Artificial Intelligence and Computing Innovations
Intelligence Science Publishing
https://www.ispublishing.com
ISSN: 3070-4944
Vo.6, No.3, 2026

IoT-Based Intelligent Trash Can Monitoring System for Scenic Areas Using Multi-Sensor Detection and LoRa Communication

Caelan Redford[1], Mireille Fenwick[1]

[1] *Thompson Rivers University, Kamloops, Canada*

**Corresponding Author: Caelan Redford; caelan.redford0@gmail.com*

Abstract: Traditional manual inspection of trash cans in scenic areas often faces low efficiency, delayed anomaly detection, and high maintenance costs due to the wide distribution of bins and complex terrain. To address these issues, this paper designs an intelligent trash can monitoring system based on the Internet of Things (IoT) that integrates multi-sensor fusion and low-power wide-area communication technology. The proposed system employs ultrasonic and pressure sensors to monitor the overflow state in real time, while temperature and orientation sensors detect fire and tilting anomalies. The STM32F103 microcontroller serves as the main control unit, responsible for data acquisition and system coordination. The collected data are transmitted via a LoRa communication module, enabling long-distance and low-power data exchange across mountainous scenic environments. The software design includes real-time sensing, data fusion, and event-triggered communication to enhance energy efficiency and response speed. Experimental validation demonstrates that the system can accurately detect overflow, fire, and tilt states, providing reliable real-time monitoring and alerting. This solution significantly improves the management efficiency of waste collection in scenic areas and supports the sustainable development of smart tourism infrastructure.

Keywords: Internet of Things (IoT); Multi-sensor fusion; LoRa communication; Ultrasonic sensing; Smart scenic management; Environmental monitoring; Low-power system design

1. Introduction

With the accelerated development of Internet of Things (IoT) technologies and their deep integration into urban infrastructure, intelligent waste management systems have demonstrated significant application value in smart city construction. Existing research has primarily focused on urban waste classification systems [1]. However, a research gap remains regarding intelligent management solutions for trash cans in specialized scenarios, particularly in tourist attractions characterized by complex terrain features and strict environmental protection requirements [2].

Current manual inspection methods in scenic areas face three prominent challenges: Firstly, traditional fixed periodic inspection pattern leads to operational inefficiency. Secondly, delayed detection of abnormal conditions, such as trash can tilting or catching fire, bring security risks. Thirdly, the distribution of trash cans in large scenic spots is scattered. Some research use 5G or WiFi communication methods, but the former has a high maintenance cost, and the latter cannot solve the problem of long-distance communication in scenic spots.

To address these limitations, this study proposes a IoT-based detection system integrating multi-sensor and low-power wide-area network (LPWAN) technologies [3]. Main research includes: (1) Combined with ultrasonic ranging and pressure sensor, the system can detect the overflow state of the trash can in real time; (2) The system can detect the abnormal state of tilting and catching fire in real time; (3) The wireless communication solution based on LoRa can effectively overcome the signal attenuation problem in mountainous terrain.

2. Related work

Early research on intelligent waste monitoring systems established the technological foundation for sensor-enabled waste management infrastructures. Previous studies [4] introduced sensorized waste containers capable of estimating fill levels and enabling optimized collection scheduling through embedded sensing devices. Similarly, earlier work [5] proposed a monitoring framework integrating identification technologies and wireless communication for real-time waste tracking. Subsequent research [6] further demonstrated the feasibility of integrating sensing devices with communication modules for automated bin monitoring, highlighting the importance of embedded sensing architectures for large-scale waste management systems.

Subsequent work extended these early infrastructures by exploring distributed sensing networks and system-level architectures. A wireless sensor network-based architecture for solid waste monitoring was proposed in [7], enabling distributed data acquisition and centralized management. Another study developed the SmartBin system, which integrates sensor-based fill-level detection with communication technologies to support intelligent waste collection [8]. In addition, the concept of self-describing objects in smart waste management environments was introduced in [9], allowing sensor nodes to autonomously provide contextual information and improving interoperability within IoT infrastructures. These studies collectively demonstrate the feasibility of combining sensing devices, embedded processors, and wireless communication to construct intelligent monitoring systems.

Beyond sensing infrastructures, research has also explored the integration of dynamic decision mechanisms within smart waste management systems. Dynamic modeling approaches for prioritizing waste collection operations were investigated in [10], highlighting the importance of real-time monitoring data in optimizing collection efficiency. A later survey on IoT-enabled waste management [11] systematically summarized the challenges and opportunities associated with integrating sensing technologies, communication networks, and intelligent management strategies within smart city environments. Complementary studies have also analyzed broader waste management and recycling frameworks, emphasizing the importance of technological solutions for improving sustainability and operational efficiency [12].

Reliable communication infrastructure is another essential component for large-scale IoT monitoring systems. Low-power wide-area network (LPWAN) technologies have emerged as effective solutions for long-distance communication with minimal energy consumption. Early comprehensive analyses of LoRa communication technology demonstrated its suitability for low-power IoT deployments [13]. Subsequent studies further examined the performance characteristics and limitations of LoRaWAN networks, including scalability and communication constraints in dense deployments [14], [15]. These communication frameworks provide the technical foundation for implementing long-distance wireless data transmission in distributed monitoring environments. In addition, the integration of IoT devices with cloud computing infrastructures has been widely investigated as a means of enabling scalable data management and system coordination, as demonstrated by the Cloud of Things framework [16].

