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A Novel Framework for Automatic Object Detection and Classification of Bio-Degradable and Non-Bio-Degradable Waste Materials Using Cyber Physical System

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ABSTRACT:

Effective waste management continues to be a major issue for contemporary urban areas, significantly affecting environmental sustainability and the general well-being of residents. In recent years, progress has been made through initiatives such as door-to-door waste segregation and collection. However, the success of these programs largely depends on active citizen participation. The digital transformation of the waste management sector is a gradual process that requires both time and efficient handling of waste segregation and collection. In this regard, advancements in hardware and software technologies, particularly those enabled by the Internet of Things (IoT), are playing a crucial role in accelerating this transformation. Artificial Intelligence (AI) is revolutionizing traditional waste management by integrating smart sensors into waste collection systems. These sensors enable real-time monitoring, improving efficiency and resource utilization. The proposed project aims to develop a smart waste management system using IoT communication protocols alongside an AI-based cyber physical model for predictive analytics. Hardware sensors will continuously monitor bin status, while an image processing system will perform real-time object detection and classification. The AI-driven object detection model, pre-trained with images of various waste materials, will generate a frozen inference graph for accurate waste classification. This process will be carried out through a camera connected to a PC, serving as the primary processing unit. Additionally, each waste compartment will be embedded with intelligent sensors to track fill levels, ensuring timely waste collection. By integrating smart bins, a user-friendly application, and a robust visualization and decision-making platform, this system stands out as one of the most comprehensive and effective solutions in the field. Tests conducted on our platform using an extended dataset have demonstrated high reliability, confirming the effectiveness of our approach.

Keywords: Waste Management System, AI, Cyber Physical, IoT, Automated Object Detection, Smart Sensors and actuators

INTRODUCTION :

A communication paradigm known as the Internet of Things (IoT) imagines a time when commonplace items will be outfitted with a microcontroller and a communication protocol. The smart city, which is characterised as a metropolis with smart technology, smart people, and smart collaboration, is one well- known outcome of the Internet of Things. IoT will openly access certain data subsets for the creation of a wide range of digital services while transparently and smoothly integrating a big number of diverse end systems.

Smart waste management is one of the main topics of the smart city. The success of waste management systems is largely dependent on the communication distance between the garbage collection location and the waste collection centre. The waste management system requires long-distance connection, however current communication technologies like LoRa and SigFox, which run on a low power, wide-area network (LPWAN), can meet this requirement while compromising data transmission speed. Research on wireless communication in the Internet of Things has also been picking up speed. On the other hand, although communication technologies like Bluetooth, Wi-Fi, and Zigbee provide higher data transmission rates, their data transmission ranges are constrained.

Fig.1.1 Smart City Applications

Smart Cities and the Future of Solid Waste Management

As urban populations continue to grow, municipalities worldwide are embracing the "smart cities" movement to enhance efficiency in managing solid waste. This shift is driven by evolving policies, sustainability and recycling goals, and advancements in technology.

The concept of smart cities was first introduced by IBM through its global initiative, *Smarter Cities*, which aimed to help urban areas and businesses leverage data to optimize operations, including waste management. Today, with the increasing emphasis on a circular economy, smart city initiatives are gaining even more momentum.

A study conducted by an Indian university, Waste Management in IoT-Enabled Smart Cities: A Survey, highlights how the rapid adoption of the Internet of Things (IoT) is transforming urban management. It states, “The new era of Web and IoT paradigms is being shaped by various technologies, including RFID tags, sensors, and actuators. Smart devices with computational capabilities, known as ‘smart things,’ are embedded into urban environments to collect real-time data, forming the foundation of smart city frameworks.”

Smart cities are typically defined by three key characteristics:

- They enhance operational efficiency through information and communication technology.
- They use technology to share valuable data with the public.
- They leverage data and innovation to improve residents’ quality of life.

