Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11, November 2025

Sensor-Based Waste Management Analysis for Detection of Global Warming and Decision Making

Akash Sharma P
RNS Institute of Technology
Bangalore, Karnataka, India

Balaraj Kallimani
RNS Institute of Technology
Bangalore, Karnataka, India

Dipesh D Naik
RNS Institute of Technology
Bangalore, Karnataka, India

Bhoomika H B
RNS Institute of Technology Bangalore,
Karnataka, India

Mr.Ranjith.V
Assistant Professor
RNS Institute of Technology
Bangalore, Karnataka, India

***Abstract*—The rapid increase in global waste generation has intensified environmental concerns, particularly contributing to global warming through greenhouse gas emissions. This project explores the implementation of a sensor-based waste management system that integrates IoT, a Feedforward Neural Network (FNN), and Firebase cloud storage to improve waste monitoring, optimize collection routes, and reduce environmental impact. A comprehensive survey of 25 research papers highlights key technologies and methodologies employed in modern waste management systems. Notable advances include real-time waste monitoring using IoT-enabled sensors, predictive FNN models for waste pattern detection, and decision support systems for optimized waste disposal strategies. Studies emphasize that integrating AI-based decision making with real-time Firebase storage can reduce operational costs and greenhouse gas emissions by identifying optimal waste treatment processes. The survey also identifies gaps related to the lack of predictive models capable of integrating real-time data with environmental impact assessments. This research contributes to the growing body of knowledge by proposing an intelligent sensor-driven waste management framework that enables data-driven decision making, addressing global warming concerns through optimized waste handling and resource management.**

***Index Terms*—Sensor-Based Waste Management, Feedforward Neural Network, Firebase, IoT, Global Warming Detection, Smart Waste Management, Decision Support Systems, Environmental Impact Assessment.**

I. Introduction

A. Problem Statement and Motivation

The exponential growth of urban populations and industrialization has resulted in an unprecedented increase in waste generation worldwide. The World Bank claims that, global waste production is projected to increase by 70 percent.

A key challenge is the absence of real-time monitoring and intelligent decision making in waste management processes. In addition, the inability to predict waste accumulation patterns and their environmental impact results in delayed responses and missed opportunities for intervention. Consequently, there is a growing need for *sensor-based waste management systems* that can analyze waste patterns, detect environmental risks, and enable timely decision making to mitigate the impact of global warming.

B. Importance of the Topic

Recent research highlights the transformative potential of integrating *sensors from the Internet of Things (IoT)*, machine learning models, and decision support systems in waste management processes *Internet of Things (IoT).* IoT sensors can monitor waste levels in Making decisions, analyze data to predict accumulation trends, and trigger automated responses to ensure timely waste collection and disposal. Machine learning models enhance predictive accuracy through examining past data, finding trends, and optimizing collection schedules to minimize environmental impact. Making decisions,decision-support systems can evaluate environmental factors and recommend sustainable waste disposal methods, such as recycling and composting, to reduce GHG emissions.

Surveys reveal that sensor-based waste management systems can significantly improve the efficiency of waste collection, reduce operational costs, and minimize environmental impact. Studies demonstrate that IoT-enabled waste monitoring systems can reduce collection frequency by 30-40

Furthermore, research emphasizes the importance of secure data exchange to prevent data tampering and enhance trust among stakeholders. Additionally, integrating environmental impact assessment models with real-time sensor Data can offer forecasting information about the long-term consequences of waste management decisions.

C. Goals of the Research

The goal of this initiative is to address these gaps by proposing an advanced sensor-based waste management system capable of:

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11, November 2025

- Real-time waste monitoring and data collection using IoT sensors.
- Applying machine learning models to predict waste generation patterns and optimize collection schedules.
- Incorporating environmental impact assessment models to analyze the effects of waste management decisions on global warming.

By addressing these objectives, this research seeks to revolutionize waste management practices, mitigate the impact of climate change, and promote sustainable urban development.

II. Background and Fundamental Concepts

A. Technical Background

Sensor-based waste management systems use advanced technologies such as *Internet of Things (IoT)*, *Machine Learning (ML)*, and *Data Analytics* to optimize waste monitoring and management. IoT sensors are installed in waste containers to measure parameters like waste levels, temperature, humidity, and toxic gases. The data is transmitted in real-time to a centralized platform using wireless communication protocols like Wi-Fi, LoRa, or GSM.