While early IoT systems primarily focused on data collection and transmission, recent studies have increasingly incorporated intelligent modeling techniques to enhance data analysis and system reliability. Time-series modeling approaches have been developed to address the challenges of non-stationary environmental data. For example, a residual-regulated machine learning framework for time-series forecasting was proposed in [17], improving prediction accuracy under dynamic conditions. Similarly, attention-driven deep learning models have been applied to detect anomalies in complex data pipelines, enabling more robust monitoring and fault detection mechanisms [18]. Adaptive spatiotemporal modeling techniques have also been introduced to identify abnormal behaviors in large-scale distributed systems by capturing dependency drift within evolving data environments [19].

Graph-based learning methods have further advanced the modeling of complex system interactions. A structure-temporal collaborative anomaly detection framework capable of capturing structural relationships and temporal dependencies simultaneously was proposed in [20]. Subsequent work introduced self-supervised spatiotemporal graph modeling techniques for identifying performance degradation in distributed service environments [21]. In addition, adaptive graph construction mechanisms combined with contrastive learning have been developed to improve system monitoring and anomaly detection capabilities [22]. These approaches demonstrate the effectiveness of graph-structured modeling in representing complex system interactions and extracting meaningful patterns from high-dimensional monitoring data.

Several studies have also explored graph neural network architectures and distributed training strategies for large-scale data environments. Research has demonstrated the potential of graph neural networks in modeling structural dependencies for routing optimization tasks [23]. A graph-structured deep learning framework for multi-task identification in high-dimensional environments was proposed in [24], highlighting the ability of graph-based representations to capture complex dependencies across multiple metrics. To address the scalability challenges associated with graph learning, a communication-efficient distributed training approach based on on-the-fly graph condensation was introduced in [25], significantly reducing communication overhead in distributed learning systems.

In addition to graph-based learning, sequence modeling and representation learning techniques have been widely explored for anomaly detection and pattern recognition tasks. A deep learning framework analyzing sequential patterns in protocol status codes was proposed in [26] for detecting abnormal behaviors. Meanwhile, a semantics-aware denoising strategy leveraging pretrained language models was introduced in [27] to improve training robustness through sample reweighting mechanisms. These techniques highlight the potential of advanced representation learning strategies in improving system monitoring and anomaly detection performance.

Recent developments in large-scale model optimization have further enhanced the adaptability and reliability of intelligent systems. Dynamic prompt fusion techniques have been proposed to improve cross-domain generalization capabilities in large language models [28]. Risk-aware learning mechanisms have also been introduced to enhance the reliability of automated decision systems by incorporating uncertainty quantification during model inference [29]. In addition, transformer-based modeling frameworks have demonstrated strong capabilities in capturing heterogeneous data dependencies through attention mechanisms [30]. Generative modeling techniques based on diffusion processes have further expanded the ability of machine learning systems to model complex structures and conditional dependencies [31].

Collectively, these studies provide a comprehensive methodological foundation for the proposed system. Early research on sensor-based waste monitoring establishes the feasibility of deploying distributed sensing infrastructures for intelligent waste management. Advances in IoT communication technologies enable reliable long-distance data transmission with minimal energy consumption. Meanwhile, recent developments in machine learning, graph modeling, and representation learning provide powerful tools for extracting insights from complex monitoring data and improving system reliability. By integrating these methodological principles, the proposed approach combines multi-sensor data acquisition, LPWAN communication, and intelligent data analysis to construct an efficient and scalable monitoring framework for waste management in distributed environments.

3. Overall System Design

In order to address the problems of trash can overflow and the inefficiency of traditional fixed periodic manual inspection, an intelligent trash can monitoring system is designed. The proposed system integrates three main functional modules: overflow state detection, abnormal state detection, and a wireless communication subsystem. Specifically, overflow detection is achieved by applying ultrasonic distance sensing together with pressure sensing to estimate the filling level of the trash can. Abnormal state detection focuses on identifying hazardous situations such as fire and bin tilting through temperature sensing and orientation monitoring. The communication subsystem adopts a LoRa-based low-power wide-area communication mechanism to enable reliable long-distance data transmission in complex scenic environments.

From the methodological perspective, the abnormal monitoring mechanism of the system builds upon the IoT anomaly detection framework proposed in [32], which introduces a federated contrastive representation learning model for heterogeneous IoT data environments. The core idea of this method is to apply contrastive representation learning to distinguish normal and abnormal device behaviors by learning discriminative feature embeddings. Normal operational patterns are aggregated as compact clusters in the learned representation space, while anomalous behaviors are separated through contrastive objectives. Furthermore, the framework leverages federated learning to support distributed collaborative training among IoT devices, enabling anomaly detection under heterogeneous sensing conditions without centralized data aggregation.

Inspired by these methodological principles, the proposed system adopts and incorporates the concept of distributed anomaly perception within the IoT sensing architecture. Rather than implementing a full federated learning pipeline, the system leverages the representation-based anomaly discrimination concept to design a lightweight multi-sensor anomaly detection strategy. By integrating temperature sensing, orientation sensing, and fill-level sensing signals, the system builds upon the principle of distinguishing normal and abnormal states, enabling reliable identification of fire hazards and abnormal tilting events. The overall architecture of the system is illustrated in Figure 1.

