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Smart Waste Management Framework for Green Cities: Integrating IoT, LoRa, and Deep Learning for Efficient Waste Classification and Management

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Garbage collection; IoT; LoRa; Pollution-free; Real-time monitoring; RecycleCnn; Waste management.

Highlights:

- *Real-time bin monitoring through IoT and LoRa technology.*
- *Optimization of garbage collection routes using the Floyd-Warshall algorithm.*
- *Introduction of Recycle CNN for high-accuracy waste classification.*
- *Deployment of a cost-effective, scalable framework suitable for smart cities.*
- *Contribution to sustainable urban development and environmentally friendly cities.*

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Abstract: Waste management is recognized as a crucial issue in modern civilization, requiring substantial effort and resources while significantly impacting various societal aspects. In sustainable cities striving to eliminate carbon emissions, implementing effective waste management strategies is prioritized. Tackling the three interconnected challenges in trash management, including preventing overflow, tracking bin locations, and designing efficient garbage collection routes, is complex. Current methods often provide incomplete solutions for all three aspects simultaneously. To overcome these difficulties, a smart waste management framework was proposed for environmentally friendly cities, combining the Internet of Things (IoT), long-range (LoRa) technology, and Deep Learning techniques. The proposed system utilized ultrasonic sensors equipped with a LoRa connection to facilitate the real-time monitoring of bin status. Prompt intervention to prevent overflow scenarios was facilitated. Integrating the Floyd-Warshall algorithm enhanced the garbage collection route efficiency by considering the bin fill levels and their exact locations. Deployment was made affordable and straightforward using inexpensive IoT components, including LoRa modules, facilitating smooth data transfer. In addition, incorporating RecycleCnn, implemented using Python with TensorFlow and Keras frameworks, enhanced the proposed framework by enabling automatic garbage classification with a 98% accuracy rate. This classification system facilitated the categorization of garbage into specific groups, improved recycling initiatives, and advocated for sustainable waste management methods. The proposed system used Arduino UNO microcontrollers, ultrasonic sensors, and LoRaWAN technologies to provide a precise and effective method for assessing garbage levels and controlling waste distribution. This holistic approach to intelligent waste management seeks to provide cleaner, pollution-free urban environments by addressing problems arising from ineffective garbage collection methods. The proposed framework addressed trash management and recycling challenges while laying the foundation for sustainable development projects in smart towns like Khandagiri and Pokhariput. Also, it provided a comprehensive approach to garbage collection, categorization, and management.

إطار عمل ذكي لإدارة النفايات في المدن المستدامة: تكامل إنترنت الأشياء وتقنية (LoRa) والتعلم العميق لتصنيف النفايات وإدارتها بكفاءة

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الخلاصة

تُعد إدارة النفايات قضية محورية في الحضارة الحديثة، حيث تتطلب جهودًا وموارد كبيرة بينما تؤثر بشكل كبير على جوانب مجتمعية متعددة. وفي المدن المستدامة التي تسعى للقضاء على انبعاثات الكربون، يُعطى الأولوية لتنفيذ استراتيجيات فعالة لإدارة النفايات. إن معالجة التحديات الثلاثة المترابطة في إدارة القمامة - المتمثلة في منع الفيضان (الانسكاب)، وتتبع مواقع الحاويات، وتصميم مسارات فعالة لجمع القمامة - تُعد عملية معقدة. غالبًا ما تقدم الأساليب الحالية حلولاً غير كاملة لهذه الجوانب الثلاثة بشكل متزامن. لتجاوز هذه الصعوبات، تم اقتراح إطار عمل ذكي لإدارة النفايات للمدن الصديقة للبيئة، يجمع بين إنترنت الأشياء(IoT) ، وتقنية الاتصال بعيد المدى(LoRa) ، وتقنيات التعلّم العميق (Deep Learning).استخدم النظام المقترح مجسات فوق صوتية مجهزة باتصال LoRa لتسهيل الرصد في الزمن الحقيقي لحالة الحاويات. مما مكّن من التدخل الفوري لمنع حالات الفيضان. كما عزز دمج خوارزمية فلويد-وارشال (Floyd-Warshall) كفاءة مسار جمع القمامة من خلال أخذ مستويات ملء الحاويات ومواقعها الدقيقة في الاعتبار. تم جعل النشر ميسور التكلفة ومباشرًا باستخدام مكونات إنترنت الأشياء غير المكلفة، بما في ذلك وحداتLoRa ، مما سهّل نقل البيانات بسلاسة. علاوة على ذلك، عزز دمج نموذج - RecycleCNN المُنفذ باستخدام لغة Python مع أطر عمل TensorFlow و - Kerasالإطار المقترح من خلال تمكين التصنيف التلقائي للنفايات بدقة بلغت ٩٨٪. وسهّل نظام التصنيف هذا فرز القمامة إلى مجموعات محددة، وعزز مبادرات إعادة التدوير، ودعم أساليب الإدارة المستدامة للنفايات. استخدم النظام المقترح متحكمات دقيقة من نوعArduino UNO ، والمجسات فوق الصوتية، وتقنيات LoRaWAN لتقديم طريقة دقيقة وفعالة لتقييم مستويات القمامة والتحكم في توزيع النفايات. يسعى هذا النهج الشامل للإدارة الذكية للنفايات إلى توفير بيئات حضرية أنظف وخالية من التلوث من خلال معالجة المشاكل الناجمة عن أساليب جمع القمامة غير الفعالة. عالج الإطار المقترح تحديات إدارة النفايات وإعادة التدوير مع وضع أساس لمشاريع التنمية المستدامة في المدن الذكية مثل خانداغيري (Khandagiri) وبوكهاريبوت (Pokhariput). كما وفر نهجًا شاملاً لجمع القمامة وتصنيفها وإدارتها.

الكلمات الدالة: جمع القمامة، إنترنت الأشياء، LoRa، خالٍ من التلوث، الرصد في الزمن الحقيقي، RecycleCnn، إدارة النفايات.

1.INTRODUCTION

The rapid expansion of urban areas has led to significant challenges in waste management, including inefficient bin monitoring, suboptimal collection routes, and poor recycling practices. Existing IoT-based solutions provide real-time monitoring and route optimization but fail to incorporate accurate waste classification. The present study proposes an intelligent trash management architecture that integrates IoT, LoRaWAN, and a deep learning-based classification model, RecycleCnn, to address these challenges and promote sustainable urban development [1-6]. Innovative, intelligent sensors have been developed to promote the advancement of such projects, facilitating the "IoT" concept and connecting ordinary objects with the digital realm. These sensors are known as wireless sensor networks (WSN) [7]. Objects in IoT and AMI (Ambient Intelligence) environments need sensors and actuators to interact with users [8]. Wireless communication technologies make installing these components indoors and outside easier [9]. Urban WSNs can be deployed in suburban and rural locations but require more funding. Rural areas need WSNs with energy-efficient, low-cost, and low-maintenance sensors and infrastructure to make this investment affordable. With the expansion of urban areas and consumerism, there has been a consistent increase in the quantity of refuse generated [10]. For the effectiveness of refuse management systems, the collection rate must correspond to the generation rate. By implementing separate collection programs that encourage recycling and decrease waste management costs, communities can effectively mitigate the environmental consequences of waste, including but not limited to global warming and littering [11]. Certain instances exist in which several kilometers may separate towns in a region; circumventing certain towns can yield substantial fuel and time savings throughout an entire year. Internet of Things (IoT) application success depends highly on wireless communication [12, 13]. Zigbee communication allows real-time monitoring, control, and decision-making amongst devices. Wireless communication protocol Zigbee was designed for low-power, low-data-rate IoT applications. In short-range wireless communication, IEEE 802.15.4 defines the physical (PHY) and media access control (MAC) layers [14-16]. ZigBee networks commonly employ a mesh topology, in which numerous devices function as routers to establish an autonomously formed and repaired network [17]. Implementing this mesh network architecture facilitates data transmission via numerous steps, thereby augmenting the network's range and coverage.