The global adoption of smart cities is accelerating. In 2013, there were only 21 smart cities worldwide, but by 2025, experts predict that number will grow to 88, with North and South America accounting for 25 of them.

The rising urban population has made IoT-driven waste management an essential aspect of modern city planning not only for economic benefits but also for environmental sustainability. Smart waste management solutions include advanced tools such as capacity and weight sensors, RFID tags, and Wireless Sensor Networks (WSNs), all of which contribute to more efficient and eco-friendly urban waste management.

PROBLEM DEFINITION :

The traditional waste management process begins with waste being generated by individuals in cities and disposed of in nearby trash bins. At scheduled times, municipal or private company trucks collect the waste and transport it to temporary collection centers before sending it for recycling.

While this system addresses waste management to some extent, it also presents several challenges:

- Some trash bins become overfilled while others remain underfilled by the time of collection.
- Overflowing bins create unsanitary conditions.
- Inefficient truck routes lead to unnecessary fuel consumption and increased environmental pollution.
- Mixed waste collection complicates sorting at recycling facilities.

How Smart Waste Management Can Help

Implementing smart waste management solutions can help overcome these issues by ensuring a cleaner environment, optimizing resources, and preventing waste overflow. These systems also improve recycling efficiency and enable better route planning for collection trucks, reducing both traffic congestion and fuel consumption.

A modern smart waste management system typically includes sensors attached to trash bins to measure their fill levels. This data is then transmitted to the Cloud, where it is processed to optimize truck collection routes.

Some companies use ultrasonic distance measurement for these systems, where sonar technology determines the distance between a sensor and the trash inside the bin. This works by emitting a sound pulse and measuring the time it takes for the pulse to bounce back after hitting an object. Other companies take an alternative approach, using cameras and image processing as passive sensors to monitor bin levels.

Beyond fill level monitoring, smart waste management systems can incorporate additional sensors to collect valuable data. GPS tracking can be used to monitor bin locations, motion sensors can register when a container is emptied, and movement detection can help identify possible cases of vandalism. By integrating these advanced technologies, smart waste management solutions create a more efficient, sustainable, and cost- effective system for urban waste disposal.

CURRENT SOLUTIONS

- Trash recycling is a difficult undertaking. The following are potential challenges in carrying out this task:
- Recyclables are dispersed throughout the city (municipality), and collecting them and other materials is difficult;
- Recyclables and city trash are produced not only in every residence, building, and manufacturing facility, but also in public areas (streets, parks); each recyclable has a unique end-of-life management strategy.

LITERATURE SURVEY :

H. El-Sayed, et al. [1] proposed an edge computing (EC) paradigm to enhance the efficiency of Internet of Things (IoT) applications by reducing latency and network congestion. Traditional IoT systems rely on centralized cloud infrastructures, which can cause delays due to increased data traffic and processing bottlenecks. The study explores how shifting computation and analytics to the edge of the network—closer to IoT devices like smartphones, sensor nodes, and wearables—improves response time, resource utilization, and network efficiency. Various IoT applications, such as smart cities, smart grids, and intelligent traffic management, benefit from EC integration. The paper compares EC with traditional cloud computing, discussing resource management, computation optimization, and challenges in scalability. The authors also highlight open research areas, such as efficient task offloading, security measures, and interoperability concerns. The study concludes that while EC enhances real-time processing and reduces cloud dependency, further research is needed to optimize load balancing and data security in distributed networks.

Montori, et al. [2] introduced a collaborative Internet of Things (C-IoT) architecture called SenSquare for data gathering and service sharing in smart cities and environmental monitoring applications. The authors emphasize the need for efficient data handling methods due to the complexity and volume of crowdsourced and sensor-generated data in urban environments. The SenSquare system integrates heterogeneous data sources, unifies information representation, and manages mobile crowdsensing (MCS) campaigns for environmental data collection. The study explores IoT service composition, deployment, and data classification techniques, proposing a structured method for handling multi-source data while ensuring efficient system scalability. The paper presents potential solutions for open challenges in IoT-based smart city implementations, such as interoperability and data privacy. Finally, the researchers validate SenSquare's capabilities through both desktop and mobile applications, showcasing its potential in enabling more intelligent urban planning and environmental management.