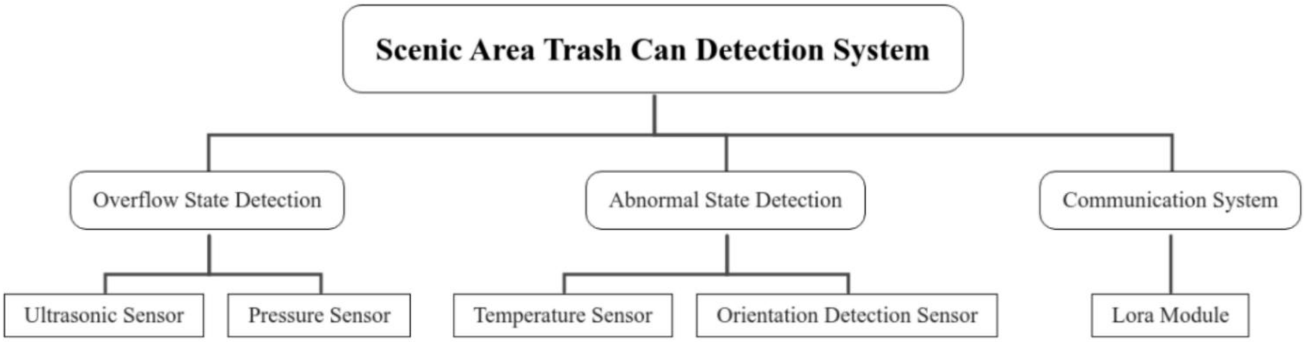

Figure 1. Overall design of scenic area trash can detection system

The overflow state detection function is mainly composed of ultrasonic sensor and pressure sensor. The ultrasonic sensor emits ultrasonic waves into the inside of the trash can, and the ultrasonic wave is reflected after encountering the trash, and the sensor receives the echo. The real-time distance from the sensor to the trash surface, is calculated by measuring the time difference between the emission and reception of the sound wave. The pressure sensor is installed at the bottom of the trash can to detect the weight of the trash in real time. The microprocessor integrates the real-time data of the ultrasonic sensor and the pressure sensor, calculates the space occupation of the trash can in real time.

Abnormal state detection mainly includes temperature sensor and orientation detection sensor. The temperature sensor can detect the temperature state inside the trash can in real time to avoid the spontaneous combustion of trash caused by high ambient temperature or improperly discarded cigarette butts. The orientation detection sensor can detect the tilting state of the trash can caused by high winds or human factors.

The communication system is mainly composed of LoRa communication module, which is used for updating the detection results of overflow state and abnormal state to the system in real time. It's a lower-power method to realize the long-distance wireless communication of the scenic spot.

4. System Hardware Design

4.1 Overflow State Detection

The hardware of overflow state detection function is mainly composed of the main control chip, ultrasonic sensor and pressure sensor. The main control chip adopts STM32F103, which has rich peripheral resources and is cost-effective, meeting the needs of the system. The ultrasonic sensor HC-SR04 [4] is a widely used low-cost ranging module, which is installed on the upper inside of the trash can. After sending a high-level pulse of at least 10 us to the ultrasonic sensor Trig pin, the sensor will automatically send out eight 40 kHz ultrasonic waves. When the ultrasonic wave is reflected back from the trash surface, a high-level pulse will be generated in the Echo pin. The width of the pulse is proportional to the distance. The hardware circuit of the ultrasonic sensor HC-SR04 is shown in Figure 2.

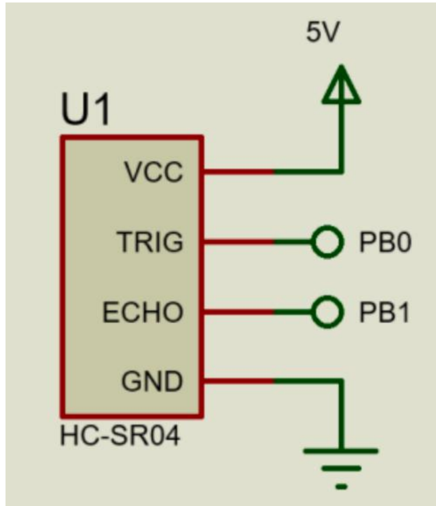

Figure 2. The hardware circuit of the ultrasonic sensor HC-SR04

The pressure sensor HX711 [33] is a high-precision 24-bit A/D converter chip that integrates peripheral circuits, including a regulated power supply and an on-chip clock oscillator. It has the advantages of high integration, low cost, fast response, and strong anti-interference ability. A stable power supply is provided to the full-bridge circuit composed of four pressure resistors through E + and E-, and no additional power supply circuit is required. Channel A connects the differential signal of the bridge sensor, and the programmable gain of channel A is 128 or 64. The sensor can communicate with the main control chip via serial port protocol through the PD_SCK and DOUT pins. The hardware circuit of the pressure sensor HX711 is shown in Figure 3.