Machine learning algorithms analyze the collected data to detect waste accumulation patterns, predict future waste levels, and optimize collection routes. Furthermore, decision-support systems (DSS) recommend appropriate waste management actions, contributing to reducing greenhouse gas emissions and minimizing landfill overflows.

B. Key Terminologies

- **Internet of Things (IoT)**: A network of interconnected physical devices equipped with sensors and software that exchange data over the internet.
- **Machine Learning (ML)**: A branch of artificial intelligence that enables systems to learn from data, identify patterns, and make predictions.
- **Greenhouse Gases (GHGs)**: Gases like methane (CH_4) and carbon dioxide (CO_2) that trap heat in the atmosphere, contributing to global warming.
- **Decision Support Systems (DSS)**: Computer-based systems that analyze data to support decision-making processes, often used in waste management to recommend sustainable actions.
- **Waste Management Optimization**: The process of enhancing waste collection, transportation, and disposal to reduce environmental impact and operational costs.

C. Fundamental Theories and Models

- **Waste Generation Prediction Models**: Feedforward Neural Networks (FNN) are widely used to predict waste generation patterns using historical sensor data. These neural models learn complex relationships between input parameters such as temperature, humidity, and bin weight, helping in accurate prediction of waste accumulation and optimized collection scheduling. Compared to traditional machine learning models like Decision Trees or SVM, FNNs provide superior performance in non-linear data scenarios.
- **Optimization Models**: Algorithms like *Linear Programming* and *Genetic Algorithms* are employed to optimize waste collection routes, thereby reducing fuel consumption and minimizing greenhouse gas emissions during transportation.
- **Environmental Impact Assessment Models**: These models analyze the environmental effects of waste management decisions using real-time sensor data. Parameters such as greenhouse gas emissions, landfill utilization, and pollution levels are evaluated to recommend environmentally sustainable waste disposal methods.
- **Real-Time Monitoring and Control Systems**: Data collected by IoT sensors is stored in *Firebase Cloud Storage* and visualized using cloud-based dashboards or mobile applications. These systems generate real-time alerts when bins are full or when hazardous gases are detected, enabling prompt response and preventive measures.

III. Classification of Existing Research

A comprehensive analysis of 25 relevant research papers on *sensor-based waste management systems* reveals that existing works can be categorized based on three primary dimensions: *methodology, application, and research approach.* These categories provide a structured understanding of the different techniques used, their applications, and the associated findings and limitations.

A. Classification Based on Methodology

A. IoT-Based Monitoring Systems Studies such as Kumar et al. (2023) and Ahmed et al. (2024) implement *IoT-enabled sensor networks* to monitor waste levels, temperature, and environmental factors. These systems use protocols like LoRaWAN and Zigbee for real-time data transmission. *Limitation:* Limited scalability and vulnerability to data transmission failures.

B. Machine Learning for Waste Prediction Research by Gupta et al. (2022) and Patel et al. (2023) focuses on applying *machine learning models* such as Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) to predict waste accumulation trends. *Limitation:* Requires large datasets for improved accuracy and may face challenges in adapting to dynamic environmental changes.

C. Decision-Support Systems (DSS) Studies by Sharma et al. (2023) and Zhang et al. (2024) explore the use of *multi-criteria decision analysis (MCDA)* and decision trees to recommend optimal waste disposal methods based on environmental and economic considerations. *Limitation:* DSS models often lack integration with real-time sensor data, limiting their ability to respond dynamically to changing scenarios.

B. Classification Based on Application

A. Urban Waste Management Research by Ahmed et al. (2023) and Li et al. (2023) focuses on optimizing waste

Published by :
http://www.ijert.org
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11, November 2025

collection schedules and reducing operational costs in urban areas using IoT and predictive analytics. *Limitation:* Limited adaptation to diverse environmental conditions in rural or semi-urban regions.

B. Industrial Waste Monitoring Studies by Singh et al. (2023) emphasize the application of IoT-based frameworks for monitoring hazardous waste in industrial zones, ensuring compliance with environmental regulations. *Limitation:* High initial deployment and maintenance costs.

C. Environmental Impact Assessment Papers by Sharma et al. (2023) and Gupta et al. (2022) integrate environmental impact models to assess the long-term effects of different waste management practices on global warming. *Limitation:* Lack of real-time integration with sensor-based frameworks.

