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The Implementation Paper on An Internet of Things Based Smart Waste Management System using LoRa and Tensor Flow Deep Learning Model

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A B S T R A C T

The traditional waste management system works according to a daily schedule that is less efficient and more expensive. The recycling bin also showed its ineffectiveness in the community as people are not reusing their waste properly. With the development of Internet of Things (IoT) and Artificial Intelligence (AI), the traditional waste management system can be replaced by smart sensors integrated into the system to create real-time monitoring and a reduction in better waste management. The aim of this study is to develop an intelligent waste management system using LoRa communication protocol and an in-depth Tensor Flow learning model. LoRa sends sensor data and Tensor flow enables real-time object detection and segmentation. The bin contains several waste disposal chambers including metal, plastic, paper and waste disposal controlled by servo motors. Object detection and waste disposal are done on a Tensor Flow framework with a pre-trained object detection model. This detection model is trained with debris images to produce a frozen display graph used for camera detection connected to the Raspberry Pi 3 Model B + as the main processing unit. Ultrasonic sensor is installed in each disposal chamber to monitor the level of waste filling. The GPS module is integrated to monitor the location and real time of the drum. LoRa communication protocol is used to transmit information about location, real time and drum installation rate.

Keywords:Internet of Things, LoRa, Object Discovery, Smart Waste Management System, TensorFlow

1. System Analysis

1.1 Proposed System and Merits

Advances in the IoT sector have made it possible to improve the existing waste management system. The installation of sensors in the trash can and IoT connectivity allows real-time monitoring, which is not in the existing waste management system. Information such as filling rate, temperature, humidity, and any other required data may be collected. This data can be transferred to the cloud for storage and processing. The data used can be used to study and reach the limit of the existing waste management system and thus improve the overall efficiency of the system. Applying IoT to a trash can is just one step away from a wise city.
Some of these benefits are:

- Time consumption is less.
- There is no need for a human being to separate waste.

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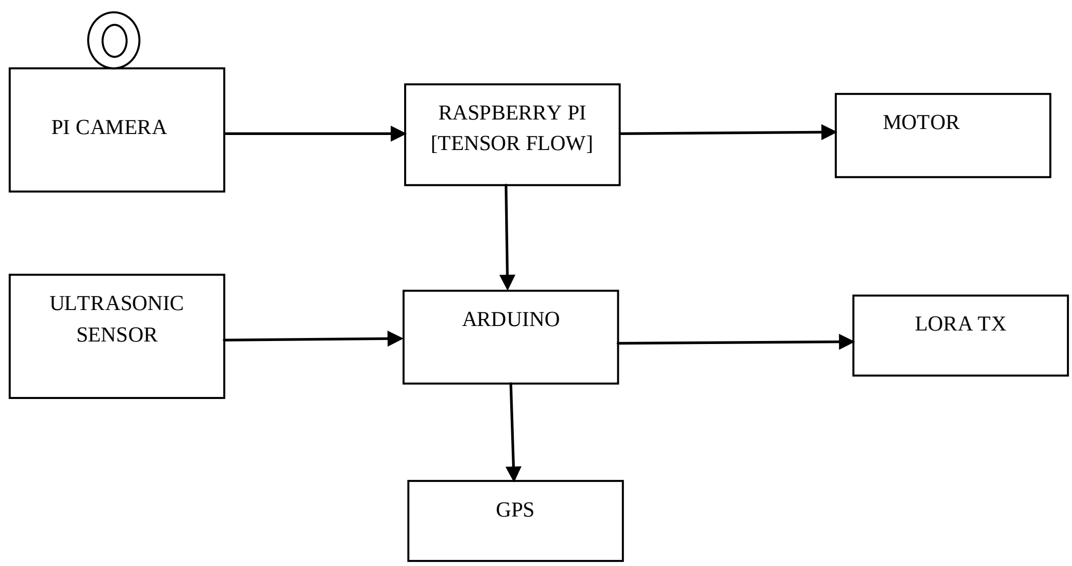
1.2 Methodology