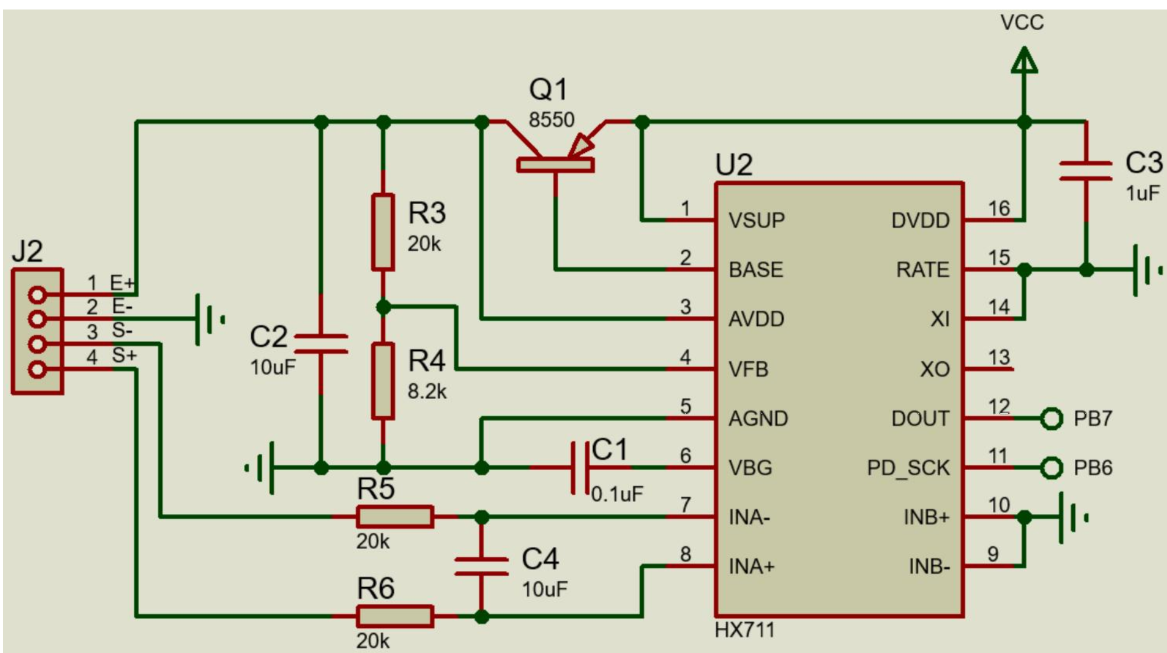

Figure 3. The hardware circuit of the pressure sensor HX711

4.2 Abnormal State Detection

The hardware of abnormal state detection is mainly composed of temperature sensor DS18B20 and orientation detection sensor MPU6050.

Temperature sensor DS18B20 [34] is a digital temperature sensor with small size, wide voltage power supply and simple interface with microprocessor, which is suitable for digital temperature measurement in narrow space of trash can. The working power supply of the sensor is directly connected to the power supply of the microprocessor. No other peripheral components are needed in use. The main control chip only needs to communicate with DS18B20 through the single wire protocol. The hardware connection is simple and the circuit cost is greatly reduced. The hardware circuit of the temperature sensor DS18B20 is shown in Figure 4.

The orientation detection sensor MPU6050 [35] is a chip that can simultaneously detect three- axis acceleration and three-axis gyroscopes. The main control chip can obtain sensor data directly through the IIC interface. After filtering the original data, combining the multi-sensor data and calculating the tilting angle, the main control chip can get the tilting state of the trash can. The hardware circuit of the orientation detection sensor MPU6050 is shown in Figure 5.

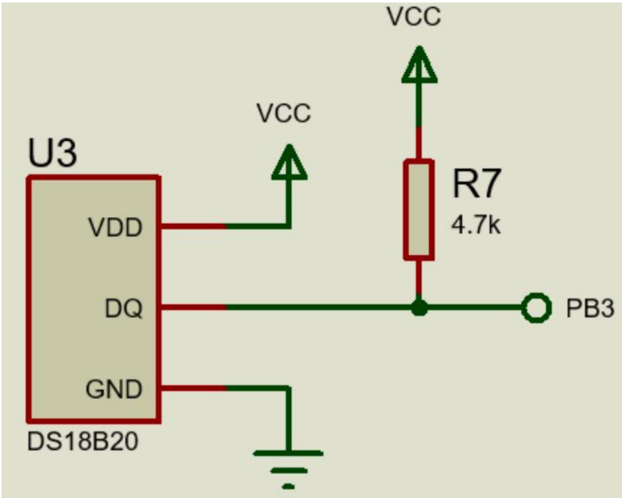

Figure 4. The hardware circuit of the temperature sensor DS18B20

4.3 Communication System

LoRa, as a representative technology of low-power wide-area network, is a wireless communication technology specifically for IoT applications. It has the advantages of long transmission distance, low power consumption and strong anti-interference performance, and is suitable for scenic spot trash can detection system. The system adopts E32-TTL-100 module, and the core chip is SX1278 chip. After data communication via UART serial port, the results of overflow state detection and abnormal state detection can be uploaded to the LoRa gateway in real time. The hardware circuit of LoRa module is shown in Figure 6.