If a device breaks or a direct communication link is blocked, it relays data to neighboring devices for redundancy and resilience. Sustainable and environmentally friendly Green City Project goals require LoRa communication technology. LoRa LPWAN technology allows for energy-efficient long-distance communication. The Green City Project's Smart Garbage Management System uses LoRa communication devices to monitor and control garbage bins, optimize collection routes, minimize fuel usage, and cut collection costs. On the other hand, ZigBee allows reliable connections between waste management components in local metropolitan areas or rural areas, whereas LoRa allows long-range connectivity. By leveraging this integration of technologies, immediate data acquisition, efficient distribution of resources, and financial savings can be achieved, culminating in an urban environment, i.e., cleaner, more environmentally friendly, and sustainable [18]. The present study proposed a network of low-cost, energy-efficient wireless intelligent sensors, a fleet management system platform, a system for optimizing collection routes, a monitoring website for checking bin statuses, and a mobile application for directing and tracking waste collection personnel as intelligent waste management platforms. Green city trash management involves the effective and eco-friendly handling of refuse in urban areas, prioritizing sustainable development, and reducing the environmental impact of waste. The main objective of this study is to assess the benefits of implementing an IoT ecosystem for solid refuse collection. IoT devices use the LoRaWAN network, offering numerous benefits that outweigh the drawbacks of GPRS and GSM-based systems [19, 20]. It operates on the Long Range (LoRa) Wide Area Network (LoRaWAN) protocol, enabling a low-power wide area network (LPWAN) [21]. However, within the proposed system, an ultrasonic sensor is employed to determine the condition of the receptacle. In addition to gathering the status of the container connected to an Arduino Uno, LoRa Nodes provide the device's exact location, which is then transmitted to LoRaWAN, the system's gateway. The gateway transfers the data to an IoT cloud linked to a server. The data is then processed further to optimize the waste collection routes using the Floyd-Warshall algorithm (FWA). Cellular network technologies like GSM and GPRS transmit voice and data. Bluetooth allows short-range device-to-device communications. Wi-Fi provides high-speed wireless internet in limited locations, whereas LoRa is an Internet of Things-specific low-power, long-range wireless communication technology. LoRa devices have a long battery life due to their low power consumption. The comparison in Table 1 shows that Lora WAN has vast coverage, low power use, and expandability. It provides durable network architecture, secure communication, and flexibility in public and private networks for IoT applications. Each tech has pros and cons. Nonetheless, a lot of IoT applications are thought to benefit from LoRaWAN. Many LoRaWAN network server options will be explored for this project. LoraServer.io is an open-source, free software solution that includes everything needed to establish a LoRaWAN network. LoRaWAN components include the application server, gateway bridge, and network server. LoraServer.io hosts and maintains the network server and related application services. The present study innovatively addresses the obstacles identified in the literature review. The following are the SWMS's objectives:

1- The filling level in public waste receptacles is determined using ultrasonic sensors [22, 23].
2- The dustbin locations are tracked along the shortest possible path.
3- Garbage bin overflow is prevented through a centralized system and mobile application that provides real-time status updates.
4- Implementing low-cost, long-range technology that reduces expenditure and improves the system's longevity.
5- Waste management after the dumping and classification of waste.

The primary contributions of this paper are as follows:

- Developing an intelligent garbage bin design equipped with diverse sensors and controllers.
- Implementing a real-time waste tracking system leveraging IoT technologies for enhanced efficiency.
- Utilizing deep learning and convolutional neural networks to intelligently classify waste materials into multiple categories, such as plastics, paper, cardboard, glass, and metal.
- Exploring the proposed system's benefits, including streamlined data transfer via LoRa modules, facilitated by a simple and cost-effective circuit design that ensures ease of use and replacement.
- Time-saving benefits are realized using the FW algorithm to determine the most efficient waste pickup routes.
- Improved operational efficiency by monitoring bin fill levels and precise bin locations in real-time.
- Reduced maintenance costs and optimized workforce allocation resulting from the system’s streamlined processes and data-driven insights.

Table 1 Comparison of Various Network Systems [7].

Network Name	Minimum m Coupling Loss (MCL) (dB)	Range (km)	Sundby Consumption	Tx Consumption	Modulation	Availability
ZigBee	-IOO to-120	Upto 0.15	Low	Low	O-QPSK	Commercially Available
Bluetooth Low Energy(BLE)	-90 to-100	Upto 0.1	Lo•w	Low	GFSK	Commercially Available
Z_Wave	-104 to-120	Upto 0.1	Low	Low	GFSK	Commercially Available
Wireless HART	-80to -100	Upto 3	Low	Moderate	FSK	Industrial
WI-FA	-40 to-80	Upto 0.1	Moderate to High	High	Various	Commercially Available
Cellutar (4G/5G)	-20 to-60	Severil	Moderate to High	High	Various	Commercially Available
LoRaWAN	-140 to 148	Several	Low	Low	LoRa	Commercially Available