J. W. Lu, et al. [3] focused on optimizing urban solid waste collection through a smart and green system that incorporates advanced computational techniques for efficient route planning. The study identifies key deficiencies in existing waste management systems, particularly in handling time- sensitive and complex scheduling challenges. The proposed approach models a multi-constrained and multi-compartment routing problem using roll-on roll-off scheduling, addressing real-world challenges such as time windows, intermediate facilities, multi- shift operations, and split deliveries. The authors introduce a heuristic algorithm combining initialization and improvement phases to optimize waste collection routes while balancing cost- effectiveness and environmental sustainability. The research demonstrates that differentiated waste collection enhances routing efficiency but at the expense of increased operational costs. Sensitivity analysis confirms that strategic scheduling improves resource allocation and minimizes environmental impact. The study highlights the importance of integrating smart waste management technologies with real-time monitoring and adaptive route planning for sustainable urban environments.

T. Anagnostopoulos, et al. [4] presented a comprehensive survey on IoT-enabled waste management models, focusing on the role of smart devices such as RFID tags, sensors, and actuators in improving waste collection efficiency. The paper discusses the transformation of urban environments into smart cities, where IoT devices facilitate real- time monitoring of waste levels, optimize collection routes, and enhance overall waste disposal practices. The study categorizes different ICT-enabled waste management frameworks and compares their effectiveness based on operational efficiency, scalability, and cost implications. The authors highlight challenges such as data security, interoperability, and the need for real-time decision- making in large-scale deployments. Various models are evaluated for their strengths and weaknesses, revealing key factors that influence the adoption of IoT-driven waste management solutions. The study concludes that integrating smart technologies with adaptive waste management policies can significantly reduce environmental impact and improve urban cleanliness.

B. Tang, et al. [5] explored the incorporation of intelligence in fog computing to enhance big data analysis for smart city applications. The paper addresses challenges associated with the massive influx of sensor-generated data, which requires real- time processing and intelligent control to ensure efficient urban management. The authors propose a hierarchical distributed fog computing architecture that enables location-aware and latency-sensitive monitoring. The study focuses on integrating machine learning and sequential learning algorithms for anomaly detection in smart infrastructure, particularly in a smart pipeline monitoring system using fiber optic sensors. A prototype system was developed to detect 12 distinct hazardous events, demonstrating the feasibility of fog computing in ensuring urban safety. The research highlights the need for further advancements in distributed intelligence, security, and real-time event detection to facilitate large-scale smart city deployments. The results suggest that fog computing enhances decision-making capabilities while reducing cloud dependency, making it a promising approach for future smart city applications.

EXISTING SYSTEM :

In order for an Internet of Things-based solution to be deployed, it must be able to communicate, share data, and use less energy. Data transfer to the server is carried out using an embedded system based on the Internet of Things that uses GSM communication technology. Web-based Android apps are created to communicate with a web server and deliver data from sensors that track the condition of the bin, the volume of waste within, and the time of waste pickup. To effectively manage the garbage collection tactics, a graph theory optimisation algorithm processes the data to determine the shortest path to the bin. Three sections make up a second IoT-based smart bin, and each one has a unique purpose: A metal detector and an infrared IR sensor make up the first compartment. To identify dry and wet waste, the second compartment has an infrared sensor and a moisture sensor. For the collection of separate waste, the final compartment is separated into three bins. To send data to a designated server, the system establishes a WiFi connection. Three bins—dry, wet, and metal—are arranged on a revolving table in the storage area. Depending on the kind of trash found in the previous compartment, it rotates. One important feature of a smart bin that may be placed in a distant area is its transmission range, which is limited when Wi-Fi is used as a communication medium.