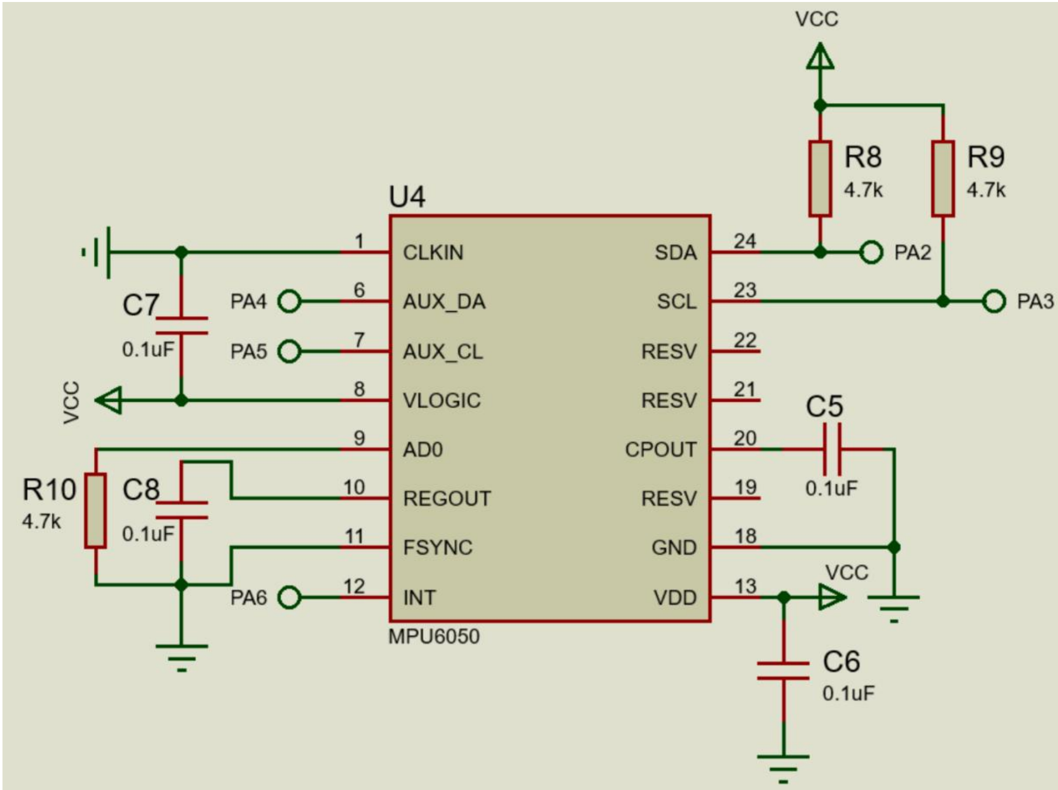

Figure 5. The hardware circuit of the orientation detection sensor MPU6050

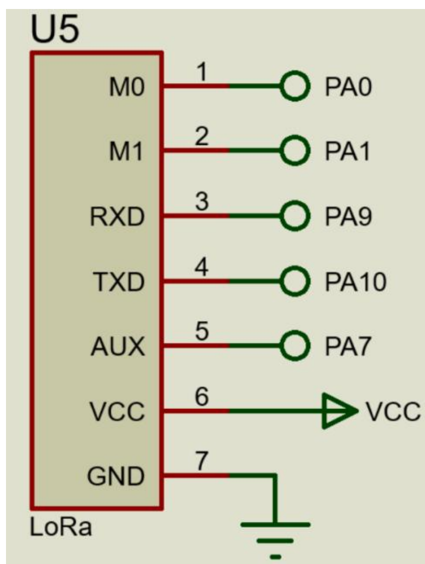

Figure 6. The hardware circuit of LoRa module

5. System Software Design

In the Keil5 development environment, the main program is programmed in C language. The main control chip main program first initializes the conFigureuration of system clock, GPIO pin, timer, UART serial port, IIC interface, etc., and then enters the main loop. Then the main loop periodically executes ultrasonic ranging program, trash weight detection program, temperature detection program, orientation detection program, and communication program.

5.1 Ultrasonic Ranging Program Design

The ultrasonic ranging program firstly outputs a high-level pulse of 20 us to the Trig pin, and waits for the high-level pulse output by the Echo pin. If the high-level voltage is detected in the Echo pin, it starts the timer to capture the time of the high-level pulse, and the ultrasonic wave round-trip time t can be obtained. The distance s can be determined using the formula $s = t \times v/2$, where t represents the ultrasonic wave round-trip time and v is the speed of sound (340 m/s). The result s is the distance from the top of the trash can to the trash, when the measured distance s is less than 5cm, the trash can are regarding as in a full overflow state. The flow chart of the ultrasonic ranging program is shown in Figure 7.

