, optimization of the bioconversion process of waste into valuable products, and data integration to support decision-making and program sustainability.

RESEARCH METHODS

Research Approach

This research employs the Research and Development (R&D) method, which is a systematic approach to developing and validating products used in education and technology (Syafaat & Syafaat, 2023). The R&D method was chosen because it allows researchers not only to develop the system but also to empirically test its effectiveness through a series of structured stages. The stages undertaken in this research consist of literature study, needs analysis, system design, implementation, testing, and evaluation (Syafaat & Syafaat, 2023).

This approach aligns with similar system development research that utilizes R&D methodology to produce appropriate technological products (Nurhakim & Septianti, 2024; Patel et al., 2025). The literature study was conducted to examine the theories underlying system development, including the concepts of IoT, edge computing, circular economy, and bioconversion of organic waste using BSF maggots (Dewi & Hidayat, 2024; Gomes et al., 2024). Needs analysis was performed to identify the technical specifications required from both hardware and software perspectives, considering field conditions and resource availability (Sari & Wijaya, 2025).

System design encompasses architectural design, component selection, and the design of the overall system working mechanism (Penelitian Telkom University, 2025). Implementation is the realization phase where the design is transformed into a prototype ready for testing (Nurhakim & Septianti, 2024). Testing is conducted to measure system performance based on predetermined parameters, while evaluation aims to assess the extent to which the system achieves its intended objectives and identify areas for improvement in subsequent development iterations (Syafaat & Syafaat, 2023; Li et al., 2025).

Needs Analysis

Needs analysis constitutes a crucial stage in system development, aimed at identifying in detail all components and technical specifications required for the system to function according to established objectives. Based on in-depth literature study and field observations conducted at several SPPG (Nutrition Fulfillment Service Units) locations of the MBG program, system requirements can be grouped into two main categories: hardware requirements and software requirements (Nurhakim & Septianti, 2024; Syafaat & Syafaat, 2023).

For hardware requirements, the system requires a microcontroller as the main processing unit, with Arduino Uno and ESP32 selected for their adequate processing capabilities and support for wireless connectivity (Nurhakim & Septianti, 2024; Penelitian Institut Teknologi Sumatera, 2025). The SRF-04 ultrasonic sensor is used to detect waste height within the container, enabling real-time capacity monitoring and notification when the bin is nearly full (Nurhakim & Septianti, 2024; Patel et al., 2025).

The DHT11 or BME280 sensor is implemented to monitor temperature and humidity around the waste, as both parameters significantly affect the decomposition process of organic waste and BSF maggot activity (Nurhakim & Septianti, 2024; Rahayu et al., 2025). The TCS3200 color sensor or capacitance sensor is used to classify waste types based on physical and dielectric characteristics, with previous research showing that capacitance sensors can distinguish organic and non-organic waste with high accuracy (Penelitian Telkom University, 2025).

A camera module is also added for visual identification and pattern recognition of more complex waste types, such as distinguishing plastic packaging waste from paper waste, which requires further image processing (Zhang et al., 2025). Communication modules such as WiFi or LoRa are required for data transmission from edge devices to the cloud platform, where WiFi is more suitable for areas with good internet access while LoRa is more appropriate for regions with limited network coverage (Syafaat & Syafaat, 2023; Gomes et al., 2024). NodeMCU is used as an internet gateway, also functioning as a communication gateway between sensor devices and the cloud (Nurhakim & Septianti, 2024).

For software requirements, the system requires an embedded development platform such as Arduino IDE, which supports microcontroller programming in C++ (Nurhakim & Septianti, 2024).

Edge operating systems such as Edge Impulse or TensorFlow Lite are used to run machine learning models on edge devices with low power consumption (Gomes et al., 2024; Sari & Wijaya, 2025). Cloud platforms such as Firebase or Amazon Web Services (AWS) are selected to store, manage, and analyze data sent from edge devices, as well as provide monitoring dashboards accessible in real-time (Penelitian Telkom University, 2025; Li et al., 2025). Additionally, a mobile application is required to send notifications to officers when certain conditions occur, such as waste capacity reaching maximum limits or temperature and humidity exceeding normal thresholds (Syafaat & Syafaat, 2023).

System Architecture Design

The system is designed with a three-layer architecture that adopts edge computing and IoT paradigms to ensure efficiency, responsiveness, and scalability in MBG food waste management, where each layer has specific functions that are integrated to form a coherent ecosystem (Gomes et al., 2024; Sari & Wijaya, 2025). The first layer is the Edge Layer, consisting of sensor and actuator devices installed on the smart trash bin, where sensors such as ultrasonic, DHT11, capacitance sensors, and cameras are integrated to perform real-time data collection (Nurhakim & Septianti, 2024; Penelitian Telkom University, 2025). At this layer, the microcontroller acts as an edge processing unit that performs local data processing (edge computing), including data filtering, initial classification using pre-trained machine learning models, and initial decision-making such as determining waste type (organic or non-organic) and activating actuators for sorting (Gomes et al., 2024; Zhang et al., 2025).

The advantage of edge processing is the system's ability to provide very rapid responses (low latency) without needing to transmit all data to the cloud, which is critical for applications requiring real-time decisions such as waste sorting that occurs within seconds (Gomes et al., 2024; Sharma et al., 2025). The second layer is the Gateway Layer, which uses NodeMCU or ESP32 as a connector between edge devices and the cloud, where this gateway is responsible for collecting data from various edge devices, performing data aggregation, and sending selected data to the cloud via communication protocols such as MQTT or HTTP (Penelitian Institut Teknologi Sumatera, 2025; Patel et al., 2025). MQTT protocol is chosen for its lightweight and efficient nature for IoT communication, especially when bandwidth is limited, while HTTP is used for communication requiring large data transfers such as images from cameras (Penelitian Institut Teknologi Sumatera, 2025).

The gateway also functions as a buffer or temporary storage when internet connectivity is disrupted, ensuring data is not lost and can be retransmitted when connectivity is restored, which is crucial for maintaining data integrity in areas with unstable connectivity (Gomes et al., 2024). The third layer is the Cloud and Application Layer, which functions as a center for historical data storage and analysis, where all data sent from the gateway is stored in a cloud database for long-term analysis and reporting purposes (Penelitian Telkom University, 2025). At this layer, a real-time monitoring dashboard is provided to facilitate officers and stakeholders in monitoring waste conditions across various SPPG locations centrally, including information such as waste volume, temperature, humidity, and sorting status (Nurhakim & Septianti, 2024; Sari & Wijaya, 2025).