The DHT22 temperature sensor, MQ-135 gas sensor, IR sensor, passive infrared, PIR sensor, and load cell are used in a third IoT-based solid waste management system to monitor temperature and humidity, the presence of hazardous gases, the quantity of rubbish, the presence of users, and the weight of garbage, respectively. Data is provided to a cloud for cloud monitoring after being transmitted via LoRa communication to a gateway. The system's overall cost is raised by the fact that it utilises five waste containers to manage five different types of waste, each of which has its own set of sensors.

- Manual systems where workers empty the dumpsters on a regular basis;
- no organised method for doing so; uncertainty regarding the condition of a certain site; • workers are not aware of the necessity of a specific location
- There is no methodical strategy for emptying the dumpsters; the city is much less effectively cleaned.
- Ineffective at cleaning the city; unclear about the state of a certain location.
- The current system has three sections, each of which has a distinct purpose:
- To detect dry and wet waste, the second compartment has an IR sensor and a moisture sensor. The first compartment has a metal detector and an infrared IR sensor.

EXISTING BLOCK DESCRIPTION

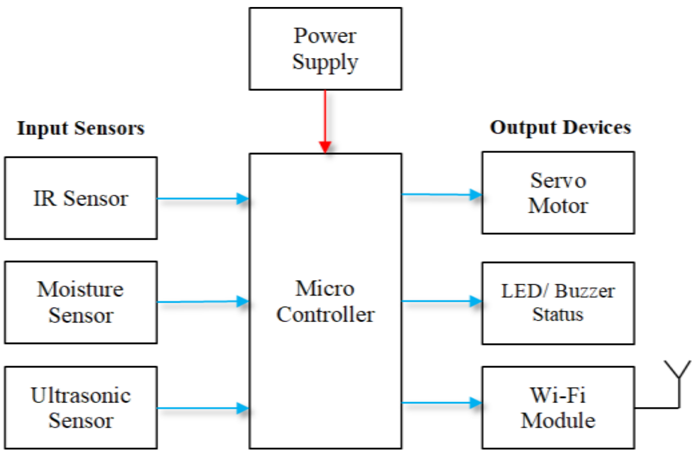
For the collection of separate waste, the final compartment is separated into three bins.

- To send data to a designated server, the system establishes a WiFi connection.
- Three bins dry, wet, and metal are arranged on a revolving table in the storage area. Depending on the kind of trash found in the previous compartment, it rotates.
- One important feature of a smart bin that may be placed in a distant area is its transmission range, which is limited when Wi-Fi is used as a communication medium.

However, the current waste management systems described in the literature do not have a strong communication network in addition to a comprehensive waste segregation system. Rather, their system only contains one of those.

EXISTING SYSTEM BLOCK DIAGRAM

Fig. 3.1 Existing System



PROPOSED SYSTEM :

Traditional trash cans are typically divided into categories based on the kind of waste, such as recyclable and non-recyclable waste. Paper, metal, and plastic garbage are among the various categories into which the recyclable bin is further divided. As a result of this norm, a waste collection station may now have up to four different kinds of bins. Eventually, this raises the total cost of operating the bin for maintenance. The public will frequently not use the designated bins appropriately and will instead just toss rubbish in any container, regardless of classification, even if they are fully equipped for public use. As a result, the public now views traditional bins as ineffective.

By creating distinct waste compartments to handle various waste kinds, including plastic and general waste, this initiative provides a solution to this problem. A Tensorflow framework is used to train an object identification model, which is then exported to a Python language to carry out waste detection in order to efficiently identify and separate various garbage categories. keeps track of the bin's level of filling while a GPS module keeps track of its location. For monitoring purposes, an IoT module then transmits the location and filling level of the bin to the server.

- Additionally, the bin itself is dispersed throughout the city where connectivity to the database might not be practical, and an AI predictive system is suggested that uses predictive maintenance approaches to assess the status of equipment.
- The bin would have to fall within that range in order to identify garbage, which is not ideal, if we were to lower the latency of waste classification by using PC connectivity to upload the image at a greater data rate.
- Therefore, in order to decrease the latency of waste classification, the system would function better if waste classification were done on the board itself.