Generally bins are often classified as a type of waste, for example, recyclable and non-renewable waste. The used bin is also divided into different types, such as paper, metal and plastic waste. This meeting resulted in many of the 4 types of bins found in the garbage collection area. This ultimately increases the operating costs of drum storage. Although the prescribed bins are designed for public use, the public will usually not use them properly and will simply dispose of waste in any of the bins regardless of the designation. Thus, standard drums have proven its failure in the eyes of the public. This paper provides a solution to this issue by separating waste dumps into different types of waste, such as paper, plastic, metal, and general waste. In order to accurately identify and differentiate different types of waste, an object acquisition model is trained using a Tensor flow framework and sent to a Raspberry Pi microprocessor mobile to perform waste detection. The ultrasonic sensor monitors the filling rate of the drum, while the GPS module checks its location. The status of the drum filling level and location is then sent to the server via the LoRa module for monitoring purposes. The RFID module is also used in the system to provide access to authorized personnel in the bin for repair purposes.

2. System Design

Block Diagram:

TRANSMITTER SIDE



RECEIVER SIDE

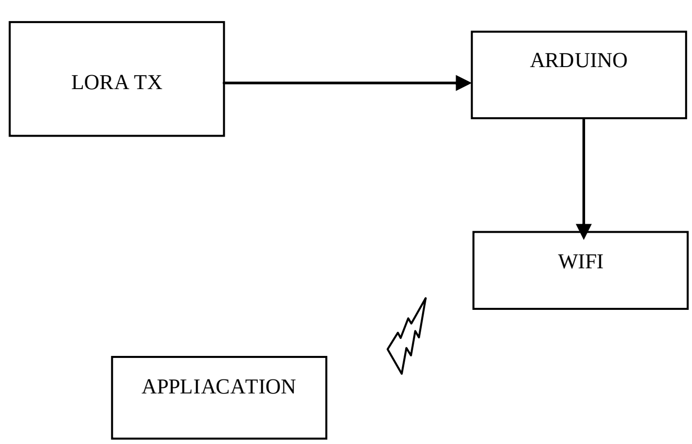


Figure 1: *The overall Block Diagram (Transmitter Side and Receiver Side)*

Figure 1 represents a general block diagram, in which the intelligent drum development process is provided. The Arduino Uno and Raspberry Pi are independent and do not interact with each other. The camera module is connected to the Raspberry Pi to take a picture of the waste for the purpose of detecting and identifying the object. Following the discovery of the waste, servo motors controlled by the Raspberry Pi will trigger the opening and closing of the dump cover cover. The opening of the lid allows waste to fall into the waste disposal chamber to its waste disposal facility, an ultrasonic sensor connected to the Arduino Uno to monitor the filling rate of each waste room, including plastic, metal, paper and standard waste disposal chamber. The ultrasonic sensor uses the sonar to measure the time it takes for the signal to travel from the transmitter end to the receiver end, and the time difference is used to calculate the waste filling rate inside the barrel. The GPS module provides location information (latitude, longitude) and real-time drum from satellite. The filling level, location, and real-time barrel are collected and transferred via the LoRa module from the barrel to the Waspmote gate, which is connected to a computer. LoRa should be used in this system because the drums are usually placed within a few meters to a few miles away, and LoRa is able to transmit data from a distance when using low power.

3. System Implementation

3.1 Sensors and LoRa Implementation

A complete process for the development of a smart drum is given here. The Arduino Uno and Raspberry Pi are independent and do not interact with each other. The camera module is connected to the Raspberry Pi to take a picture of the waste for the purpose of detecting and identifying the object. Following the discovery of the waste, servo motors controlled by the Raspberry Pi will trigger the opening and closing of the dump cover. The opening of the lid allows waste to fall into the waste disposal chamber into its sewage system. Once the waste has been identified, it will create an Arduino Uno to open a proper disposal facility.

The ultrasonic sensor connected to the Arduino Uno monitors the filling level of each waste room, including plastic, metal, paper, and standard waste disposal facility (We use only two types of waste chambers in our project). The ultrasonic sensor uses the sonar to measure the time it takes for the signal to travel from the transmitter end to the receiver end, and the time difference is used to calculate the waste filling rate inside the barrel. The GPS module provides location information (latitude, longitude) and real-time drum from satellite. The filling level, location, and real-time barrel are collected and transferred via the LoRa module from the barrel to the Waspmote gate, which is connected to a computer. Figure 2 represents the sensor and modules used in the system. Table 1 represents the sensor model and modules used in the system.

