Name: Rishab Mandal
Batch: C23
Roll_No.:2103110

EXPERIMENT NO. 1

CNN-Based Smart Waste Management System

Introduction : -

As urban populations surge, waste management in cities faces significant challenges, with the World Bank estimating an increase from 2.01 billion tons of waste in 2016 to 3.40 billion tons by 2050. Despite the European Union recycling 56% of its waste in 2016, challenges persist, with 24% ending up in landfills. Effective waste management involves multiple steps, from collection to regulation, and collaboration between authorities and users is crucial due to the high cost. However, government efforts often fall short, resulting in either underutilization of resources or environmental pollution.

Challenges arise in waste management when waste collection follows a schedule, leading to underfilled bins or overflow. Recycling initiatives face hurdles due to user ignorance in waste categorization. The advent of the Internet of Things (IoT) provides a transformative solution by integrating intelligence into technologies. The rapid growth of IoT, with 328 million devices connected monthly, underscores its crucial role in addressing waste management challenges. Additionally, machine learning, particularly deep learning, has emerged as a powerful technology, with the market size expected to increase from 1.4 billion dollars in 2016 to 59.8 billion dollars by 2025. Deep learning, exemplified by Convolutional Neural Networks (CNN), excels in image processing and object recognition. Integrating CNN into a smart waste management system holds promise for accurate waste classification, resource conservation, and waste reduction. This paper introduces a smart waste management system utilizing SSD MobileNetV2 for waste detection, integrated with IoT sensors and LoRa-GPS modules for location tracking and long-distance status transfer.

SECTION II. Literature Review/Related Work : -

Urban waste management faces challenges in monitoring and optimizing waste levels in bins. Various authors propose methods utilizing different sensors and communication technologies to address these challenges. Researchers have explored various waste monitoring systems:

Researchers have explored various waste monitoring systems, including cost-effective solutions like infrared sensors and IR wireless systems for real-time garbage status (Navghane et al.). Aasim et al. introduced a GSM-based monitoring system using ultrasonic sensors, alerting authorities when bins are full but with limitations. Efficient telecommunication protocols, incorporating LPWAN technologies like LoRa for extended data transmission, and Bhor et al.'s integration of ultrasonic sensors and GSM in smart bins, enhance waste collection efficiency but lack automated categorization. Norfadzlia et al.'s smart garbage alert system and Kumar et al.'s microcontroller and IoT-based waste alert system address specific aspects, highlighting the need for integrated approaches in urban waste management.

An IoT system with low-power LoRa sensor nodes addresses power consumption concerns in waste management but lacks automatic waste categorization. CNN-based models like WasteNet on Jetson Nano achieve high accuracy in waste classification. However, existing systems often lack comprehensive solutions such as real-time alerts, long-distance monitoring, and automated waste categorization, emphasizing the need for integrated approaches in urban waste management.

SECTION III. Methodology : -

The development of the smart waste management system involves several key components and stages, including the design of the smart bin, the implementation of a CNN-based waste classification and categorization system, and the integration of bin status monitoring with an RFID-based locker system. Each component contributes to creating an efficient and automated waste disposal system.

A. Smart Bin Design

1. Bin Structure and Compartments:

- Design the smart bin structure using acrylic plastic with dimensions of 0.50 m (length) × 0.50 m (width) × 1.20 m (height).

- Incorporate multiple compartments within the bin to facilitate waste sorting and categorization.

2. Electronic Component Compartment:

- Allocate a top compartment for storing electronic components, ensuring protection against external factors.

- Integrate an RFID-based locker system to secure the electronic component compartment.

3. Waste Categorization Compartments:

- Design compartments for specific waste categories (e.g., paper, cardboard, glass, plastic, and metal).

- Implement a system for automatic waste categorization using servo motors controlled by a CNN-based object detection model.

B. CNN-Based Object Detection Model

1. Choice of TensorFlow Lite:

- Opt for TensorFlow Lite over TensorFlow for compatibility with low-power mobile platforms like Raspberry Pi.

2. Object Detection Model Selection:

- Choose the SSD MobileNetV2 Quantized 300×300 model for its real-time detection capabilities and suitability for low-power devices.

3. Dataset Acquisition:

- Obtain the dataset through a combination of free sources and capturing images using a 12-megapixel camera module.

- Resize all images to 300×300 pixels using Batch Image Resize to match the model's requirements.

4. Data Labelling and Augmentation:

- Label waste images using Labelling software, categorizing them into paper, cardboard, glass, plastic, and metal.

- Apply data augmentation techniques (e.g., image shifts, flips, brightness adjustments) to enhance model robustness.

5. Training on Google Colab and Exporting to TensorFlow Lite:

- Utilize Google Colab for training the CNN model, leveraging the superior GPU capabilities for faster convergence.

- Implement hyperparameter tuning with Adam optimizer and cosine decay learning rate.

C. Waste Classification and Categorization System

1. Integration with Hardware:

- Integrate electronic components such as Raspberry Pi, camera module, ultrasonic sensor, and servo motors for waste classification.

- Connect servo motors to a servo driver HAT for effective control.

2. Waste Movement Mechanism:

- Utilize ultrasonic sensors to detect non-detectable waste in the placement area.