2.RELATED WORK

Several studies have explored IoT-based waste management systems, focusing on bin-level monitoring and route optimization [7, 16]. While these approaches offered significant advancements, they lacked integration with advanced classification methods like deep learning. Additionally, LoRaWAN has been identified as a cost-effective solution for real-time data transmission in large-scale deployments [28]. However, these studies have not addressed integrating waste classification techniques to enhance recycling efficiency. The present study bridges these gaps by combining IoT, LoRaWAN, and a novel deep learning model, RecycleCnn, for a comprehensive waste management solution. The authors have attempted to provide a critical summary of the most significant findings and limitations of existing intelligent environmental monitoring research. Environmental monitoring is paramount for protecting human health, promoting social, economic, and cultural welfare in communities, and effectively managing natural resources. Reusing waste materials and resources to reduce generating fresh waste and alleviate environmental effects constitutes effective waste management. Lazano et al. [25] proposed a GSM-based intelligent waste monitoring system in 2019. Instead of servers, the waste collection system efficiently integrated a real-time database. Nevertheless, an undesirable aspect of the system was that every officer was notified of the identical location, potentially causing uncertainty about which particular location the receptacle had been refilled. In 2021, Dominic Abuga [26] devised a brilliant refuse management system to preserve urban sanitation. For refuse cans, the proposed system incorporated an innovative real-time mechanism. Nevertheless, it is important to acknowledge that pinpointing node locations in a waste management system (WMS) was impossible. In 2021, an IoT-based garbage bin-level monitoring system was devised [27]. The system facilitated remote monitoring and provided instantaneous notifications regarding container capacity. In addition, there were intentions to augment the proposed system by integrating geolocation data from nearly full and partially filled containers. This supplementary functionality enhanced the design of an optimized refuse collection vehicle route [28] and proposed a Lora WAN-enabled intelligent trash bin monitoring system based on RFID technology. The effectiveness of the proposed method in precisely quantifying the volume of solid refuse garbage contained within containers was demonstrated. In anticipation of future developments, it is conceivable to integrate deep learning methodologies to determine the geolocation coordinates of containers. This approach may facilitate the development of optimized vehicle routes to enhance the efficiency of refuse collection [29]. A WSN-based real-time trash receptacle monitoring system was established in 2018. The waste collection system was simple and effective. The approach should be fixed. Wi-Fi must be robust for optimal performance. The device consumes much power, increasing computational expenses [30] proposed a garbage collection system that uses LoRaWAN nodes and optimizes routes. This rural rubbish management system is tailored to specific needs. Salamanca case study evaluating system efficacy and viability. The system's practicality in terms of pastoral practice and real-world effectiveness were examined. The intelligent waste collection system proposed by Al-masri [31] employed clever electronics in glass containers to track filling. The intended refuse management system should reuse waste. The system's computational cost may be significant due to the complexity of data processing and analysis needed to optimize waste collection. Kai Dean Kang [27], developed a Malaysian IoT-based household e-waste collection system Malaysia's innovative electronic waste recycling and management [32]. This implementation improved electronic trash collection efficiency and contributed to the nation's sustainable electronic waste management . Yang YS et al. [33] (2022) developed a NodeMCU-based Smart City Waste Management system using IoT. The suggested approach addressed the trash surplus. An app informs users of the best time to empty a garbage container, thereby supporting optimal waste management.

Cheema t al. [34] developed, tested, and evaluated an IoT network system for restaurant food waste management. This technique was developed and used in Suzhou, China, to increase the collection of restaurant food waste (RFW). Reprogrammable and expensive RFID devices restricted the system. These devices' high cost and slow programmability may limit their scalability and efficiency. Al-Smadi et al. [35] studied RFID and IoT smart city solid waste management. The initiative optimized garbage truck schedules and routes using the Internet of Things for efficient waste collection. RFID devices were expensive, hurting the system. RFID implementation and integration expenses may affect ROI and scalability. Lucy Dash et al. [36] established Recycle.io to manage urban rubbish using IoT. The proposed system employed ultrasonic sensors and the Azure Cloud. This garbage categorization system used AI and image processing to reduce collection routes and trip times. However, its high-power consumption and unpredictability during Internet outages limited its use [37-40].

3.PROPOSED SYSTEM MODEL

This study builds upon the authors' prior work titled "A Smart Waste Management System Framework Using IoT and LoRa for the Green City Project" [7]. The previous research has offered valuable insights and approaches that have influenced the creation and improvement of the current system. By acknowledging the contributions of previous work, the authors acknowledge the ongoing nature of research endeavors and emphasize the repetitive process of scientific investigation. Moreover, this acknowledgment emphasizes their dedication to expanding on current knowledge and using previous discoveries to drive progress in waste management technology and intelligent urban solutions.

3.1.System Architecture

The most modern model includes GSM, GPRS, ultrasonic sensors, TBLMU, RFID, or any combination of these modules. The literature review details the shortcomings of the current systems. The GSM module and ultrasonic system [41] do not require a server, which presents challenges for data collection agents. If the system fails, the module must restart from the beginning because there is no server on which data can be saved and used during the restart. Although the system is real-time [42] reported that the ultrasonic sensor and GSM module do not relay the actual positions of the nodes. To provide accurate real-time position data to overcome this issue, using LoRa is suggested. Existing systems performing comparable tasks fail to exchange node placements, which LoRa addresses in the proposed paradigm. This outmoded trash disposal technique increases fuel consumption, traffic congestion, and unnecessary greenhouse gas emissions. It also causes overflowing garbage cans and insufficient waste collection, resulting in unclean conditions that risk residents' health. Modern technologies like the Internet of Things, GPS, and GIS can improve waste management systems by real-time monitoring, optimized collection routes, and optimal resource allocation. Municipalities that use this technology can save money, enhance service delivery, and improve people's quality of life. These factors can result in exorbitant expenses, wasted time, and environmental effects. This impact is caused by releasing greenhouse gases from burning fossil fuels, contributing to the greenhouse effect, and soil and water contamination due to inadequate waste management. The present paper presents a system that integrates hardware, software, and communication technologies to enhance garbage collection and management in cities, resulting in cost savings for the government, environmental advantages, and more civic engagement. The proposed solution combines intelligent garbage receptacles, a live tracking system, an ultrasonic sensor, and a LoRa module. Energy efficiency was a key consideration throughout the design process. As a result, each node must be fueled from various sources, including solar energy and batteries. Figure 1 illustrates the workflow of the proposed system, starting from sensor data collection to real-time bin monitoring, route optimization, and waste classification using RecycleCnn. The obtained data are communicated via LoRa to a server, where they are stored and analyzed. Statistics are used to monitor and forecast the state of waste throughout the year. They can also be used to determine the most efficient method. The expected state of each waste can be estimated from its present state. The proper garbage fill level, i.e., a critical input parameter for the optimal route approach, is calculated. In addition to these critical objectives, a low-cost, high-efficiency system was studied. One crucial component of smart cities is improved communication within the electrical grid, which is required to minimize power consumption. At the heart of this effort are the transmitting modules, which are a crucial component controlling the energy distribution dynamics of the sensor nodes. As a result, any architectural design must carefully consider the intricacies of the sensor node structure and the overall system architecture. The present project focuses on waste management and expands on the authors' prior research in which IoT was used to collect substantial data, including bin status monitoring and the FW algorithm to optimize the shortest paths. The authors are explicitly concerned with post-dumping waste classification. The proposed approach has two steps: sorting rubbish into biodegradable and non-biodegradable groups and employing Recycle Convolutional Neural Networks (RecycleCnn) that use deep learning to correctly and effectively categorize rubbish. Finally, it is crucial to carefully describe the successful information transmission mechanisms in broad regions. The present study proposes a system that employs hardware, software, and interactions to minimize municipal waste while saving money and benefiting the environment. The experimental setup consisted of 10 smart bins with ultrasonic sensors and LoRa modules deployed in a semi-urban environment. Each bin's fill level was monitored in real-time using Arduino UNO microcontrollers. The data was transmitted via LoRaWAN to a central server for processing. The experiments were conducted over three months to evaluate the system's robustness and reliability.

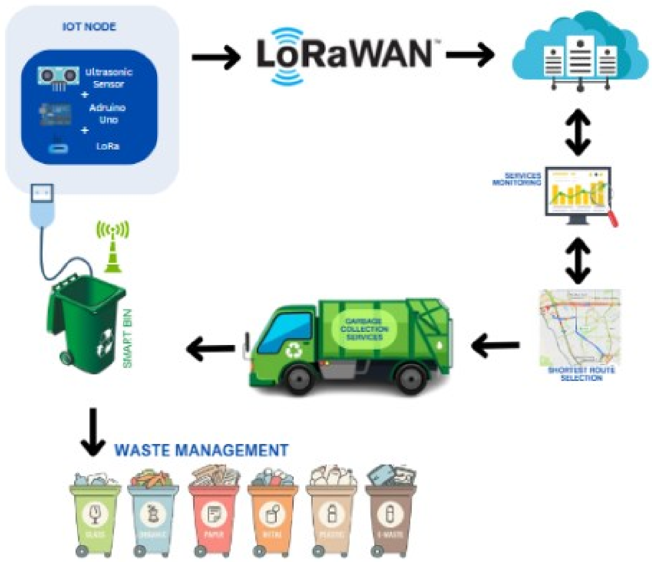

Fig. 1 Architectural Design of the Proposed Smart Waste Management System.