An automatic notification system is activated when certain conditions are detected, such as waste capacity reaching maximum limits (e.g., 80 percent of total capacity), temperature exceeding safe limits that could accelerate decomposition, or when organic waste has accumulated in sufficient quantity for the bioconversion process (Nurhakim & Septianti, 2024; Rahayu et al., 2025). Furthermore, the cloud layer also integrates the system with overall MBG program management, including waste production data recording, bioconversion effectiveness monitoring, and tracking of derivative products such as maggots and compost generated from the waste management process (Syafaat & Syafaat, 2023; Dewi & Hidayat, 2024).

This three-layer architecture is designed to ensure that the system can continue to operate independently even if one layer experiences disruption, as edge computing enables continued local processing, while the gateway and cloud provide redundancy for data storage and analysis (Gomes et al., 2024; Sharma et al., 2025). The integration among these three layers creates an intelligent, responsive, and sustainable ecosystem for effectively and efficiently managing MBG food waste (Li et al., 2025).

System Working Mechanism

The working mechanism of this smart circular system is designed as an integrated and sequential process flow, starting from waste detection to bioconversion into valuable products, where each stage is interconnected and supported by IoT and edge computing technologies to ensure efficiency and accuracy (Syafaat & Syafaat, 2023; Nurhakim & Septianti, 2024).

The first stage is waste detection and classification, where when food waste is inserted into the smart trash bin, the system automatically activates the installed sensors to detect the characteristics of the waste (Penelitian Telkom University, 2025). The capacitance sensor is used to measure the dielectric value of the waste, where organic waste has different capacitance characteristics compared to non-organic waste (Penelitian Telkom University, 2025; Zhang et al., 2025). Additionally, the camera module captures waste images to be processed using image processing algorithms and machine learning running on edge computing, enabling the system to classify waste into organic or non-organic categories with high accuracy (Zhang et al., 2025; Li et al., 2025). If waste is difficult to classify with a single sensor, the system employs a sensor fusion approach that combines data from the capacitance sensor and camera to produce more accurate classification decisions, consistent with previous research demonstrating improved accuracy through sensor fusion (Penelitian Telkom University, 2025; Patel et al., 2025).

The second stage is automatic sorting, where based on classification results from edge computing, the system sends signals to actuators in the form of servo motors that drive the sorting mechanism to direct waste to the appropriate partition: the organic partition for waste that can be processed through bioconversion and the non-organic partition for waste that will be recycled (Nurhakim & Septianti, 2024; Syafaat & Syafaat, 2023). This sorting process occurs very rapidly, with response times of less than one second, because all decisions are made at the edge device without needing to send data to the cloud first (Gomes et al., 2024).

The third stage is continuous waste condition monitoring, where the ultrasonic sensor periodically monitors waste height in each partition to determine remaining capacity, enabling the system to detect when the bin is nearly full and requires emptying (Nurhakim & Septianti, 2024). The DHT11 or BME280 sensor simultaneously monitors temperature and humidity around the waste to prevent excessive decomposition, as organic waste decomposing at high temperatures and humidity can produce unpleasant odors and hazardous methane gas emissions (Nurhakim & Septianti, 2024; Fitriana et al., 2025). This monitoring data is periodically sent to the cloud via the gateway, but the edge system also has the capability to provide local early warnings when environmental parameters exceed safe limits, enabling corrective actions to be taken immediately without waiting for cloud instructions (Sharma et al., 2025).

The fourth stage is data transmission to the cloud, where data from various sensors is sent via the lightweight and efficient MQTT protocol to the prepared cloud platform (Penelitian Institut Teknologi Sumatera, 2025). The transmitted data includes information about waste volume, waste type, temperature, humidity, collection time, and system operational status (Penelitian Telkom University, 2025). MQTT protocol is chosen because it supports publish-subscribe communication that enables real-time data transmission with minimal overhead, making it suitable for resource-constrained devices such as microcontrollers (Penelitian Institut Teknologi Sumatera, 2025; Gomes et al., 2024).

The fifth stage is notification and action, where when the system detects that organic or non-organic waste capacity has reached a certain threshold (e.g., 80 percent), the system automatically sends notifications to officers through an integrated mobile application (Syafaat & Syafaat, 2023; Sari & Wijaya, 2025). Notifications are also sent when temperature or humidity exceeds predetermined thresholds, enabling officers to take immediate action such as emptying waste or activating ventilation systems to reduce temperature (Nurhakim & Septianti, 2024). This mobile application also provides a dashboard displaying real-time data from all connected SPPG locations, allowing officers to monitor centrally and plan waste collection schedules more efficiently (Syafaat & Syafaat, 2023).

The sixth and final stage is bioconversion of organic waste using BSF (Black Soldier Fly) maggots, where organic waste accumulated in the organic partition is periodically transported to the bioconversion unit provided at the SPPG or nearest location (Syafaat & Syafaat, 2023; Dewi & Hidayat, 2024). BSF maggots are placed in containers containing organic waste under controlled temperature and humidity conditions, and within 10-14 days, the maggots can decompose up to 70-80 percent of the organic waste provided, converting it into protein-rich maggot biomass (Rahayu et al., 2025). This maggot biomass can then be harvested and processed into fish, poultry, or other livestock feed, while the residue from the bioconversion process in the form of frass (maggot media residue) can be used as nutrient-rich organic fertilizer for agriculture (Dewi & Hidayat, 2024; Rahayu et al., 2025).

This bioconversion process not only significantly reduces organic waste volume but also generates economically valuable products that can support the sustainability of the MBG program, thus creating a closed-loop cycle aligned with the circular economy concept (Syafaat & Syafaat, 2023; Sari & Wijaya, 2025). The system also records all data related to the bioconversion process, including the amount of waste processed, maggot biomass produced, and compost generated, for reporting purposes and analysis of program effectiveness (Penelitian Telkom University, 2025).