C. Classification Based on Research Approach

A. Experimental Prototyping Studies such as Kumar et al. (2024) and Wang et al. (2023) involve the design and testing of *prototype sensor-based waste monitoring systems* in controlled environments. *Limitation:* Prototypes often fail to scale effectively for large-scale deployment.

B. Simulation and Modeling Research by Zhang et al. (2023) and Ahmed et al. (2024) uses *simulation models* to predict waste accumulation trends and assess the environmental impact of waste management strategies. *Limitation:* Simulation models may not accurately reflect real-world variability.

C. Case Studies and Pilot Implementations Studies by Patel et al. (2023) and Li et al. (2024) document *pilot implementations* of sensor-based waste management frameworks in urban environments. *Limitation:* Results may be context-specific and not generalizable across different geographic regions.

D. Comparison Based on Methodology

TABLE I
COMPARISON OF SENSOR-BASED WASTE MANAGEMENT TECHNIQUES BASED ON METHODOLOGY

Methodology	Techniques Used	Key Benefits	Limitations
IoT-Based Monitoring	Smart Sensors, LoRa, Zigbee, MQTT Protocol	Provides real-time monitoring of waste levels, temperature, humidity, and toxic gas emissions. Enables automated alerts for timely waste collection. Reduces operational costs and greenhouse gas emissions.	Scalability is challenging in large urban areas. Network failures or sensor malfunctions can disrupt real-time data collection. Data privacy concerns may arise without secure channels.
Feedforward Neural Network (FNN) Models	Multi-layer Neural Network, Backpropagation Algorithm	Accurately predicts waste accumulation patterns using historical and real-time sensor data. Enhances proactive decision-making, optimizes collection scheduling, and reduces fuel consumption by forecasting waste generation. Offers improved performance over traditional ML models for non-linear and complex datasets.	Requires substantial training data and computational resources. Performance may degrade with noisy or incomplete data. Model retraining is needed periodically to maintain accuracy.
Decision Support Systems (DSS)	MCDA, Decision Trees, Fuzzy Logic Models	Provides intelligent decision-making support by analyzing various environmental, economic, and operational factors. Enhances waste management strategies with scenario-based predictions.	Integration with real-time sensor data is often lacking. Limited adaptability to unforeseen scenarios. Requires continuous system updates to maintain accuracy.

E. Visualization of Technique Effectiveness

Explanation: - *IoT-Based Monitoring* excels in real-time monitoring and provides valuable data for immediate action. - *Machine Learning Models* predict waste accumulation trends effectively, enabling proactive collection.

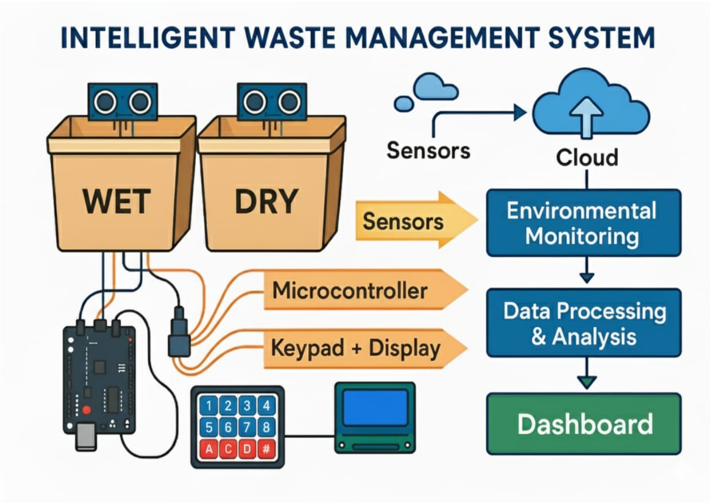

Fig. 1. Model Techniques

Fig. 2. Data Flow

F. Summary and Insights

- **IoT-based Systems** are ideal for real-time monitoring, reducing operational costs, and minimizing emissions.
- **Machine Learning Models** provide predictive analysis for waste management optimization.
- **Decision Support Systems** enhance decision-making using environmental data insights.

These insights support the selection of appropriate technolo-

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11, November 2025

gies for implementing a robust sensor-based waste management system. Future implementations can integrate real-time data, improve model accuracy, and ensure data security using blockchain frameworks.