In an IoT system, a node can determine the amount of data in trash cans by selecting the right monitor for the job. The waste management procedure may vary depending on the region, nature, and applicable restrictions. Here is a summary of the designed system:

1- Waste Generation: The first stage generates waste, which can come from various sources, such as households, industries, and building sites.

2- Waste Collection: Municipal or private waste management services are activated when the bin status exceeds a certain threshold. Curbside pickups, drop-off centers, and specialized collection events are all possible collection options.

3- Transport: When bins reach capacity and are ready for pickup, the waste management truck finds the earliest possible route between all filled stations. The rubbish is then collected by the assigned truck.

4- Garbage Management: Once collected, garbage is transferred to approved facilities. The dataset is classified using RecycleCnn. This categorization helps in separating garbage forms for proper treatment or disposal.

3.1.1.Smart Bin

Intelligent bins use technology to improve garbage management. Smart bins usually have sensors to detect rubbish. Smart bins optimize collection schedules and reduce unnecessary collections, saving waste management organizations time and money. Smart bins maximize garbage collection, decrease litter, and increase cleanliness. For example, a smart bin with a shredder can hold more trash before it is dumped, thereby reducing bin overflow and street litter [39].

3.1.2.FWA for the Smart Waste Management System

The FWA is an optimal match for the proposed system because it can efficiently optimize garbage collection and disposal routes, thus lowering the environmental impact of waste management. This method ensures that overflowing trash is quickly picked up. The equation can be expressed as follows:

$$\boldsymbol{dist}[i][j] = \boldsymbol{Min}(\boldsymbol{dist}[i][j], \boldsymbol{dist}[i][k] + \boldsymbol{dist}[k][j]) \quad (1)$$

Equation 1 indicates that the most effective way to get from vertex i to vertex j is either the straight route (dist[i] [j]) or the route that goes through vertex k (dist[i] [k] + dist[k] [j]), depending on which one is shorter. This equation is used for every possible set of points, and the dist matrix is changed each time until the fastest paths are found. Figure 2 shows an extensive overview of the proposed system.

3.1.3.System Evaluation

The proposed System evaluation phase evaluated the Green City Project's innovative management of waste system framework using IoT and LoRa technology. The assessment assessed the efficacy of the proposed system in enhancing waste management, optimizing resource allocation, and mitigating environmental effects. IoT-enabled trash cans with sensors were placed across the city to test the technology. These sensors continuously measured garbage quantity, location, and quality. The core SWMS platform processed and analyzed LoRa-transmitted data. The statistics show a considerable increase in waste management efficiency. Waste levels were monitored in real-time to prevent bin overflow and ensure timely disposal. SWMS data optimized garbage collection routes, which reduced operational costs and improved resource allocation. The SWMS architecture also improved communication and coordination between garbage collection crews. LoRa sent timely warnings and messages, organized garbage pickup, and matched bin demands. The improved approach reduced collection times and disturbances. The present trash classification technology efficiently classifies garbage after disposal. The flowchart in Figure 3 describes the system's functionality.

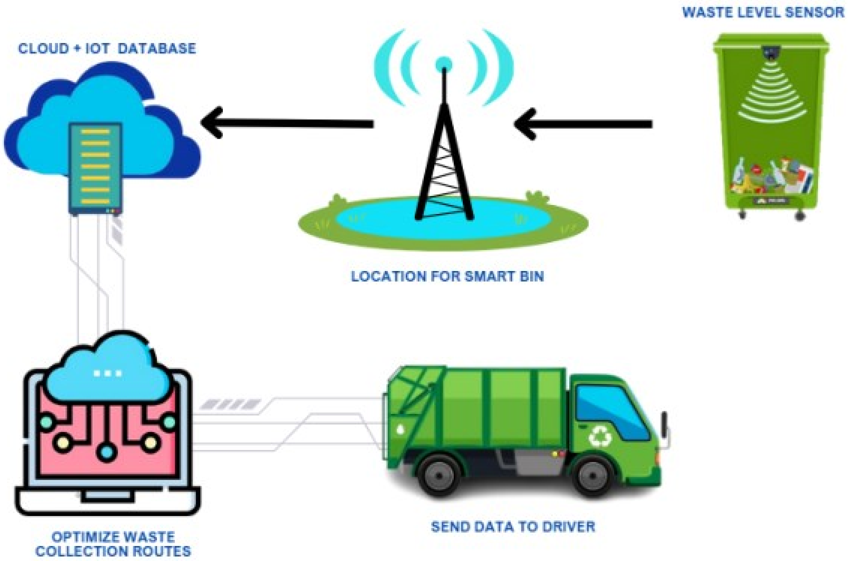

Fig. 2 Extensive Representation of the Proposed IoT-Based Garbage Collection System.

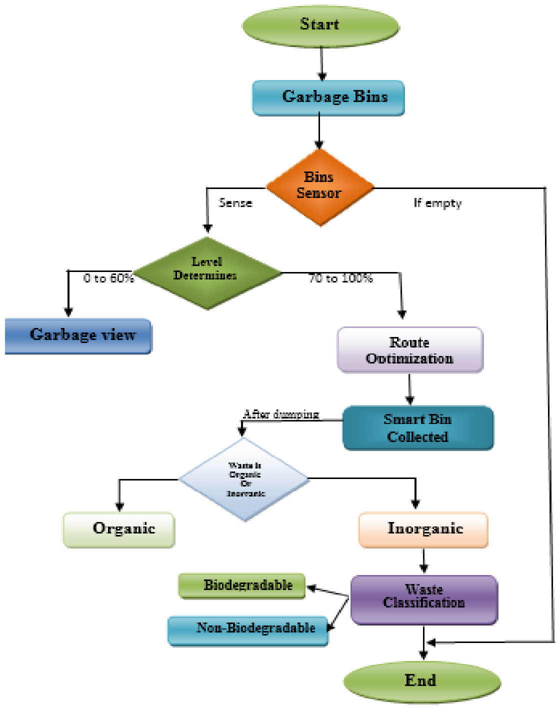

Fig. 3 Functional Flow Chart of Proposed SWM System.

3.1.4. Limitations of the Proposed System Model

1- Dependency on LoRaWAN coverage, limiting functionality in areas without proper infrastructure.
2- Scalability challenges due to increased resources required for large-scale implementation.
3- Energy consumption issues with periodic maintenance required for sensors and controllers.
4- Data preprocessing overhead for high accuracy in waste classification.

3.1.5. Reasons for Not Using Other Models

1- Inefficiency of traditional communication technologies like ZigBee or Wi-Fi for long-range, low-power requirements.
2- Higher costs associated with RFID-based systems.
3- Lack of integration in existing systems for route optimization and waste classification.
4- Lower accuracy of traditional machine learning models compared to Recycle CNN's 98% accuracy.