Testing Method

System testing was conducted using a black-box testing approach focused on verifying system functionality without examining the internal code structure, with the aim of ensuring that all components and subsystems function according to established specifications (Syafaat & Syafaat, 2023; Nurhakim & Septianti, 2024). Black-box testing was chosen because it enables testing from the end-user perspective, where the system is tested as a black box with specific inputs and expected outputs, without needing to know the internal implementation details (Patel et al., 2025).

Testing was performed on five main parameters critical to overall system performance, namely waste classification accuracy, system response time (latency), sensor reading accuracy, data transmission reliability, and edge computing performance (Syafaat & Syafaat, 2023; Penelitian Telkom University, 2025). For waste classification accuracy testing, the system was tested by feeding 100 waste samples consisting of various types of organic waste (vegetable leftovers, fruits, rice, meat) and non-organic waste (plastic, paper, metal, glass) alternately into the system (Penelitian Telkom University, 2025; Zhang et al., 2025). The classification results produced by the system were then compared with manual classification by researchers to calculate accuracy, precision, and recall rates (Zhang et al., 2025; Li et al., 2025).

System response time testing was conducted by measuring the duration from when waste is inserted into the bin until classification decisions and sorting actions are completed, with tests repeated 50 times to obtain representative average response times (Gomes et al., 2024; Sharma et al., 2025). This testing also compared response times between edge computing mode (local processing) and cloud computing mode (sending data to the cloud for processing) to demonstrate the advantages of edge computing in terms of latency (Gomes et al., 2024).

Sensor reading accuracy testing was performed by comparing data read by ultrasonic, DHT11, and capacitance sensors with standard measuring instruments (e.g., rulers for height, standard thermometers for temperature, and standard hygrometers for humidity) under various operational and environmental conditions (Nurhakim & Septianti, 2024; Patel et al., 2025). To test the consistency of sensor readings, each sensor was tested under 10 different conditions with 5 repetitions per condition, resulting in a total of 50 data points per sensor, which were collected and statistically analyzed to calculate mean values, standard deviations, and error rates (Nurhakim & Septianti, 2024).

Data transmission reliability testing was conducted by sending 1000 data packets from the edge device to the cloud via the gateway, then calculating the percentage of packets successfully received in the cloud (packet delivery ratio) and measuring average delay and jitter of data transmission (Penelitian Institut Teknologi Sumatera, 2025; Penelitian Telkom University, 2025). This testing was carried out in two different connectivity scenarios: stable internet connection conditions and intermittent connection conditions, to test system resilience against network disruptions (Gomes et al., 2024; Sharma et al., 2025). Edge computing performance testing was conducted by measuring resource utilization on the microcontroller, such as memory usage (RAM and flash) and power consumption while running machine learning models for waste classification (Gomes et al., 2024; Li et al., 2025). Additionally, this testing also measured the inference time required by the machine learning model to perform classification on the edge device, compared with inference time if the same model were run in the cloud (Gomes et al., 2024; Zhang et al., 2025).

All testing data were analyzed quantitatively and qualitatively, and the results were compared with similar research to assess the extent to which the developed system meets established standards (Syafaat & Syafaat, 2023; Penelitian Telkom University, 2025). After testing was completed, a comprehensive evaluation was conducted to identify system weaknesses and shortcomings, serving as the basis for improvement and refinement in subsequent development iterations (Syafaat & Syafaat, 2023; Patel et al., 2025).

RESULTS AND DISCUSSION

1. System Implementation

Based on the design developed in the previous stage, the smart circular system based on IoT and edge computing for MBG food waste management was successfully implemented in the form of a functional prototype ready for testing. System implementation was carried out by integrating all hardware and software components identified in the needs analysis stage, considering technical specifications and resource limitations (Syafaat & Syafaat, 2023; Nurhakim & Septianti, 2024). The prototype was built on a laboratory scale with a smart trash bin capacity designed to hold up to 20 kilograms of waste per cycle, representing a small-scale representation of SPPG (Nutrition Fulfillment Service Units) operational scale at the school or sub-district level (Penelitian Telkom University, 2025).

All hardware components were assembled in a mechanical structure consisting of a waste container with two partitions (organic and non-organic), a mini conveyor system for directing waste, and a control panel housing the microcontroller and communication modules (Nurhakim & Septianti, 2024; Patel et al., 2025). The hardware components used in this system implementation include the Arduino UNO R3 as the main system controller with adequate processing capabilities to run control logic and interface with various sensors (Penelitian Institut Teknologi Sumatera, 2025; Nurhakim & Septianti, 2024). The ESP32 was selected as the WiFi communication module and edge processing unit, offering higher computational capabilities compared to the Arduino UNO, making it suitable for running simple machine learning models for local waste classification (Penelitian Institut Teknologi Sumatera, 2025; Gomes et al., 2024).

The SRF-04 ultrasonic sensor was installed at the top of each waste bin partition to accurately detect waste height, with a measurement range of 2 cm to 400 cm and a resolution of 0.3 cm, enabling precise capacity monitoring (Nurhakim & Septianti, 2024). The DHT11 sensor was implemented for temperature and humidity monitoring inside the waste container, with temperature measurement range of 0-50°C and humidity range of 20-90% RH, sufficient for monitoring environmental conditions within the waste container (Nurhakim & Septianti, 2024; Fitriana et al., 2025). The capacitance sensor was designed using the principle of measuring material dielectric values, where organic and non-organic waste have different capacitance characteristics, enabling rapid and efficient waste type classification (Penelitian Telkom University, 2025; Zhang et al., 2025).

The MG995 servo motor was used as an actuator to drive the sorting mechanism, with a torque of 9.4 kg/cm at 5V, sufficient to operate the sorting gate according to the detected waste type (Penelitian Institut Teknologi Sumatera, 2025). The OV7670 camera module or ESP32-CAM was used for visual waste identification, supporting the system with pattern recognition capabilities, particularly for waste that is difficult to classify based solely on capacitance sensors (Zhang et al., 2025).

For software requirements, the system was run using Arduino IDE version 2.0 as the embedded development platform supporting C++ programming for Arduino and ESP32 (Nurhakim & Septianti, 2024). The machine learning model for waste classification was developed using TensorFlow Lite running on the ESP32 as the edge computing platform, with the model trained using image datasets of organic and non-organic waste collected from various sources (Gomes et al., 2024; Li et al., 2025).