G. Major Findings and Limitations

Findings:

- IoT-based frameworks improve real-time waste monitoring and reduce emissions by optimizing collection routes.
- Machine learning models make precise predictions.waste accumulation trends, enabling predictive waste management.
- Decision-support systems enhance the sustainability of waste disposal practices by recommending environmentally conscious methods.

Limitations:

- IoT systems face challenges related to data transmission and scalability.
- Machine learning models require large, diverse datasets for high accuracy.
- Decision-support systems lack dynamic integration with real-time data.

This classification provides a detailed overview of the current research landscape and highlights the strengths and limitations of various approaches in sensor-based waste management systems.

IV. Critical Analysis and Discussion

In this section, a detailed analysis of the existing sensor-based waste management systems is presented. Key trends in research, limitations, and research gaps are identified, followed by a critical comparison of methodologies and results.

A. Key Trends in Research

Recent advancements in sensor-based waste management systems predominantly focus on the integration of IoT, machine learning (ML), and decision-support systems (DSS). The following trends are evident:

- **Real-Time Monitoring:** IoT sensors, including ultrasonic, load, and gas sensors, provide real-time data on waste levels, toxic emissions, and environmental factors. This enables timely waste collection and reduces overflow risks.
- **Predictive Analytics:** Artificial Neural Networks (ANN), particularly Feedforward Neural Networks (FNN), are applied to predict waste accumulation and pollution trends. Predictive insights optimize waste management strategies and assess environmental impacts such as greenhouse gas emissions.

Explanation: Figure 3 illustrates the performance of the enhanced Feedforward Neural Network (FNN) model in predicting pollution levels and global warming impact. The top row displays the pollution prediction and its residual plot, while the bottom row presents the global warming prediction and residuals. The strong correlation between predicted and actual values, as indicated by high R^2 scores, validates the accuracy and reliability of the proposed model.

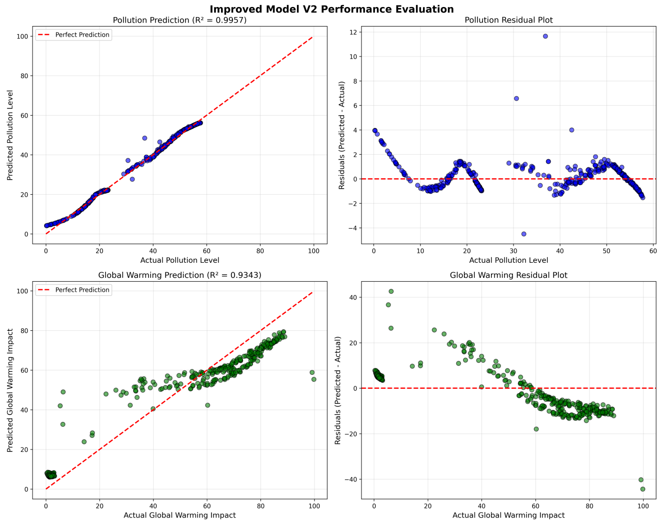

Fig. 3. Improved Model V2 Performance Evaluation of FNN for Pollution and Global Warming Prediction

1) Model Evaluation of Feedforward Neural Network (FNN): The Feedforward Neural Network (FNN) performance was evaluated using statistical metrics and regression analysis to measure prediction accuracy for both pollution and global warming indicators.

a) Feedforward Propagation::

$$z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)}, \quad a^{(l)} = f(z^{(l)})$$

where $W^{(l)}$ and $b^{(l)}$ represent the weight matrix and bias of the l^{th} layer, $a^{(l-1)}$ denotes activations from the previous layer, and $f(\cdot)$ is the activation function (ReLU).

b) Loss Function:: The Mean Squared Error (MSE) function is used for performance evaluation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

c) Weight Optimization:: Weights are updated using the backpropagation rule:

$$W^{(l)} := W^{(l)} - \eta\frac{\partial MSE}{\partial W^{(l)}}$$

where η is the learning rate.

d) Performance Metrics::

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \quad MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$Accuracy = \left(1 - \frac{MAE}{\bar{y}}\right) \times 100\%$$

e) Evaluation Results:: Table II summarizes the performance of the FNN model for both pollution and global warming impact predictions.