- Implement servo motors to move detected waste into the corresponding waste compartments.

D. Bin Status Monitoring and Locker System

1. Monitoring System with Arduino:

- Employ Arduino Uno to monitor bin status using ultrasonic sensors for waste fill levels and GPS module for location tracking.

- Use LoRa communication to transmit real-time information to a remote receiver.

2. RFID-Based Locker Integration:

- Employ Arduino Uno with RFID reader and solenoid locker to protect the electronic component compartment.

- Implement a 30-second RFID authorization window to unlock the locker when an authorized tag is detected.

E. Prototype Testing and Evaluation

1. Smart Bin Prototype Testing:

- Assemble and test the physical prototype for waste classification, bin status monitoring, and locker systems.

2. CNN Model Evaluation:

- Evaluate the CNN model's performance in terms of accuracy, precision, and inference time using a variety of waste objects.

3. System Integration Testing:

- Integrate all components and conduct thorough testing for seamless operation. Analyse results to identify optimization areas and implement iterative development cycles for refinement.

The methodology provides a comprehensive guide for developing and implementing a smart waste management system, incorporating hardware integration, CNN-based waste classification, and advanced monitoring capabilities.

Technology used in the Smart Waste Management System : -

The smart waste management system integrates a combination of hardware components and cutting-edge technologies to automate waste classification, optimize bin status monitoring, and enhance the efficiency of waste disposal. The key technologies employed in the system include:

1. Raspberry Pi:

- Role: Main processing unit for waste classification.

- Functionality: Executes the CNN-based object detection model and controls the movement of waste into respective compartments using servo motors.

- Significance: Enables real-time processing and decision-making for efficient waste sorting.

2. TensorFlow Lite:

- Role: Framework for developing and deploying machine learning models on low-power mobile platforms.

- Functionality: Hosts the SSD MobileNetV2 Quantized 300×300 model for object detection on Raspberry Pi.

- Significance: Facilitates the integration of a lightweight, yet powerful, object detection model suitable for resource-constrained devices.

3. Google Colab:

- Role: Cloud-based platform for machine learning model training.

- Functionality: Utilized for training the CNN-based object detection model with the GPU acceleration provided by Google Colab.

- Significance: Accelerates the training process, enhancing the model's accuracy and efficiency.

4. Arduino Uno:

- Role: Central microcontroller for bin status monitoring and locker system.

- Functionality: Interfaces with ultrasonic sensors, GPS module, LoRa module, RFID reader, and solenoid locker to monitor bin conditions and protect electronic components.

- Significance: Provides a flexible and versatile platform for integrating multiple sensors and communication modules.

5. LoRa (Long Range):

- Role: Wireless communication technology for long-range data transmission.

- Functionality: Facilitates the transmission of real-time bin information (e.g., location, waste fill percentage) to a remote receiver.

- Significance: Enables efficient and long-range communication between the smart bin and the monitoring system.

6. RFID (Radio-Frequency Identification):

- Role: Technology for secure access control to the electronic component compartment.

- Functionality: RFID reader authenticates registered tags to unlock the solenoid locker, providing access to the electronic components.

- Significance: Enhances security and prevents unauthorized access to sensitive electronic components.

7. GPS (Global Positioning System):

- Role: Satellite-based navigation system for accurate location tracking.

- Functionality: Tracks the latitude and longitude of the smart bin for precise location information.

- Significance: Enables real-time monitoring and tracking of the smart bin's geographical position.

8. Servo Motors:

- Role: Mechanical actuators for waste movement within the bin.

- Functionality: Control the movement of plastic boards to categorize waste into designated compartments.

- Significance: Facilitates the automated sorting of waste based on the output from the object detection model.

9. Ultrasonic Sensors:

- Role: Sensors for real-time monitoring of waste fill levels in each compartment.

- Functionality: Measure the distance to detect waste levels and optimize waste collection schedules.

- Significance: Provides accurate and efficient monitoring of waste levels within the smart bin.

10. Acrylic Plastic:

- Role: Material for constructing the physical prototype of the smart bin.

- Functionality: Provides a durable and transparent structure for accommodating electronic components and waste compartments.

- Significance: Ensures the robustness and visual clarity of the smart bin prototype.

The amalgamation of these technologies forms a comprehensive smart waste management system that combines machine learning, wireless communication, and sensor-based monitoring to create an intelligent and automated waste disposal solution.

Conclusion : -

In addressing the challenges of improper use of recycling bins and resource wastage in scheduled waste collection, our proposed system integrates a CNN model, SSD MobileNetV2 Quantized 300×300, and Pi Camera on Raspberry Pi to automate waste classification effectively. Successfully categorizing paper, cardboard, plastic, glass, and metal, the system, equipped with servo motors, swiftly moves waste into designated compartments. The bin status monitoring system, employing ultrasonic sensors and LoRa/GPS shield connected to Arduino Uno, provides accurate waste fill percentage readings and precise latitude and longitude. Utilizing the LoRa module, this information is transmitted to a connected laptop, enabling remote monitoring. While limitations include a small dataset, precision constraints without GPU support, and reliance on batteries, future improvements should focus on dataset expansion, model enhancements, and exploring renewable energy sources for sustained system longevity.