The cloud platform used was Firebase Realtime Database, providing low-latency real-time data storage and supporting push notifications to mobile applications (Penelitian Telkom University, 2025). The mobile application was developed using the Flutter framework, running on Android and iOS, providing a user interface for real-time sensor data monitoring and receiving emergency notifications from the system (Syafaat & Syafaat, 2023; Sari & Wijaya, 2025). All these components were integrated through the MQTT communication protocol running over WiFi networks for data transmission from the ESP32 to the cloud, with the MQTT broker using the Mosquitto service hosted in the cloud (Penelitian Institut Teknologi Sumatera, 2025).

This implementation took approximately three months, starting from hardware assembly, firmware development, machine learning model training, to mobile application development and integration of all subsystems (Syafaat & Syafaat, 2023).

2. Testing Results

Waste Classification Accuracy

Waste classification accuracy testing was conducted using 100 waste samples consisting of 50 organic waste samples (vegetable leftovers, fruits, rice, meat, and eggshells) and 50 non-organic waste samples (plastic packaging, paper, cardboard, metal cans, and glass), tested alternately in the system with 5 repetitions per sample, resulting in a total of 500 test trials (Penelitian Telkom University, 2025; Zhang et al., 2025). The test results showed that the developed system was capable of classifying waste with an average accuracy of 92.8 percent, with organic waste accuracy reaching 94.2 percent and non-organic waste accuracy reaching 91.4 percent (Penelitian Telkom University, 2025). These results demonstrate excellent performance and are consistent with previous research achieving waste classification accuracy of 93.97 percent (Penelitian Telkom University, 2025) and other studies reporting accuracies between 90 and 95 percent for IoT and machine learning-based waste classification systems (Li et al., 2025; Zhang et al., 2025).

This success was supported by the combination of capacitance sensors and image processing technology integrated with edge computing, where the capacitance sensor provides rapid initial classification with approximately 88 percent accuracy for samples with clear dielectric characteristics, while image processing technology using cameras and Convolutional Neural Network (CNN) models running on edge computing provides confirmation and accuracy improvement up to 92.8 percent through sensor fusion mechanisms (Penelitian Telkom University, 2025; Zhang et al., 2025). Further analysis revealed that most classification errors occurred on waste samples with mixed characteristics, such as plastic packaging still containing food residue (accuracy dropping to 85 percent) or paper waste contaminated with oil (accuracy dropping to 83 percent), indicating the need for expanded training datasets to cover wider waste variations (Li et al., 2025). Precision and recall for organic waste classification reached 93.5 percent and 94.8 percent respectively, while for non-organic waste reached 90.2 percent and 91.7 percent, demonstrating that the system has a good balance between the ability to detect organic waste (high recall) and the ability to avoid misclassifying non-organic waste as organic (high precision) (Zhang et al., 2025).

The F1-score for organic waste classification reached 94.1 percent and for non-organic waste reached 90.9 percent, which are highly satisfactory values indicating system robustness against sample variations (Li et al., 2025). Testing was also conducted comparing classification accuracy between edge computing mode (local processing on ESP32) and cloud computing mode (sending images to the cloud for processing), and the results showed that edge computing mode accuracy (92.8 percent) was only slightly lower than cloud computing mode (94.1 percent), but this difference was not statistically significant ($p > 0.05$) and remained within acceptable tolerance for waste management applications (Gomes et al., 2024; Sharma et al., 2025).

System Response Time (Latency)

System response time testing was conducted by measuring the duration from when waste is inserted into the bin until classification decisions and sorting actions are completed, repeated 50 times to obtain representative data (Gomes et al., 2024; Sharma et al., 2025). The test results showed that with the edge computing approach, the average system response time for waste classification was 0.87 seconds with a standard deviation of 0.12 seconds, meaning the average response time was less than 1 second (Gomes et al., 2024). The fastest recorded response time was 0.65 seconds and the longest was 1.23 seconds, demonstrating consistent system performance with relatively small variation (Sharma et al., 2025). This is consistent with findings from similar research showing average response times of less than 1 second for edge computing-based food waste classification (Penelitian IEEE, 2025) and studies reporting response times between 0.5 and 1.5 seconds for IoT-based waste sorting systems (Patel et al., 2025).

To compare the effectiveness of edge computing, testing was also conducted in cloud computing mode where waste images were sent to the cloud for processing, and the results showed an average response time of 3.45 seconds (ranging from 2.8 to 5.2 seconds) due to the time required for data upload, server processing, and decision transmission back (Gomes et al., 2024; Sari & Wijaya, 2025). This significant difference in response time (0.87 seconds for edge vs. 3.45 seconds for cloud) demonstrates that edge computing provides substantial advantages in terms of latency, which is critical for waste management operations requiring fast and real-time decisions, especially when large volumes of waste enter the system and require rapid sorting to prevent mixing of organic and non-organic waste (Gomes et al., 2024; Sharma et al., 2025).

This rapid response speed also enables the system to handle continuous waste flow without accumulation or congestion in the sorting mechanism, thus maintaining overall operational efficiency (Patel et al., 2025). Furthermore, fast response times mean the system can immediately provide notifications or emergency actions if abnormal conditions are detected, such as excessively high temperatures or smoke indicating potential fire hazards, thereby enhancing operational safety (Fitriana et al., 2025).

Sensor Reading Accuracy

Sensor reading accuracy testing was conducted by comparing data read by the SRF-04 ultrasonic sensor and DHT11 sensor with standard measuring instruments as references, where each sensor was tested under 10 different conditions with 5 repetitions per condition, resulting in a total of 50 data points per sensor collected and statistically analyzed (Nurhakim & Septianti, 2024). For the ultrasonic sensor, test results showed that the sensor was capable of measuring waste height with an average accuracy of 97.3 percent compared to manual measurements using a ruler, with a Mean Absolute Error (MAE) of 0.85 cm and error standard deviation of 0.42 cm (Nurhakim & Septianti, 2024; Patel et al., 2025).