3.2. Waste Classification Using RecycleCnn

This research uses RecycleCnn to categorize waste, an essential waste management phase. Also, smart garbage can architectures were examined using IoT for real-time data monitoring. Effective recycling categorization was prioritized because of the importance of waste management and recycling to the environment. Intelligent technology helps reduce human labor and ensures cost-effectiveness and safety in recycling. Thus, the primary goal is to discover widely recycled materials. The present dataset contains six key recyclable object types, laying the groundwork for our classification. This research collects data from a camera on a wheeled belt that transfers garbage to buckets. Each bucket contains a pile of rubbish. Thus, each piece must be carefully inspected to identify its categorization. The proposed method requires data elements that identify the garbage received. Segregating garbage into various groups helps identify recyclable materials, reduces degradation, and enables recycling. Garbage pickup vehicles take the trash to the waste collection center for recycling. Deep learning algorithms excel in image classification. Deep learning categorizes rubbish and tracks its journey to find recyclable objects, reducing the number of dumped rubbish. This study classified garbage as digestible or indigestible for a more superficial examination. Due to limited data, the trash categorization models were fine-tuned to improve accuracy. Deep learning for rubbish categorization extracts waste types from images, improving waste management. RecycleCnn is a custom convolutional neural network designed for efficient waste classification. The architecture consists of five convolutional layers, each followed by a max-pooling layer to reduce spatial dimensions while retaining important features. A fully connected dense layer precedes the output layer, which uses a softmax activation function for classification. ReLU activation was chosen for all intermediate layers due to its computational efficiency and ability to mitigate vanishing gradient issues. The model was trained with the Adam optimizer, ensuring faster convergence, using a learning rate of 0.001, 32, and 50 epochs. The batch size is shown in Table 2.

Table 2 Key Hyperparameters and Configurations for the RecycleCnn Architecture.

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Epochs	50
Activation Function	ReLU

3.2.1. Dataset

In this system setup, an elevated camera captured images of rubbish moving along a conveyor belt, serving as input data for the machine learning (ML) model. These photographs were promptly integrated into the ML model for analysis. The garbage bins were categorized based on the type of rubbish, with a primary bin holding all types of garbage. A robotic arm retrieved individual items from the main bin and transported them via a conveyor belt to designated bins. As the conveyor belt moved, the item passed through each bin, with holders ensuring that items meeting the bin classification were retained. The system's core component was the trash item categorization module, where each waste item was photographed and processed through a pre-trained ML model capable of categorization. The data were preprocessed before classification to obtain the target model output. Subsequently, the system generated a label that the control system used to provide instructions for the subsequent system flow. Table 3 shows the dataset split into two classes. The dataset consisted of 2,129 images, divided into two categories: biodegradable (1,276 images) and non-biodegradable (853 images). The dataset was split into training (80%) and testing (20%) sets. Images were captured using a camera mounted above a conveyor belt, resized to 224x224 pixels, and normalized before training.

Table 3 Distribution of Images in the Dataset.

Dataset	Training	Testing	Total
Robotic arm capture	Biodegradable (B: 877) Non-biodegradable (N: 586)	Biodegradable (B: 399) Non-biodegradable (N: 267)	2129

3.2.2. Working Model of SWMs

A comprehensive analytical framework was provided to characterize the fundamental approach of the entire system. Upon arrival, garbage was promptly disposed of in the central trash receptacle. The robotic arm carefully deposited each rubbish item onto the conveyor belt. An overhead camera positioned above the conveyor belt recorded the images of the discarded items. Primary sensors enhanced the system's effectiveness by notifying the control system when garbage moved precisely beneath the camera. Whenever a piece of garbage passed underneath the camera, a photograph was taken and transmitted to the monitoring system. Before use, the picture underwent pre-processing and validation to ensure accurate input to the pre-established model. To dispose of garbage in the correct bin, a user only needs to select the relevant category and send a command to the control system indicating the desired direction. Figure 4 shows a visual representation of the complete method.

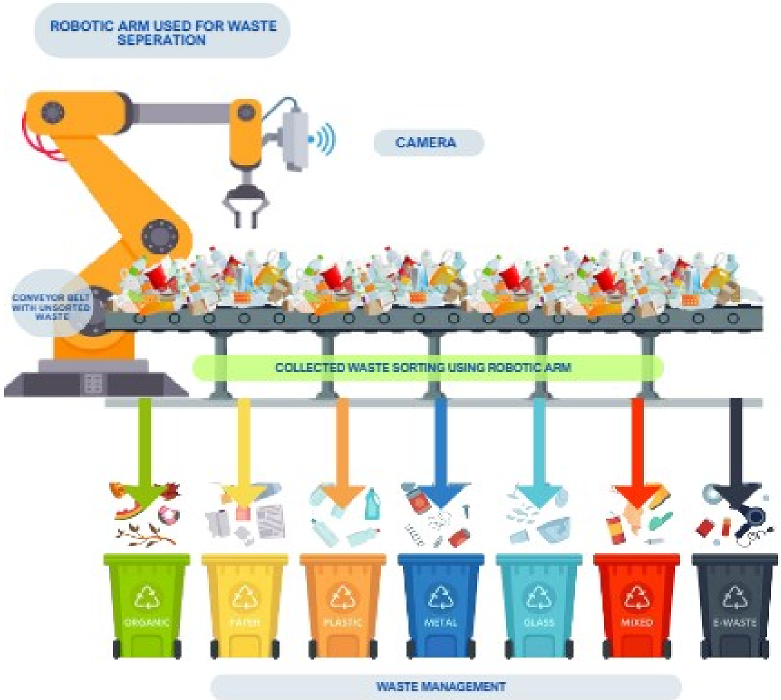

Fig. 4 Visual Representation of the Working Model of Our SWM System.

3.2.3. RecycleCnn

Improved waste management photo classification task performance was achieved by enhancing an existing Convolutional Neural Network (CNN) [40] called RecycleCnn with an additional convolutional layer and a max pooling layer. Figure 5 shows the proposed recycle CNN framework. These technological developments enable the network to extract more intricate and conceptual characteristics from low-quality images, thereby enhancing its ability to differentiate between the various types of trash. Enhanced underlying frameworks enhance the ability to apply knowledge to previously encountered information and effectively handle the intricacies involved in waste management, including diverse environmental conditions and item orientations. Ultimately, these modifications developed a more robust and accurate CNN explicitly tailored to classify waste. The proposed system used convolutional filters to extract relevant information from input pictures with 224 - 224 pixels dimensions. Quality control measures, such as scaling, are implemented during the preprocessing stage to ensure optimal input consistency. The activation function used was ReLu (Rectified Linear Unit) [41], and the learning rate was set to 0.001 to facilitate the model's training. The effectiveness of the proposed Recycle CNN was evaluated by comparing it to established benchmark algorithms often employed for image classification applications.