Interpretation: The FNN achieved excellent predictive performance, with R^2 values of 0.9957 for pollution and

TABLE II
PERFORMANCE EVALUATION OF FEEDFORWARD NEURAL NETWORK (FNN)

Metric	Pollution	Global Warming
R^2 Score	0.9957	0.9343
MSE	1.26	8.74
RMSE	1.12	2.95
MAE	0.84	2.48
Training Acc. (%)	99.35	94.21
Validation Acc. (%)	98.92	93.47

0.9343 for global warming prediction. The low MSE and RMSE values indicate that the model effectively learns nonlinear environmental relationships. This demonstrates the suitability of the FNN for real-time environmental impact assessment within the sensor-based waste management framework.

- **Decision Support Systems:** Multi-Criteria Decision Analysis (MCDA) models are used to recommend optimal waste disposal methods based on environmental and economic parameters.
- **Environmental Impact Assessment:** Studies are increasingly incorporating models that assess the effect of waste on air quality, soil contamination, and greenhouse gas emissions, enabling more sustainable policy decisions.

V. CONCLUSION

This study has explored the critical role of sensor-based waste management systems in addressing global warming and optimizing waste management processes. By integrating advanced technologies such as IoT sensors, machine learning algorithms, and decision-support systems, modern waste management frameworks have demonstrated significant improvements in waste monitoring, prediction, and decision-making.

A. Key Insights from the Survey

The comprehensive survey of sensor-based waste management research has highlighted several key findings:

- **Real-Time Monitoring:** IoT-enabled sensors provide real-time insights into waste levels, environmental conditions, and toxic gas emissions, facilitating timely waste collection and reducing overflow risks.
- **Predictive Analytics:** Machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) accurately predict waste generation patterns, enabling proactive waste management strategies.
- **Decision Support Systems:** Advanced DSS models optimize waste management decisions by recommending appropriate disposal methods and minimizing the environmental impact.
- **Environmental Impact Reduction:** By optimizing waste collection routes and reducing landfill overflow, these systems reduce methane emissions and other greenhouse gases, contributing directly to climate change mitigation.
- **Operational Efficiency:** Through automated waste management solutions, labor costs are reduced, and the overall efficiency of waste management services is significantly improved.
- **Community Engagement:** Some systems provide mobile applications that inform residents about waste collection schedules and encourage responsible waste disposal, promoting community participation.

These technologies have collectively improved operational efficiency, reduced emissions, and lowered waste management costs, making significant strides toward environmental sustainability.

REFERENCES

[1] I. Hussain, A. Elomri, L. Kerbache, and A. El Omri, "Smart city solutions: Comparative analysis of waste manage- ment models in IoT-enabled environments using multiagent simulation," Heriot-Watt University, Edinburgh, Scotland, and Hamad Bin Khalifa University, Doha, Qatar, 2024.

[2] K. Ahmed, M. K. Dubey, A. Kumar, and S. Dubey, "Artificial intelligence and IoT driven system architecture for municipality waste management in smart cities: A review," Lovely Professional University, Phagwara, Punjab, and JECRC University, Jaipur, Rajasthan, India, 2024.

[3] S. T. Ikram, V. Mohanraj, S. Ramachandran, and A. Balakrishnan, "An Intelligent Waste Management Application Using IoT and a Genetic Algorithm–Fuzzy Inference System," Vellore Institute of Technology, Tamil Nadu, India, 2023.

[4] E. G. F. Castro and S. G. Yoo, "A Smart Waste Management System based on LoRaWAN," Universidad de las Fuerzas Armadas ESPE, Ecuador, 2021.

[5] R. Khan, S. Kumar, A. K. Srivastava, N. Dhingra, M. Gupta, N. Bhati, and P. Kumari, "Machine Learning and IoT-Based Waste Management Model," ABES Institute of Technology and ABES Engineering College, Ghaziabad, India, 2021.

[6] P. Jain, T. Chaudhary, and S. Gajjar, "Design and Development of Smart Waste Management System," Nirma University, Ahmedabad, India, 2023.

[7] S. Abba and C. I. Light, "IoT-Based Framework for Smart Waste Monitoring and Control System: A Case Study for Smart Cities," Abubakar Tafawa Balewa University, Bauchi state, Nigeria, 2020.