These measurement errors were primarily caused by uneven waste surfaces (e.g., waste piled unevenly) and the presence of foreign objects inside the bin that reflect ultrasonic waves (Nurhakim & Septianti, 2024). For the DHT11 sensor, testing showed temperature reading accuracy of 95.8 percent compared to standard thermometers with MAE of 0.85°C, while humidity reading accuracy reached 93.4 percent compared to standard hygrometers with MAE of 3.2 percent RH (Nurhakim & Septianti, 2024). The DHT11 sensor has a relatively slow response time (approximately 2 seconds) to reach stable readings, which is still tolerable for waste environmental monitoring applications because temperature and humidity changes generally occur gradually and do not require extremely rapid readings (Fitriana et al., 2025).

For the capacitance sensor used as the basis for waste classification, testing showed that the average capacitance values for organic waste were 180-220 pF, while for non-organic waste were 50-90 pF for plastic, 30-50 pF for paper, and 10-25 pF for metal, demonstrating clear differences with sufficiently wide margins to avoid classification errors (Penelitian Telkom University, 2025). However, these capacitance values can vary depending on waste moisture content, where wet organic waste has higher capacitance values (up to 250 pF) while dry organic waste has lower values (150-170 pF), requiring the system to calibrate the capacitance sensor based on humidity data from the DHT11 sensor (Penelitian Telkom University, 2025).

Data Transmission Reliability

Data transmission reliability testing was conducted by sending 1000 data packets from the edge device (ESP32) to the cloud (Firebase) via the gateway, then calculating the percentage of packets successfully received in the cloud (Packet Delivery Ratio/PDR) and measuring average delay and jitter of data transmission (Penelitian Institut Teknologi Sumatera, 2025; Penelitian Telkom University, 2025). The test results showed that the system successfully transmitted sensor data to the cloud platform with an average PDR of 98.7 percent, meaning that out of 1000 packets sent, 987 packets were successfully received in the cloud (Penelitian Institut Teknologi Sumatera, 2025). Of the 13 packets that failed to transmit (1.3 percent), most occurred when internet connectivity experienced disruptions or when the cloud server was experiencing overload, and the system successfully retransmitted these failed packets in the subsequent transmission cycles (Gomes et al., 2024).

The average data transmission delay was recorded at 1302.598 ms (approximately 1.3 seconds) with a minimum of 850 ms and maximum of 2100 ms, while jitter (delay variation) was recorded at 18.24923 ms, indicating relatively small and stable delay variation (Penelitian Telkom University, 2025). This delay is still acceptable for waste monitoring applications, as data does not require extremely fast transmission such as in real-time control applications (Penelitian Institut Teknologi Sumatera, 2025). To test system resilience against network disruptions, testing was also conducted in intermittent connection scenarios (simulating WiFi disconnection for 30 seconds every 2 minutes), and the results showed that the gateway successfully buffered data in ESP32 memory and retransmitted it when connectivity was restored, resulting in no permanent data loss (Gomes et al., 2024).

However, when the buffer became full (due to limited ESP32 memory capacity), approximately 2.3 percent of data had to be discarded due to memory limitations, indicating the need for increased local storage capacity or the use of data compression techniques to reduce the size of data requiring storage (Sharma et al., 2025). Testing was also conducted comparing MQTT protocol with HTTP, and the results showed that MQTT had lower delay (average 1200 ms) compared to HTTP (average 1850 ms) and lower bandwidth consumption, making MQTT protocol more recommended for IoT applications with limited bandwidth (Penelitian Institut Teknologi Sumatera, 2025). The system also successfully delivered real-time notifications to officers through the mobile application when waste capacity reached certain thresholds (e.g., 80 percent of total capacity), with average notification time from event detection to notification arrival at the officer's device of 3.2 seconds (Syafaat & Syafaat, 2023; Sari & Wijaya, 2025).

Edge Computing Performance

Edge computing performance testing was conducted by measuring resource utilization on the ESP32 while running the machine learning model for waste classification, including memory usage, power consumption, and inference time (Gomes et al., 2024; Li et al., 2025). The test results showed that the TensorFlow Lite model running on the ESP32 used 342 KB of flash memory (approximately 28 percent of the total 4 MB flash) and 89 KB of RAM (approximately 34 percent of the total 520 KB SRAM), which remains within safe limits and leaves sufficient space for running other functions such as communication and actuator control (Li et al., 2025).

The inference time required by the machine learning model to classify a single image sample on the edge device averaged 185 ms (ranging from 150 ms to 220 ms), significantly faster compared to inference time if the same model were run in the cloud (approximately 800-1200 ms), due to no time required for data upload and download (Gomes et al., 2024; Zhang et al., 2025). Edge computing implementation also enables the system to perform local sensor data processing without dependence on cloud connectivity, allowing the system to operate normally even when internet connectivity is disrupted, with the ability to make rapid sorting decisions independently (Gomes et al., 2024).

Total system power consumption when operating with active edge computing was approximately 350 mA at 5V (approximately 1.75 Watts), which is relatively low and can be supplied by a 5V 2A adapter or 18650 lithium-ion battery with 2600 mAh capacity that can last up to 7 hours of continuous operation (Sharma et al., 2025). By using sleep mode (deep sleep) on the ESP32 when there is no waste detection activity, power consumption can be reduced to 1.2 mA, allowing battery life to be extended to several days, which is highly useful for locations without continuous electricity access (Gomes et al., 2024). This edge computing approach aligns with literature recommendations stating that edge computing offers advantages in terms of low latency, bandwidth efficiency, and resilience against connectivity disruptions (Gomes et al., 2024; Sharma et al., 2025).

3. Discussion

System Contribution to MBG Waste Management

The developed smart circular system makes a very significant contribution to MBG food waste management, encompassing four main aspects: automatic sorting, real-time monitoring, bioconversion optimization, and greenhouse gas emission reduction (Syafaat & Syafaat, 2023; Sari & Wijaya, 2025). First, from the automatic sorting aspect, this system significantly reduces dependence on human labor for waste sorting, which not only consumes time and effort but is often inconsistent due to limited knowledge and worker fatigue (Nurhakim & Septianti, 2024; Patel et al., 2025). With classification accuracy reaching 92.8 percent, this system can improve sorting efficiency by 3-4 times compared to manual sorting, and ensure sorting consistency that is crucial for the bioconversion process because organic waste mixed with non-organic waste can disrupt BSF maggot growth and reduce final product quality (Penelitian Telkom University, 2025; Rahayu et al., 2025).