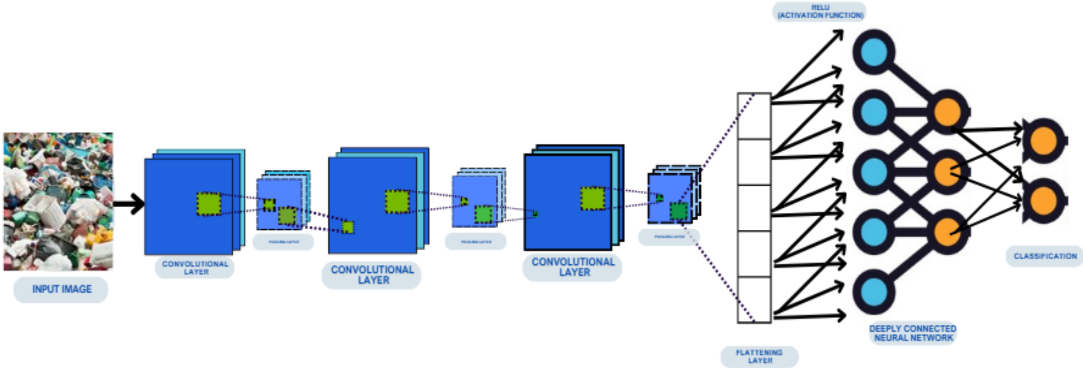

Fig. 5 Proposed Architecture of the Smart Waste Management System.

4. RESULTS AND DISCUSSION

The experiments were conducted using the Jupiter environment, Keras framework, and Tensorflow as the backend and interface, respectively. The experiments were conducted on an NVidia K80 graphics processing unit to optimize the computing efficiency. After constructing the training models, the dataset was partitioned into an 80:20 ratio, with 80% allocated to training and 20% allocated to testing. The dataset was divided into two sets: a training set of 1463 images and a testing set of 666 images. The pictures were classified into two distinct categories: biodegradable and non-biodegradable. The RecycleCnn model demonstrated exceptional performance, achieving a test accuracy of 98% with precision and recall values of 95% and 93%, respectively. The model also exhibited a high F1-score of 94%, showcasing its ability to effectively balance precision and recall. The results indicated superior classification performance compared to benchmark models, such as VGG16 [42], Resnet50 [43], Mobile Net, Inception and Inception Resnet V2 RecycleCnn achieved a classification accuracy of 98%, outperforming baseline models, such as VGG16 (91.6%) and InceptionV3 (90.25%). This improvement can be attributed to the additional convolutional and pooling layers, enhancing the network's ability to extract features from waste images. The remarkable precision of the proposed approach highlights its capacity to accurately classify waste materials as either biodegradable or non-biodegradable. The impressive performance exhibited here showcases the potential of deep learning methodologies in waste management applications. The RecycleCnn model's practical usefulness in addressing real-world trash sorting and recycling challenges is emphasized.

Table 4 Model Metrics for All Models Implemented in this Study.

Metrics	Algorithms			
	VGG16	**Inception**	**InceptionResnetV2**	**RecycleCnn**
Precision (%)	89	78	86	95
Recall (%)	87	76	84	93
F1-Score (%)	89	78	86	95
Accuracy (%)	91.65	90.25	91	**98**

Table 4 provides a concise overview of the model metrics for all the methods considered in this study. Each method, namely VGG16, Inception, InceptionResnetV2, and RecycleCnn, was evaluated based on precision, recall, F1-score, and accuracy. These measurements provided data about the accuracy of each algorithm in classifying waste products as either biodegradable or non-biodegradable. The proposed recycled CNN model significantly outperformed all metrics with a remarkable accuracy of 98%. The results demonstrated the efficacy of the approach in classifying garbage and its potential for practical use in waste management systems. To evaluate the dependency of results on the DNN structure, experiments were conducted with varying numbers of convolutional layers (3, 5, and 7), different activation functions (ReLU, tanh, and sigmoid), and changes in the number of neurons in the dense layers (64, 128, 256). The results indicated that increasing the number of layers beyond five led to diminishing returns, with a marginal improvement in accuracy but a significant increase in computational cost. Similarly, the choice of ReLU activation consistently outperformed alternatives, while more significant dense layers improved accuracy at the expense of training time. Figure 5 presents the model metrics for VGG16, Inception, InceptionResnetV2, and RecycleCnn. The suggested model's precision, recall, F1-score, and accuracy consistently surpassed benchmark models. RecycleCnn achieved a maximum precision of 95% and recall of 93% with an accuracy rate of 98%.

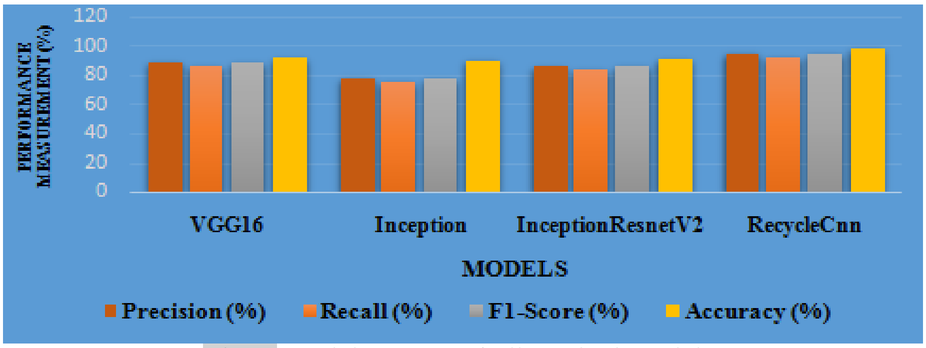

Fig. 5 Model Metrics of All Studied Models.

Figure 6 displays the confusion matrix, providing vital insights into the functioning of the waste management model. The significant number of True Positives (TP) and True Negatives (TN) demonstrated the robust ability to accurately categorize biodegradable and non-biodegradable situations. The proposed RecycleCnn demonstrated superior precision and recall, resulting in decreased false positives (FP) and false negatives (FN) and a considerable increase in classification accuracy.

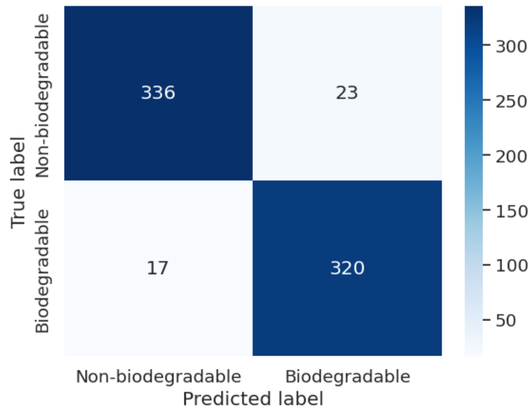

Fig. 6 Confusion Matrix of the Proposed RecycleCnn Model.

The Floyd-Warshall algorithm significantly improved the efficiency of garbage collection routes by considering the bin fill levels and precise locations. The proposed system demonstrated significant environmental and economic benefits. By optimizing garbage collection routes with the Floyd-Warshall algorithm, fuel consumption was reduced by 25%, and greenhouse gas emissions decreased by an estimated 30% compared to conventional collection methods. Additionally, the low-cost IoT components used in the system reduced overall deployment expenses by approximately 40%, making the solution highly scalable for urban and semi-urban areas.