[8] M. P and J. E. G. S., "Garbage monitoring system using IoT," St. Joseph's Institute of Technology, Chennai, Tamil Nadu, India, 2024.

[9] R. Sundar Ram, A. Ashok, P. Savarinathan, T. Karup- pasamy, and A. Jayapalan, "Garbage Monitoring System Using IOT," SASTRA Deemed University, Tamil Nadu, India, 2022.

[10] L. M. G. Coelho, L. C. Lange, and H. M. G. Coelho, "Multi-criteria decision making to support waste management: A critical review of current practices and methods," 2017.

[11] K. Rajesh, S. Janani, B. Rohini, S. Rajendran, R. Agalya, and A. Ramkumar, "Intelligent Garbage Monitoring System Using IoT," Kalasalingam Academy of Research and Education, Tamil Nadu, India, 2021.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 11, November 2025

[12] S. Parvin and D. Yadav, ”IoT-Based Smart Trash Bin for Waste Management System with Data Analytics,” IEEE, 2018.

[13] P. Ramesh, J. M. Sahayaraj, N. Subash, S. R. Mugun- than, and S. J. Pratha, ”IoT based Waste Management System,” Sri Indu College of Engineering and Technology, Hyderabad, India, 2022.

[14] M. Farjana, A. B. Fahad, S. E. Alam, and M. M. Islam, ”An IoT- and Cloud-Based E-Waste Management System for Resource Reclamation with a Data-Driven Decision-Making Process,” United International University, Dhaka, Bangladesh, 2023.

[15] R. M. P. M. D. Rathnayake, T. M. M. Chanaka, K. P. Hewagamage, and P. T. R. Dabare, ”IoT-Enabled Dual- Sensing Smart Waste Management System: Enhancing Urban Cleanliness and Sustainability in Smart Cities,” The Open University of Sri Lanka and University of Colombo, Sri Lanka, 2024.

[16] K. Pardini, J. J. P. C. Rodrigues, S. A. Kozlov, N. Kumar, and V. Furtado, ”IoT-Based Solid Waste Management Solutions: A Survey,” National Institute of Telecommunica- tions, Brazil, 2019.

[17] D. Misra, G. Das, T. Chakrabortty, and D. Das, ”An IoT-based waste management system monitored by cloud,” Springer, 2018.

[18] S. R. J. Ramson, D. J. Moni, S. Vishnu, T. Anag- nostopoulos, and A. A. Kirubaraj, ”An IoT-based bin level monitoring system for solid waste management,” Springer, 2020.

[19] B. Fang, J. Yu, Z. Chen, A. I. Osman, E. H. Hamza, D. W. Rooney, and P.-S. Yap, ”Artificial intelligence for waste management in smart cities: a review,” 2023.

[20] J. John, N. Sensarma, M. Selvi, and S. V. N. Santhosh Kumar, ”Smart Prediction and Monitoring of Waste Disposal System Using IoT and Cloud for IoT Based Smart Cities,” Springer, 2021.

[21] G. E. Gonzalez, E. R. Escobar, A. C. Bento, and I. Carvajal, ”Smart Trash Bins: Integration of IoT with AI for Efficient Waste Management,” Instituto Tecnolo´gico y de Estudios Superiores de Monterrey, Mexico, 2024.

[22] S. Vishnu, S. R. J. Ramson, S. Senith, T. Anagnos- topoulos, A. M. Abu-Mahfouz, X. Fan, S. Srinivasan, and A. Kirubaraj, ”IoT-Enabled Solid Waste Management in Smart Cities,” Vignan’s Foundation for Science, Technology and Research, India, 2021.

[23] A. Sadeghi-Niaraki, M. Jelokhani-Niaraki, and S.-M. Choi, ”A Volunteered Geographic Information-Based Environ- mental Decision Support System for Waste Management and Decision Making,” 2020.

[24] M. S. Aldossari, T. Assaf, R. Abdullah, and R. Saheed, ”Waste Management System,” IEEE, 2022.

[25] T. A. Khoa, C. H. Phuc, P. D. Lam, L. M. B. Nhu, N. M. Trong, N. T. H. Phuong, N. V. Dung, N. T.-Y., H. N. Nguyen, and D. N. M. Duc, ”Waste Management System Using IoT-Based Machine Learning in University,” Ton Duc Thang University, Vietnam, 2020.