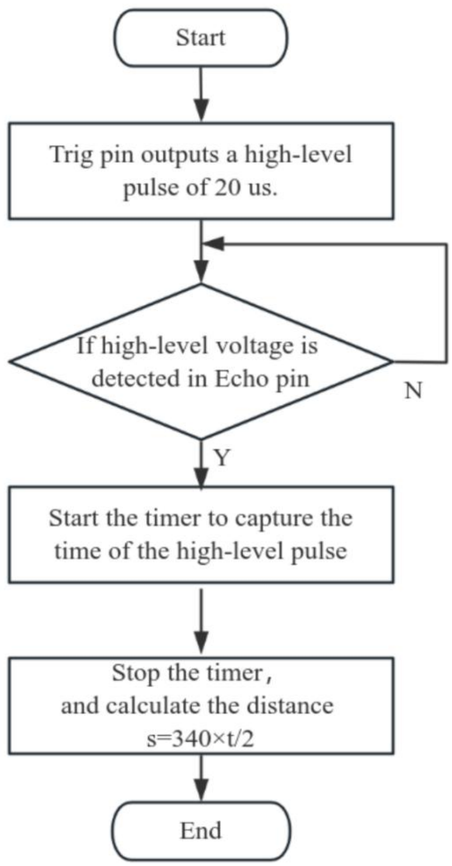

Figure 7. The flow chart of ultrasonic ranging program

5.2 Trash Weight Detection Program Design

The trash weight detection program mainly processes the data of the pressure sensor. Firstly, the main control chip outputs 25 clock pulse signals to the PD_SCK pin of the pressure sensor in turn. At the rising edge of the first clock pulse, the highest bit (MSB) of the output 24-bit data is read from the DOUT pin. Until the 24th clock pulse is completed, and the 24-bit output data is read bit by bit from the highest bit to the lowest bit. The 25th clock pulse is used to select the channel and channel gain of the next A/D conversion. The selected input channel is A channel and the selected gain is 128. According to the filtered sampling value, the trash weight can be calculated. The flow chart of the trash weight detection program is shown in Figure 8.

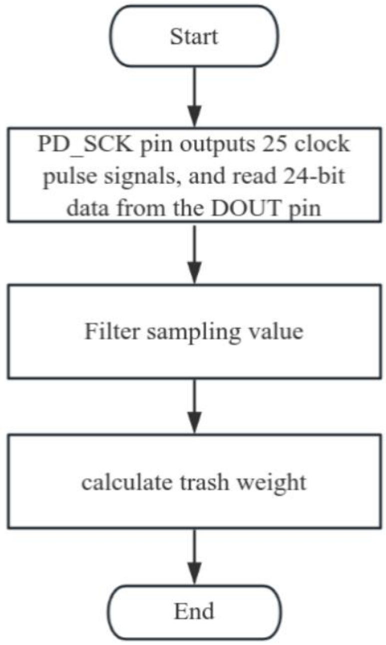

Figure 8. The flow chart of trash weight detection program

5.3 Temperature Detection Program Design

The main control chip uses a single bus for half-duplex communication with the temperature sensor DS18B20. Firstly, the main control chip generates a reset pulse on the bus, which needs to output a low level holding time of at least 480 us. Then the main control chip releases the bus and waits for DS18B20 to generate a low-level response pulse. At this time, the pull-up resistance of the hardware circuit will raise the bus level. After receiving the response pulse, the main control chip outputs 2us low-level pulse on the bus to enter the read operation, and then sets the pin mode to input mode to read 1bit bus temperature data. After a delay of 50 us, the main control chip repeats the read operation until 2 bytes are read. Through the temperature calculation rules of DS18B20, the current temperature of the trash can is calculated. When the collected temperature is greater than 50 ℃, it indicates that the cigarette butts may be put into the trash can. It will trigger the system to upload the alarm event of catching fire. The flow chart of the temperature detection program is shown in Figure 9.

5.4 Orientation Detection Program Design

The main control chip uses I2C to communicate with the orientation detection sensor MPU6050. After obtaining the original data of accelerometer and gyroscope through serial communication, the data filtering is carried out by Kalman filter algorithm [36]. Then the accelerometer and gyroscope data are combined by the complementary filtering algorithm to calculate the Euler angle. The tilting state of the system can be judged by the pitch angle or roll angle. The flow chart of the design of the orientation detection program is shown in Figure 10.

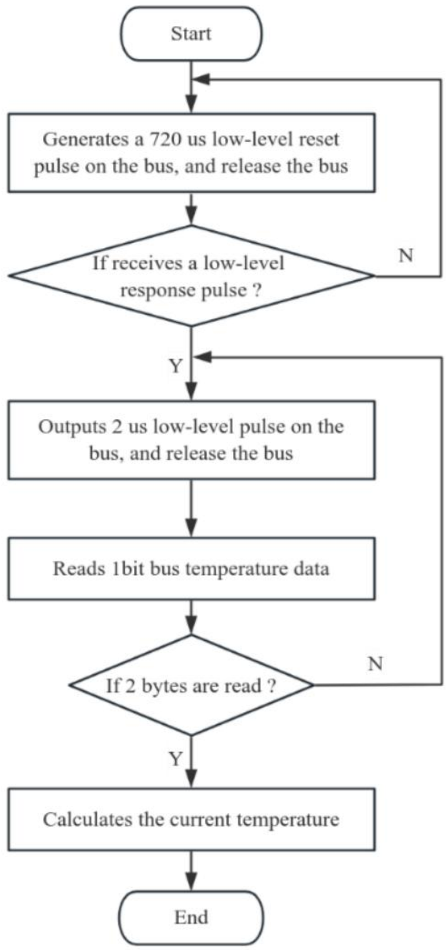

Figure 9. The flow chart of temperature detection program

5.5 LoRa Communication Program Design

The main control chip communicates with the LoRa module through the UART serial port. In order to reduce power consumption [37], all sensor data of the trash can detection system will be sorted into a certain format data packet and sent to the gateway periodically. However, when the system detects an alarm event, it can immediately trigger a communication event and send the data to the gateway to improve the response speed. The flow chart of the LoRa communication program is shown in Figure 11.