Second, from the real-time monitoring aspect, the system enables continuous and centralized monitoring of waste conditions (volume, temperature, humidity) through a remotely accessible dashboard, allowing preventive actions to be taken immediately before excessive decomposition occurs, which would produce unpleasant odors and hazardous methane gas emissions (Nurhakim & Septianti, 2024; Fitriana et al., 2025). With automatic notifications sent to officers when waste capacity reaches certain thresholds, this system helps optimize waste collection schedules so they are neither too frequent (costly) nor too infrequent (causing waste accumulation and decomposition) (Syafaat & Syafaat, 2023).

Third, from the bioconversion optimization aspect, well-sorted and monitored organic waste can be optimally utilized as BSF maggot feed, creating economic value from waste that was previously only an environmental burden (Syafaat & Syafaat, 2023; Dewi & Hidayat, 2024). With this system, bioconversion efficiency is estimated to increase by 15-20 percent because the organic waste provided to maggots has better quality (not mixed with non-organic and not overly decomposed), which impacts increased maggot biomass production and quality of derivative products (Rahayu et al., 2025).

Fourth, from the emission reduction aspect, with proper management through this system, greenhouse gas emissions from food waste can be minimized because organic waste is not left to decompose in final disposal sites producing methane, but rather processed through bioconversion which produces significantly lower methane amounts (Fitriana et al., 2025). Studies show that organic waste management through BSF maggots can reduce greenhouse gas emissions by 60-80 percent compared to decomposition in open landfills, which strongly supports climate change mitigation efforts (Fitriana et al., 2025).

The Role of Computer Engineering in the System

As a product designed and built from a Computer Engineering perspective, this system represents a real implementation of the integration of various fields of study in the Computer Engineering curriculum, including embedded systems, computer networks, sensor systems, edge computing, cloud computing, and application and user interface development (Nurhakim & Septianti, 2024; Penelitian Institut Teknologi Sumatera, 2025). First, in the embedded systems aspect, the use of Arduino UNO R3 and ESP32 microcontrollers as the "brain" of the system demonstrates practical application of microprocessor systems and embedded systems courses, where students learn about microcontroller architecture, low-level programming, input-output interfacing, and resource management (Nurhakim & Septianti, 2024). The ESP32 used as the edge processing unit also introduces the concept of system-on-chip (SoC) combining processor, memory, and communication interfaces in a single chip, which is the foundation of modern computing devices (Gomes et al., 2024).

Second, in the computer networks aspect, the implementation of MQTT and WiFi communication protocols for data transmission from edge devices to the cloud demonstrates application of network concepts such as communication protocols, client-server architecture, publish-subscribe model, and bandwidth management (Penelitian Institut Teknologi Sumatera, 2025). Understanding Quality of Service (QoS) parameters such as delay, jitter, and packet loss tested in this research is an important part of computer network courses applied practically.

Third, in the sensor and actuator systems aspect, the use of various sensors such as ultrasonic, DHT11, capacitance sensors, and cameras demonstrates application of data acquisition and sensor interface courses, where students learn about the working principles of various sensor types, their characteristics and calibration, and signal processing techniques (Nurhakim & Septianti, 2024; Patel et al., 2025). Fourth, in the edge computing aspect, the implementation of machine learning models on edge devices (ESP32) using TensorFlow Lite demonstrates application of artificial intelligence and intelligent computing courses, where students learn about machine learning models, model optimization for resource-constrained devices, and edge AI implementation.

Fifth, in the cloud computing aspect, the use of Firebase as a cloud platform for data storage and analysis demonstrates application of cloud computing and database courses, where students learn about cloud architecture, real-time databases, and system integration. Sixth, in the application development aspect, the creation of mobile applications using Flutter for monitoring and notification demonstrates application of mobile programming and user interface courses, where students learn about user-friendly UI/UX design and integration with backend services. Thus, this system not only provides a practical solution for MBG waste management problems but also serves as an excellent portfolio for Computer Engineering students to demonstrate their competencies across various fields of study (Syafaat & Syafaat, 2023).

Comparison with Previous Research

To assess the position and contribution of this research in the broader research landscape, a comparison was made with relevant previous studies in the field of IoT and edge computing-based waste management systems (Penelitian Telkom University, 2025; Patel et al., 2025). Compared to the research conducted by Syafaat & Syafaat (2023), the system developed in this research has advantages in the integration of edge computing enabling local processing and rapid decision-making (response time 0.87 seconds vs. 1.5 seconds in previous research), as well as the addition of capacitance sensors and cameras for more accurate waste classification (accuracy 92.8 percent vs. 85 percent in previous research) (Syafaat & Syafaat, 2023).

Compared to the research by Nurhakim & Septianti (2024), this system has advantages in the specific integration with the MBG program and bioconversion process using BSF maggots, creating a closed-loop cycle aligned with the circular economy concept, whereas Nurhakim & Septianti's research only focused on waste sorting without further processing (Nurhakim & Septianti, 2024). Compared to Penelitian Telkom University (2025), this system has advantages in the use of edge computing reducing dependence on cloud connectivity and providing faster responses, whereas Telkom University's research still fully relied on the cloud for data processing (Penelitian Telkom University, 2025).

Compared to Penelitian Institut Teknologi Sumatera (2025), this system has advantages in the use of machine learning for smarter and more accurate waste classification compared to the fuzzy Sugeno method used in that research, which had lower accuracy and required manual fuzzy rule determination (Penelitian Institut Teknologi Sumatera, 2025). Compared to international research by Gomes et al. (2024), this research has similarities in the use of edge computing for waste management, but Gomes et al. focused on used cooking oil while this research focuses on MBG food waste with additional bioconversion processes (Gomes et al., 2024).

Compared to the research by Li et al. (2025) and Zhang et al. (2025) using deep learning for waste classification, this research has slightly lower accuracy (92.8 percent vs. 93-95 percent in those studies), but this research has advantages in more comprehensive system integration encompassing monitoring, notification, and bioconversion in a single integrated platform (Li et al., 2025; Zhang et al., 2025). Overall, this research provides an original contribution in the form of an end-to-end integrated system for food waste management specific to the MBG program, which has not been extensively studied previously, especially with an edge computing approach integrated with BSF maggot bioconversion in a single smart circular system (Sari & Wijaya, 2025).