PROPOSED BLOCK DIAGRAM

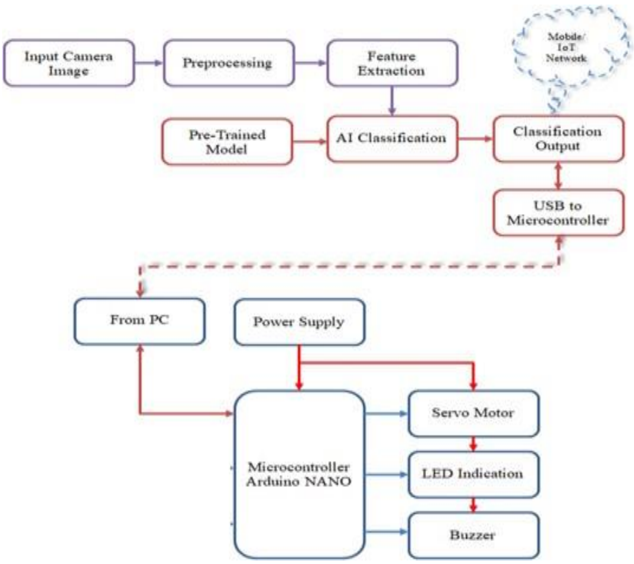


Fig. 4.1 Overall Proposed Block Diagram

A block schematic of the bin utilising the modelling is shown in Figure 4.1. Electronic components are kept in the electronic compartment. The garbage is temporarily held in place by a retractable platform in the waste detection compartment. Waste identification is being carried out concurrently by taking a picture of the waste and using a computer to process it. The trash can has two distinct sections for ordinary rubbish and plastic waste.

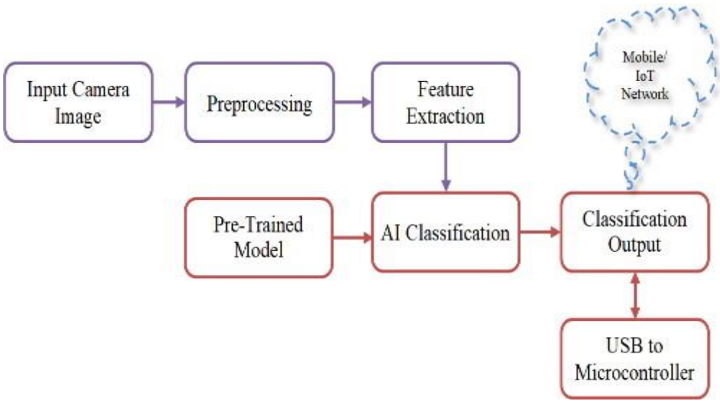


Fig. 4.2 Image Processing – Waste Object Detection

To handle and analyse the data, a statistical analysis system is suggested, which calls for a lot of processing capacity. The suggested method involves sending data to the cloud for analysis and forecasting the region's waste generation patterns. In order to execute waste classification on the board itself rather of uploading information to a database for cloud analysis, we have chosen to use the mobility of the Raspberry Pi, a mobile CPU in conjunction with
MobileNetV2, a lightweight model, and a mobile architecture in our suggested system. We can lower the latency in trash classification as a result.

- This system is made to keep an eye on dumpsters around-the-clock.
- A clever and well-structured mechanism for selective clearing is created here.
- It is employed to gauge the amount of garbage in the dumpster.
- A platform with a DC motor is utilised to separate dry and moist garbage.
- The dumpster sends out an alarm message if either container is full. Employees can then empty the appropriate dumpster.
- An Arduino Uno board is linked to each of these sensors.