6. Conclusion

In order to solve the problems of manual inspection of trash cans in scenic spots, this paper designs a trash can detection system based on IoT technology. The system can intelligently detect the overflow state, tilting state and fire incidents through sensors. The detection results are uploaded to the gateway in real time through LoRa long-distance wireless communication. The detection system helps scenic spot manage the status of trash cans more conveniently and contributes to the sustainable development of scenic areas.

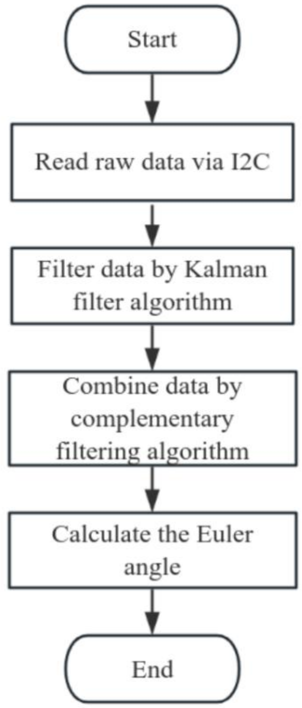

Figure 10. The flow chart of orientation detection program

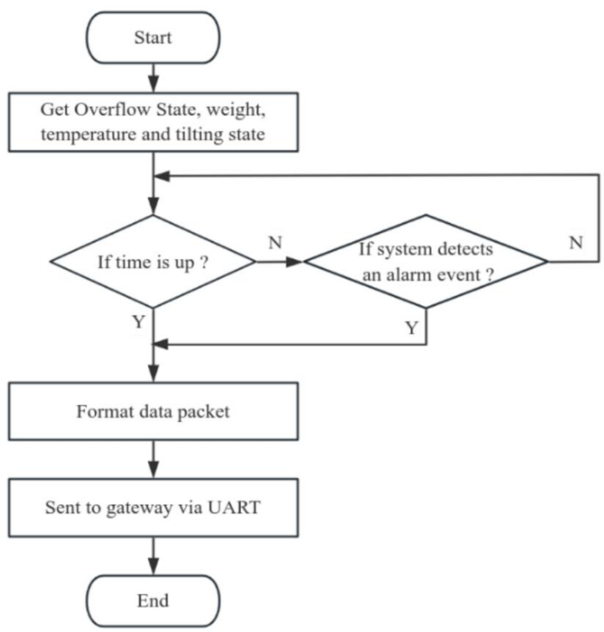

Figure 11. The flow chart of the LoRa communication program

References

[1] X. Y. Liang, "Intelligent Management Research on Municipal Solid Waste Collection and Transportation-Using Dalian City as an Example," M.S. thesis, Dalian University of Technology, China, 2015.

[2] H. Zhang and Y. Chen, "The design of intelligent dustbin control system in scenic area," Journal of Huanghe S&T College, vol. 24, no. 2, pp. 44-50, 2022.

[3] X. W. Qian, Z. M. Hao, Y. X. Li et al., "Smart scenic area management system based on LoRa+WiFi wireless network," Internet of Things Technologies, vol. 14, no. 7, pp. 66-70, 2024.

[4] F. Vicentini, A. Giusti, A. Rovetta, X. Fan, Q. He, M. Zhu and B. Liu, "Sensorized waste collection container for content estimation and collection optimization," Waste Management, vol. 29, no. 5, pp. 1467-1472, 2009.

[5] M. Arebey, M. A. Hannan, H. Basri and H. Abdullah, "Solid waste monitoring and management using RFID, GIS and GSM," Proceedings of the IEEE Student Conference on Research and Development (SCORED), pp. 37-40, 2009.

[6] M. A. Hannan, M. Arebey, R. A. Begum and H. Basri, "Radio frequency identification (RFID) and communication technologies for solid waste bin and truck monitoring system," Waste Management, vol. 31, no. 12, pp. 2406-2413, 2011.

[7] S. Longhi, D. Marzioni, E. Alidori, G. Di Buo, M. Prist, M. Grisostomi and M. Pirro, "Solid waste management architecture using wireless sensor network technology," Proceedings of the 5th International Conference on New Technologies, Mobility and Security (NTMS), pp. 1-5, 2012.

[8] F. Folianto, Y. S. Low and W. L. Yeow, "Smartbin: Smart waste management system," Proceedings of the IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), pp. 1-2, 2015.

[9] Y. Glouche and P. Couderc, "A smart waste management with self-describing objects," Proceedings of the International Conference on Smart Systems, Devices and Technologies (SMART), 2013.

[10] T. Anagnostopoulos, K. Kolomvatsos, C. Anagnostopoulos, A. Zaslavsky and S. Hadjieftymiades, "Assessing dynamic models for high priority waste collection in smart cities," Journal of Systems and Software, vol. 110, pp. 178-192, 2015.