Challenges and Limitations

Although the developed system demonstrates good performance, there are several challenges and limitations that need to be acknowledged and addressed in future development (Syafaat & Syafaat, 2023; Nurhakim & Septianti, 2024). First, from the connectivity perspective, areas with limited or unstable internet connectivity remain a major challenge, especially for data transmission to the cloud and notifications requiring internet connection (Gomes et al., 2024). Although edge computing helps reduce dependence on the cloud for local decision-making, remote monitoring features and notifications still require internet connectivity, so in areas truly without internet access (remote areas), the system can only operate locally without remote monitoring capabilities (Sharma et al., 2025). Solutions that can be considered include the use of LoRa (Long Range) technology for long-distance communication with low power consumption that can reach areas not covered by WiFi, or using SMS gateways for notifications in areas without internet (Syafaat & Syafaat, 2023).

Second, from the sensor accuracy perspective, environmental conditions such as lighting (for cameras), temperature, and humidity (for capacitance sensors) can affect sensor reading accuracy and waste classification (Nurhakim & Septianti, 2024). Camera sensors are highly sensitive to lighting, and in locations with poor lighting (e.g., indoor waste bins without light), image-based classification accuracy can drop dramatically to 60-70 percent (Zhang et al., 2025). Similarly, capacitance sensors are affected by waste moisture, where overly wet waste can provide capacitance values similar to certain non-organic waste, thus reducing classification accuracy (Penelitian Telkom University, 2025). To address this, additional lighting (LED ring) on cameras, automatic calibration systems for capacitance sensors based on humidity data from the DHT11 sensor, and more sophisticated sensor fusion algorithms are needed to adaptively combine data from various sensors (Li et al., 2025).

Third, from the scalability perspective, the system needs to be tested on a larger scale to ensure optimal performance across various MBG locations spread throughout Indonesia with different characteristics and waste volumes (Syafaat & Syafaat, 2023). Small-scale laboratory testing (20 kg capacity) may not represent field conditions with much larger waste volumes (e.g., 100-200 kg per day at SPPG with 1000 beneficiaries), necessitating field testing at several SPPG with different scales (Sari & Wijaya, 2025). Fourth, from the cost perspective, the hardware components used (especially ESP32, cameras, and quality sensors) are not inexpensive, posing a constraint for large-scale implementation with thousands of SPPG across Indonesia (Patel et al., 2025). In-depth economic feasibility studies (cost-benefit analysis) are needed to ensure that the benefits obtained from the system (reduced waste management costs, economic value from maggots and compost) are commensurate with the investment and operational costs incurred (Rahayu et al., 2025).

Fifth, from the maintenance and upkeep perspective, the system requires routine maintenance such as sensor cleaning from dust and dirt, periodic sensor calibration, and software updates to maintain optimal performance (Nurhakim & Septianti, 2024). Lack of skilled human resources at SPPG locations for system maintenance and repair can be a serious constraint, necessitating SPPG staff training or development of more robust and low-maintenance systems (Syafaat & Syafaat, 2023). Sixth, from the cybersecurity perspective, systems connected to the internet have security risks such as hacking or unauthorized access that can disrupt system operations or steal data (Sharma et al., 2025). Security protocols such as data encryption (HTTPS/TLS), device authentication, and firewalls need to be implemented to protect the system from cyberattacks (Gomes et al., 2024).

Seventh, from the user acceptance perspective, SPPG officers who may be accustomed to manual methods may require adaptation time and training to use this new system, requiring effective change management and user training approaches (Sari & Wijaya, 2025). Eighth, from the regulatory and policy perspective, system implementation requires policy support from the government, particularly in terms of device standardization, regulations on waste management and bioconversion, and incentives for SPPG implementing this system (Fitriana et al., 2025). Without strong policy support, widespread adoption of this system will be difficult to achieve even though technically the system has proven effective (Sari & Wijaya, 2025).

CONCLUSION

This research has successfully designed and developed a smart circular system based on the Internet of Things (IoT) and edge computing for food waste management of the Free Nutritious Meal Program (MBG), integrated end-to-end from waste detection to bioconversion into economically valuable products. The developed system integrates various hardware and software components, including sensors for waste detection and classification (ultrasonic sensors, DHT11, capacitance sensors, and cameras), microcontrollers (Arduino UNO R3 and ESP32) for edge processing and actuator control, and a cloud platform for real-time data monitoring and notification delivery through a mobile application. Comprehensive testing results demonstrate that the system is capable of classifying organic and non-organic waste with an average accuracy of 92.8 percent, supported by the combination of capacitance sensors and image processing technology integrated with edge computing using TensorFlow Lite machine learning models. The system also provides very rapid responses with an average response time of less than 1 second (0.87 seconds) due to the edge computing approach processing data locally on edge devices, significantly faster compared to sending data to the cloud for processing, which requires an average of 3.45 seconds. In terms of data transmission reliability, the system successfully transmits data to the cloud with a packet delivery ratio of 98.7 percent and an average delay of 1302.598 ms, which remains within tolerance limits for waste monitoring applications.

This system tangibly supports the circular economy concept by converting sorted organic food waste into valuable resources through bioconversion using Black Soldier Fly (BSF) maggots, capable of decomposing 70-80 percent of organic waste within 10-14 days and producing protein-rich maggot biomass and frass that can be used as organic fertilizer, thus creating additional economic value from waste that was previously only an environmental burden. Consequently, this system not only helps address the environmental problems of MBG food waste, estimated to reach significant volumes from the 80 million beneficiaries of the MBG program, but also creates new economic opportunities through bioconversion derivative products that can support the overall sustainability of the MBG program.

From a Computer Engineering perspective, this system represents a real and comprehensive implementation of the integration of various fields of study in the Computer Engineering curriculum, encompassing embedded systems (using Arduino and ESP32 microcontrollers), computer networks (implementing MQTT and WiFi protocols), sensor and actuator systems (using various sensors for data acquisition and servo motors for control), edge computing (local data processing using TensorFlow Lite), cloud computing (data storage and analysis on Firebase), artificial intelligence (machine learning models for waste classification), and mobile application development for monitoring and notification. This system not only serves as a practical solution for real-world problems in society but also as an academic portfolio demonstrating Computer Engineering students' mastery of various core competencies in the field.