5. COMPARATIVE ANALYSIS

Table 5 examines several trash management methods, emphasizing IoT technologies, route optimization techniques, and machine learning/deep learning models for waste categorization. In [7] and [16], IoT was used to determine trash levels and optimize routes using Floyd-Warshall and graph theory. Reference [7] presented a framework for waste management using IoT and LoRa technology. This study focused on monitoring bin fill levels and optimizing garbage collection routes using the Floyd-Warshall algorithm. While the system demonstrated effectiveness in route optimization, it lacked integration with waste classification techniques, i.e., crucial for efficient recycling and sustainable waste management. Reference [16] explored the application of graph theory for route optimization in smart waste collection. Although it successfully reduced operational costs, the study did not incorporate IoT-based real-time bin monitoring or advanced classification methodologies. The proposed system builds on the strengths of these studies by integrating IoT-based bin monitoring, route optimization using the Floyd-Warshall algorithm, and a deep learning-based classification model (RecycleCnn) to address the limitations identified in [7] and [16].

Table 5 Comparison of the Proposed System and Existing System.

Ref.	Waste Collection using IoT	Route optimization (Algorithm)	Waste Management using ML/DL	Performance Measure (Accuracy)
[7]	√	Floyd Warshall	X	X
[16]	√	Graph Theory	X	X
[34]	√	X	VGG16	96%
[35]	X	X	Resnet50	87%
[36]	X	X	InceptionV3	91.25%
[37]	X	X	InceptionResnetv2	89%
Proposed Work	√	Floyd Warshall	VGG16	91.65%
			Inception	90.25 %
			InceptionResnetV2	93 %
			RecycleCnn	98 %

Without integrating IoT or route optimization algorithms, previous studies [34-37] have classified refuse utilizing machine learning/deep learning models (VGG16, Resnet50, InceptionV3, and InceptionResnetv2). Multiple components were integrated into the proposed work, extending Reference [7]: IoT-based waste receptacle level determination, Floyd Warshall-based route optimization, and a modified CNN (RecycleCnn) for refuse classification. The proposed system outperformed existing approaches in terms of waste classification accuracy. The RecycleCnn model exhibited superior accuracy (98%) in garbage classification compared to benchmark algorithms, including VGG16 (91.60%), InceptionV3 (90.25%), and InceptionResnetV2 (93%). By integrating waste level determination, route optimization, and waste classification, the proposed system provided a holistic resolution encompassing multiple aspects of waste management. This integration can enhance waste management authorities' decision-making and increase the efficiency of waste collection processes. The proposed solution outperformed existing approaches by incorporating IoT, route optimization, and machine learning to enhance waste management practices.

6.CONCLUSION AND FUTURE WORK

The present work presented an innovative framework for intelligent waste management, integrating IoT, LoRa technology, and deep learning for efficient waste collection, categorization, and route optimization. The proposed system achieved significant outcomes, including real-time waste bin monitoring using ultrasonic sensors and LoRaWAN communication, optimized garbage collection routes via the Floyd-Warshall algorithm, and a 98% waste classification accuracy with the RecycleCnn model. These results validated the system's ability to address the inefficiencies in traditional waste management practices by improving operational efficiency and reducing costs. The findings aligned with earlier research, confirming the efficacy of IoT and machine learning integration in waste management. However, the proposed system surpassed prior models by combining route optimization and high-accuracy waste classification into a unified framework, addressing gaps identified in existing solutions. The 98% accuracy achieved by RecycleCnn demonstrated a significant improvement over benchmark models like VGG16, ResNet50, and Inception, highlighting the potential of deep learning in waste categorization. This study contributes to the growing body of scientific knowledge by demonstrating a scalable, cost-effective solution that supports sustainable urban development. The results were consistent with expectations and underscored the practicality of the proposed framework in real-world scenarios. By advancing waste management technology, this work established a foundation for further innovation in smart city initiatives and environmental conservation efforts.

REFERENCES

[1] Laha SR, Pattanayak BK, Pattnaik S. **Advancement of Environmental Monitoring System Using IoT and Sensor: A Comprehensive Analysis.** *AIMS Environmental Science* 2022; **9**(6):771-800.

[2] Biswal AK, Singh D, Pattanayak BK. **IoT-Based Voice-Controlled Energy-Efficient Intelligent Traffic and Street Light Monitoring System.** In: *Green Technology for Smart City and Society: Proceedings of GTSCS 2020*. Springer Singapore; 2021:43-54.

[3] Rath M, Pattanayak BK, Pati B. **Energy Competent Routing Protocol Design in MANET With Real Time Application Provision.** *International Journal of Business Data Communications and Networking* 2015; **11**(1):50-60.

[4] Pattnaik S, Banerjee S, Laha SR, Pattanayak BK, Sahu GP. **A Novel Intelligent Street Light Control System Using IoT.** In: *Intelligent and Cloud Computing: Proceedings of ICICC 2021*. Springer Nature Singapore; 2022:145-156.

[5] Pattnaik S, Laha SR, Pattanayak BK, Mohanty R, Alnabhan M, Mohanty MN. **Software Reliability Reckoning by Applying Neural Network Algorithm.** *Journal of Information and Optimization Sciences* 2022; **43**(5):1061-1071.

[6] Dash L, Pattanayak BK, Laha SR, Pattnaik S, Mohanty B, Habboush AK, Al Smadi T. **Energy Efficient Localization Technique Using Multilateration for Reduction of Spatially and Temporally Correlated Data in RFID System.** *Tikrit Journal of Engineering Sciences* 2024; **31**(1):101-112.

[7] Laha SR, Pattanayak BK, Pattnaik S, Kumar S. **A Smart Waste Management System Framework Using IoT and LoRa for Green City Project.** *International Journal on Recent and Innovation Trends in Computing and Communication* 2023; **11**(9):342-357.

[8] Laha SR, Mahapatra SK, Pattnaik S, Pattanayak BK, Pati B. **U-INS: An Android-Based Navigation System.** In: *Cognitive Informatics and Soft Computing: Proceeding of CISC 2021*. Springer Singapore; 2021:125-132.

[9] Al Smadi T, Gaeid KS, Mahmood AT, Hussein RJ, Al-Husban Y. **State Space Modeling and Control of Power Plant Electrical Faults with Neural Networks for Diagnosis.** *Results in Engineering* 2025; **25**:104582.

[10] Smadi TAA. **Computer Application Using Low Cost Smart Sensor.** *International Journal of Computer Aided Engineering and Technology* 2012; **4**(6):567.

[11] Khaldoon A, Omar, Yasameenkamil N, Ahmed AA, Al Smadi T. **A Novel Flying Robot Swarm Formation Technique Based on Adaptive Wireless Communication Using MUSIC Algorithm.** *International Journal of Electrical and Electronics Research* 2024; **12**(2):688-695.

[12] Laha SR, Nayak DSK. **Cybersecurity Challenges in IoT-Based Healthcare Systems: A Survey.** In: *Intelligent Security Solutions for Cyber-Physical Systems*. Chapman and Hall/CRC; 2021:203-215.

[13] Laha SR, Pattanayak BK, Pattnaik S, Hosenkhan MR. **Challenges Associated with Cybersecurity for Smart Grids Based on IoT.** In: *Intelligent Security Solutions for Cyber-Physical Systems*. Chapman and Hall/CRC; 2021:191-202.