[11] T. Anagnostopoulos, A. Zaslavsky, K. Kolomvatsos, A. Medvedev, P. Amirian, J. Morley and S. Hadjieftymiades, "Challenges and opportunities of waste management in IoT-enabled smart cities: a survey," IEEE Transactions on Sustainable Computing, vol. 2, no. 3, pp. 275-289, 2017.

[12] M. N. K. R. Al-Maaded, N. K. Madi, R. Kahraman, A. Hodzic and N. G. Ozerkan, "An overview of solid waste management and plastic recycling," Journal of Polymers and the Environment, vol. 20, no. 1, pp. 186-194, 2012.

[13] A. Augustin, J. Yi, T. Clausen and W. M. Townsley, "A study of LoRa: Long range & low power networks for the internet of things," Sensors, vol. 16, no. 9, p. 1466, 2016.

[14] U. Raza, P. Kulkarni and M. Sooriyabandara, "Low power wide area networks: An overview," IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 855-873, 2017.

[15] X. T. Li, X. P. Zhang, D. P. Mao and J. H. Sun, "Adaptive robust control over high-performance VCM-FSM," Opt. Precis. Eng., vol. 25, pp. 2428-2436, 2017.

[16] M. Aazam, I. Khan, A. A. Alsaffar and E. N. Huh, "Cloud of Things: Integrating Internet of Things and cloud computing and the issues involved," Proceedings of the IEEE International Bhurban Conference on Applied Sciences & Technology (IBCAST), pp. 414-419, 2014.

[17] Y. Ou and W. C. Chang, "A residual-regulated machine learning method for non-stationary time series forecasting using second-order differencing."

[18] H. Wang, C. Nie and C. Chiang, "Attention-driven deep learning framework for intelligent anomaly detection in ETL processes," 2025.

[19] J. Jiang, C. Shao, C. Zhang, N. Lyu and Y. Ni, "Adaptive AI spatiotemporal modeling with dependency drift awareness for anomaly detection in large-scale clusters," 2025.

[20] D. Wu, "Deep learning approach to structure-temporal collaborative anomaly detection in microservice architectures," 2026.

[21] Y. Liu, "AI-driven performance degradation identification via self-supervised spatiotemporal graph modeling in microservice systems," 2026.

[22] Y. Wang, "Adaptive graph construction and spatiotemporal contrastive learning for intelligent cloud service monitoring," 2026.

[23] C. Hu, Z. Cheng, D. Wu, Y. Wang, F. Liu and Z. Qiu, "Structural generalization for microservice routing using graph neural networks," Proceedings of the International Conference on Artificial Intelligence and Automation Control (AIAC), 2025.

[24] X. Yang, Y. Ni, Y. Tang, Z. Qiu, C. Wang and T. Yuan, "Graph-structured deep learning framework for multi-task contention identification with high-dimensional metrics," 2026.

[25] Z. Zhang, Y. Xue, H. Zhu, S. Li, Z. Wang and Y. Xiao, "CondenseGraph: Communication-efficient distributed GNN training via on-the-fly graph condensation," 2026.

[26] C. Zhang, H. Zhu, A. Zhu, J. Liao, Y. Xiao and Z. Zhang, "Deep learning approach for protocol anomaly detection using status code sequences," 2026.

[27]X. Yang, Y. Wang, Y. Li and S. Sun, "Semantics-aware denoising: A PLM-guided sample reweighting strategy for robust recommendation," 2026.

[28]X. Hu, Y. Kang, G. Yao, T. Kang, M. Wang and H. Liu, "Dynamic prompt fusion for multi-task and cross-domain adaptation in LLMs," Proceedings of the International Conference on Computer and Information Processing Technology (ISCIPT), 2025.

[29]S. Pan and D. Wu, "Trustworthy summarization via uncertainty quantification and risk awareness in large language models," Proceedings of the International Conference on Computer Vision and Data Mining (ICCVDM), 2025.

[30]A. Xie and W. C. Chang, "Deep learning approach for clinical risk identification using transformer modeling of heterogeneous EHR data," 2025.

[31]R. Liu, L. Yang, R. Zhang and S. Wang, "Generative modeling of human-computer interfaces with diffusion processes and conditional control," 2026.

[32]L. Yan, Q. Wang and J. Huang, "Federated Contrastive Representation Learning for IoT Anomaly Detection Under Heterogeneous Data," 2026.

[33]Y. B. Wang, "High-precision ultrasonic ranging system based on HC-SR04 module," Science and Technology & Innovation, no. 17, pp. 57-59, 2023.

[34]F. F. Liang, "Design of a multifunctional smart electronic scale based on HX711," Engineering and Technological Research, vol. 6, no. 15, pp. 136-140, 2021.

[35]Q. Y. Wang, J. T. Gu, P. H. Ding et al., "Temperature measurement and alarm system based on DS18B20," New Technology & New Products of China, no. 7, pp. 24-27, 2023.

[36]X. H. Yuan and X. Wang, "Balancing vehicle attitude detection and control scheme based on MPU6050 six-axis sensor," China Computer & Communication, no. 23, pp. 103-104, 2018.

[37]Y. Liu, Y. Yang and J. T. Xu, "Attitude calculation algorithm for fusion complementary filtering and Kalman filtering," Journal of Xi’ an University of Posts and Telecommunications, vol. 26, no. 4, pp. 98-104, 202