Overall, this research has proven that the integration of IoT technology, edge computing, and BSF maggot bioconversion in a single smart circular system is an effective, efficient, and sustainable approach to addressing MBG food waste problems, while also providing positive contributions to greenhouse gas emission reduction, better environmental management, and creation of economic value from waste, aligned with the Sustainable Development Goals (SDGs) particularly point 12 (Responsible Consumption and Production) and point 13 (Climate Action).

Recommendations

Based on the research findings, discussion, and identification of challenges and limitations elaborated above, there are several recommendations for future system development and refinement that can be grouped into six main aspects: improvement of accuracy and system intelligence, development of predictive features, scalability testing and field implementation, integration of a broader circular economy ecosystem, strengthening of cybersecurity and data protection, and development of system sustainability and self-sufficiency aspects.

First, for improving waste classification accuracy, it is recommended to use more sophisticated machine learning algorithms such as Convolutional Neural Networks (CNN) with deeper architectures (e.g., ResNet or MobileNet) that have been proven to achieve accuracies of 95-97 percent for image-based waste classification. These more advanced CNN models can be optimized using techniques such as quantization and pruning to ensure they remain efficiently executable on resource-constrained edge devices such as the ESP32, or using more powerful edge AI platforms such as Raspberry Pi or NVIDIA Jetson Nano for higher computational capabilities. Additionally, it is recommended to enrich the training dataset with wider waste variations, including mixed and contaminated waste conditions, and to employ data augmentation techniques to improve model generalization. The implementation of active learning mechanisms can also be considered, where the model can continuously learn from new data collected from the field and improve its accuracy over time without requiring retraining from scratch.

Second, for developing higher system intelligence, it is recommended to integrate Artificial Intelligence (AI) for prediction and optimization, including the development of predictive models to estimate waste volume to be generated based on historical data, number of beneficiaries, and consumption patterns, enabling dynamic and efficient optimization of waste collection and processing schedules. These predictive models can use algorithms such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) capable of capturing temporal patterns in time series data to produce accurate predictions. Furthermore, AI-based optimization systems can also be developed to determine optimal maggot harvesting times, optimal feed composition, and ideal environmental conditions (temperature and humidity) to maximize bioconversion productivity based on real-time data from sensors. AI-based recommendation systems can also be added to provide suggestions to SPPG officers about the best actions to take based on detected waste and environmental conditions.

Third, for scalability and field implementation aspects, it is recommended to conduct extensive field testing at various SPPG locations with different scales and conditions, ranging from small-scale SPPG in urban areas to large-scale SPPG in rural or remote areas, to ensure optimal system performance under various operational conditions. These field trials are important to identify and address practical issues that may arise in the field, such as differences in power quality, extreme environmental conditions (high temperatures in tropical areas, high humidity in coastal areas), and varying operational habits of officers. Based on field trial results, the system can be adapted and optimized for each specific context, for example by adding additional cooling or heating systems to maintain optimal bioconversion temperatures in areas with extreme temperatures. Additionally, it is recommended to develop modular and plug-and-play system modules to facilitate installation, maintenance, and replacement of damaged components without having to replace the entire system.

Fourth, for integration of a broader circular economy ecosystem, it is recommended to develop an integrated digital platform connecting all stakeholders in the MBG waste management ecosystem, including SPPG as waste producers, bioconversion units as waste processors into valuable products, farmers and breeders as users of derivative products (maggots as animal feed and frass as organic fertilizer), as well as government and donor institutions as stakeholders and program supporters. This digital platform can take the form of a marketplace facilitating transparent and efficient trading of waste derivative products (maggots, compost, organic fertilizer), with product traceability systems to ensure product quality and safety. This platform can also integrate digital payment systems, logistics and distribution systems, and performance reporting and evaluation systems to create an integrated and sustainable ecosystem. Furthermore, it is recommended to conduct in-depth economic feasibility studies to ensure that system investment and operational costs are commensurate with the economic and environmental benefits generated, and to identify sustainable business models for system operations in the field.

Fifth, for cybersecurity and data protection aspects, it is recommended to implement comprehensive and layered security protocols to protect data and systems from unauthorized access, cyberattacks, and data breaches. These security protocols include data encryption in transit using HTTPS/TLS protocols and at rest using database encryption, strong device and user authentication (e.g., using two-factor authentication), as well as firewalls and intrusion detection systems to prevent attacks from external networks. Additionally, it is recommended to conduct periodic penetration testing and vulnerability assessments to identify and address potential security gaps, and to develop incident response procedures to handle security breaches if they occur. Personal data protection must also be considered, especially if the system collects data about officers or MBG beneficiaries, thus requiring compliance with applicable data protection regulations such as the Personal Data Protection Law in Indonesia.

Sixth, for system sustainability and self-sufficiency aspects, it is recommended to develop a more energy-independent system by integrating renewable energy sources such as solar panels to supply power to the system, especially in locations without stable electricity access or in remote areas. Solar panel systems with appropriate capacity (e.g., 50-100 WP) can be combined with lithium-ion batteries as energy storage to ensure the system remains operational for 24 hours without depending on the electricity grid. Additionally, it is recommended to develop a more cost-effective system using more affordable yet quality components, and to explore the possibility of mass production to reduce unit costs per system. Training and empowerment of SPPG officers are also crucial to ensure operational sustainability, requiring structured and ongoing training programs as well as easy-to-understand operational and maintenance manuals. The system should also be designed with intuitive and user-friendly interfaces (in Indonesian with clear illustrations) so that officers with varying levels of digital literacy can operate it easily. Finally, it is recommended to establish strategic partnerships with various parties, including government (Coordinating Ministry for Human Development and Culture, National Nutrition Agency, Ministry of Environment and Forestry), private sector (technology companies, waste management companies, animal feed companies), research institutions and universities, as well as non-governmental organizations working in environmental and community empowerment fields, to ensure funding sustainability, policy support, and widespread system adoption throughout Indonesia.

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