It is linked to an Arduino to track the amount of waste that is in each of the bin's sections, including the general and plastic waste sections. The amount of rubbish that is placed in the bin is determined by measuring the time it takes for the signal to move from the transmitter end to the reception end using sonar. The location (latitude, longitude) and the bin's current position are provided by a GPS module from the satellite. Through the use of an Internet of Things module, the bin's position, filling level, and real-time bin are gathered and sent to the gateway, which is linked to the computer.

- The bin has multiple waste-separation sections, such as ones for paper, plastic, and metal, which are managed by servo motors.
- Using a pre-trained item identification model, object recognition and trash classification are carried out within an AI framework.

SENSORS IMPLEMENTATION

The entire block diagram, which shows the smart bin's development process, is shown in Figure 4.1. The Python-based image processing system and Arduino Uno run separately and connect to one another via USB interface connections. To take a waste image for object identification and detection, the camera module is linked to a PC. Servo motors that are managed by the Arduino will open and close the waste compartment lid after the rubbish has been identified. As seen in Figure 4.3, waste can fall from the waste detection compartment into the appropriate waste compartment when the lid is opened.
Each trash compartment in the bin, including the metal and plastic waste compartments, has an Arduino NANO linked to it to track the level of filling. The amount of rubbish that is placed in the bin is determined by measuring the time it takes for the signal to move from the transmitter end to the reception end using sonar. The location (latitude, longitude) and the bin's current state are provided by a Sensor node id module from the satellite. Through the use of a WiFi module, the bin communicates its location, filling level, and real-time bin information to the computer-connected IoT gateway.

OBJECT DETECTION MODEL

A predictive system that uses predictive maintenance approaches to assess equipment status is offered. The PC Python software also handles the video or picture data input. Prior to being sent to the database via USB interface connectivity for cloud analysis, the data is pre-processed by an Arduino. To handle and analyse the data, a statistical analysis system is suggested, which calls for a lot of processing capacity. Instead of sending the garbage to a database for cloud analysis, we have chosen to use the mobility of a PC, a CPU, MobileNetV2, a lightweight model, and a mobile architecture to execute waste classification on the board itself in our suggested solution. This enables us to decrease the trash classification latency. Additionally, the bins themselves are dispersed throughout the city, making it possible that communication to the database will not be possible. A 5MP photograph, for instance, typically has a file size of 15.0MB. Wi-Fi connectivity would be selected to upload the image at a higher data rate in order to lower the delay of garbage sorting. However, Wi-Fi's 50-meter transmission range limits its usability. This would suggest that in order to classify waste, the container needs to fall within that range, which is not ideal. Therefore, in order to decrease the latency of waste classification, the system would function better if waste classification were done on the board itself.
The TensorFlow object detection API, which runs on the Raspberry Pi, is used to identify waste.
This object recognition API is based on SSD MobileNetV2, a pre-trained object identification model that is lightweight and appropriate for low-processing-power devices like Python programming. The architecture of MobileNetV2, which is advancement over MobileNetV1, is based on linear bottlenecks depth-separable convolution with inverted residuals. By dividing convolution into two distinct layers—depth-wise convolution and point-wise convolution—depth-separable convolution uses less processing power. The depthwise and pointwise convolution processes are shown in Figure 6. Depthwise convolution lowers the number of parameters and processing cost by extracting the spatial properties of each input feature independently. Conversely, pointwise convolution is a 1x1 convolution that uses the output of depthwise convolution to create additional features using linear combination.

CONCLUSION :

Waste could be identified and categorised by the model based on classes including paper, plastic, and metal. Nevertheless, by increasing the quantity of training data in this case, garbage images and training duration, the model's accuracy can be raised. The servo motor that controls the lid of each waste compartment and the Python application that performs object identification, both can work together to effectively interface and coordinate waste segregation. The amount of waste photographs in the dataset should be increased in the future to enhance the garbage identification model and provide the system more versatility in recognising rubbish. Additionally, for maintenance purposes, an automated routing system can be created to determine the shortest route to the trash.

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