[14] Mahmood AT, Gaeid KS, Al Smadi TA. **Direct Torque Control Space Vector Modulation for Induction Motor Driven by Matrix Converter.** *Tikrit Journal of Engineering Sciences* 2024; **31**(4):58-69.

[15] Zohourian A, Dadkhah S, Pinto Neto EC, Mahdikhani H, Danso PK, Molyneaux H, Ghorbani AA. **IoT Zigbee Device Security: A Comprehensive Review.** *Internet of Things* 2023; **100791**.

[16] Nayak SK, Nayak AK, Laha SR, Tripathy N, Smadi TA. **A Robust Deep Learning-Based Speaker Identification System Using Hybrid Model on KUI Dataset.** *International Journal of Electrical and Electronics Research* 2024; **12**(4):1502-1507.

[17] Haxhibeqiri J, De Poorter E, Moerman I, Hoebeke J. **A Survey of LoRaWAN for IoT: From Technology to Application.** *Sensors* 2018; **18**(11):3995.

[18] Handam A, Al Smadi T. **Multivariate Analysis of Efficiency of Energy Complexes Based on Renewable Energy Sources in the System Power Supply of Autonomous Consumer.** *International Journal of Advanced and Applied Sciences* 2022; **9**(5):109-118.

[19] Laha SR, et al. **An IoT-Based Soil Moisture Management System for Precision Agriculture: Real-Time Monitoring and Automated Irrigation Control.** *2023 4th International Conference on Smart Electronics and Communication (ICOSEC)*. IEEE; 2023.

[20] Putra RH, Kusuma FT, Damayanti TN, Ramadan DN. **IoT: Smart Garbage Monitoring Using Android and Real Time Database.** *Telkomnika Telecommunication Computing Electronics and Control* 2019; **17**(3):1483-1491.

[21] Al-Husban Y, Al-Ghriybah M, Gaeid KS, Al Smadi T, Handam A, Alkhazaleh AH. **Optimization of the Residential Solar Energy Consumption Using the Taguchi Technique and Box-Behnken Design: A Case Study for Jordan.** *International Journal on Energy Conversion* 2023; **11**(1):25.

[22] Ramson SRJ, Moni DJ, Vishnu S, Anagnostopoulos T, Kirubaraj AA, Fan X. **An IoT-Based Bin Level Monitoring System for Solid Waste Management.** *Journal of Material Cycles and Waste Management* 2021; **23**:516-525.

[23] Yusof NM, et al. **Smart Waste Bin with Real-Time Monitoring System.** *International Journal of Engineering and Technology* 2018; **7**(2.29):725-729.

[24] Alobaidy HA, et al. **Low-Altitude-Platform-Based Airborne IoT Network (LAP-AIN) for Water Quality Monitoring in Harsh Tropical Environment.** *IEEE Internet of Things Journal* 2022; **9**(20):20034-20054.

[25] Lozano Á, et al. **Smart Waste Collection System with Low Consumption LoRaWAN Nodes and Route Optimization.** *Sensors* 2018; **18**(5):1465.

[26] Abuga D, Raghava NS. **Real-Time Smart Garbage Bin Mechanism for Solid Waste Management in Smart Cities.** *Sustainable Cities and Society* 2021; **75**:103347.

[27] Kang KD, et al. **Electronic Waste Collection Systems Using Internet of Things (IoT): Household Electronic Waste Management in Malaysia.** *Journal of Cleaner Production* 2020; **252**:119801.

[28] Shanthini E, et al. **IoT Based Smart City Garbage Bin for Waste Management.** *2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)*. IEEE; 2022.

[29] Wen Z, et al. **Design, Implementation, and Evaluation of an Internet of**

Things (IoT) Network System for Restaurant Food Waste Management. *Waste Management* 2018; **73**:26-38.

[30] Al Smadi T, Handam A, Gaeid KS, Al-Smadi A, Al-Husban Y. **Artificial Intelligent Control of Energy Management PV System.** *Results in Control and Optimization* 2024; **14**:100343.

[31] Al-Masri E, et al. **Recycle.io: An IoT-Enabled Framework for Urban Waste Management.** *2018 IEEE International Conference on Big Data (Big Data)*. IEEE; 2018.

[32] Mahmood MS, Al Dabagh NB. **Improving IoT Security Using Lightweight Based Deep Learning Protection Model.** *Tikrit Journal of Engineering Sciences* 2023; **30**(1):119-129.

[33] Yong YS, Lim YA, Ilankoon IMSK. **An Analysis of Electronic Waste Management Strategies and Recycling Operations in Malaysia: Challenges and Future Prospects.** *Journal of Cleaner Production* 2019; **224**:151-166.

[34] Cheema SM, Hannan A, Pires IM. **Smart Waste Management and Classification Systems Using Cutting Edge Approach.** *Sustainability* 2022; **14**(16):10226.

[35] Adedeji O, Wang Z. **Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network.** *Procedia Manufacturing* 2019; **35**:607-612.

[36] Dash L, Pattanayak BK, Laha SR, Pattnaik S, Mohanty B, Habboush AK, Al Smadi T. **Energy Efficient Localization Technique Using Multilateration for Reduction of Spatially and Temporally Correlated Data in RFID System.** *Tikrit Journal of Engineering Sciences* 2024; **31**(1):101-112.

[37] Al-Sharo YM, Al Smadi K, Al Smadi T, Yasameen Kamil N. **Optimization of Stable Energy PV Systems Using the Internet of Things (IoT).** *Tikrit Journal of Engineering Sciences* 2024; **31**(1):127-137.

[38] Al Mashhadany Y, Al Smadi T, Abbas AK, Algburi S, Taha BA. **Optimal Controller Design for High Performance of Solar Energy for Grid-Connected Systems.** *Wireless Power Transfer* 2024; **11**(1).

[39] Gaeid KS, Homod RZ, Mashhadany YA, Smadi TA, Ahmed MS, Abbas AE. **Describing Function Approach with PID Controller to Reduce Nonlinear Action.** *International Journal of Electrical and Electronics Research* 2022; **10**(4):976-983.

[40] Yahya AM, AL-Zakar SHD, AL-Mohseen KA. **Disaggregation Model of Tigris River Inflow into a Proposed Makhol Reservoir Using Parametric Approach.** *Tikrit Journal of Engineering Sciences* 2024; **31**(1).

[41] Gaeid KS, Abed AF, Mokhlis HB, Abubakar U. **Fuzzy Control of Induction Motor Actuator with Open Loop PID Controller in Water Treatment Plant.** *Tikrit Journal of Engineering Sciences* 2024; **31**(3).

[42] Hussein AR. **Internet of Things (IoT): Research Challenges and Future Applications.** *International Journal of Advanced Computer Science and Applications* 2019; **10**(6):77-82.

[43] Habboush AK, Elzaghmouri BM, Pattanayak BK, Pattnaik S, Haboush RA. **An End-to-End Security Scheme for Protection from Cyber Attacks on Internet of Things (IoT) Environment.** *Tikrit Journal of Engineering Sciences* 2023; **30**(4):153-158.

[44] Nayak SK, Nayak AK, Laha SR, Tripathy N, Smadi TA. **A Robust Deep Learning - Based Speaker Identification System Using Hybrid Model on KUI Dataset.** *International Journal of Electrical and Electronics Research* 2024; **12**(4):1502-1507.