(a) *(b)* *(c)*

Figure 2: *(a) Ultrasonic Sensor (b) GPS (c) Camera Module*

3.2 Tables

Table 1 – Model of Sensor and Modules

Sensor	Module
Ultrasonic sensor	HC-SR04
GPS Module	GY-NE06MV2
Camera Module	Pi Camera

LoRa should be used in this system because the drums are usually placed within a few meters to a few miles away, and LoRa is able to transmit data from a distance when using low power. Table 2 represents the LoRa specifications used in the system. The LoRa module is connected to Arduino via a multiprotocol radio shield, which acts as an Arduino connection shield and is designed to connect two simultaneous communication modules. The module uses astronomical topology as nodes (device node / sensor node) to establish point and point connections per gate using parameters such as node address. Figure 4 represents the star topology installed by the LoRa module. It comes with frequency bands, 868 MHz and 915 MHz ISM bands, which include several channels in each frequency band. Three bandwidth options are available, 125 kHz, 250 kHz, or 500 kHz. High bandwidth is preferred for fast transfers, while low bandwidth is preferred for longer access. At the end of the gateway, a hyper-terminal called RealTerm is used to receive and specify data streams sent from LoRa node.

Table 2 – Specification of LoRa

Characteristics	Specification
Module	SX1272
Dual Frequency Band	902-928MHz
Transmission Power	14 dBm
Sensitivity	-134 dBm
Channels	13
Distance	22+km

4. Object Detection Model

A forecasting system was proposed when the system assessed the state of the equipment using predictive correction techniques. Raspberry Pi is used to process data collected from sensors, and data is uploaded to a database via a WiFi connection for cloud analysis. The Statistical Analysis System is proposed to analyze and analyze data, which requires high computational power when data is sent to the cloud to analyze and predict waste generation practices in the region. In our proposed program, we decided to use the Raspberry Pi, portable CPU and MobileNetV2, lightweight model and cellular construction to create waste on the board itself instead of adding it to the database to analyze the cloud. This allows us to reduce the delay in waste disposal. In addition, the bin itself is spread around the city where database connectivity may not be possible. For example, a 5MP image has a standard file size of 15.0MB. If we were to reduce the delays in waste disposal, a Wi-Fi connection would be preferred to upload an image with a higher data rate. However, the Wi-Fi connection is limited to a transmission distance of 50m. This could mean that the bin must be at that level in order to separate the garbage, which is wrong. Therefore, the system will work better by doing the waste separation on the board itself to reduce the waste separation delays.

Waste identification is done using the TensorFlow detection API that works on the Raspberry Pi. This discovery API works on a pre-trained acquisition model, SSD MobileNetV2, which is lightweight and suitable for working on low-end computer devices like the Raspberry Pi. A single-shot multibox detector (SSD) is an object detector used to detect multiple objects within a single image. The acquisition model is based on a supply chain network that predicts binding boxes and confidence scores for each item. SSD implementation is independent of the basic network, which is responsible for feature extraction. It uses layers of multi-dimensional features to predict the binding box and the confidence of the various elements in the image. In our proposed tem, we have used the SSD as the object detector.

The pre-trained object detection model is trained using waste images as a training database. This method of training is known as transfer of learning. Figure 6 represents a sample image used as a database to train the model, and 365 images of waste with different shape, background, and lighting conditions are collected. Prior to training, waste images are labeled in the classroom to perform supervised learning where we feed on data training with well-known training model classes. Image labeling is done using the software LabelImg as shown representing the process of obtaining an object acquisition model. After the image labels have been collected and installed, it is used to train the object acquisition model until the model reaches less than 1,0000 error. A frozen summary graph is produced and sent to the Raspberry Pi for object detection. The accuracy limit of the model is determined based on the average accuracy (mAP) of the model obtained from the test images and the test results obtained during real-time waste acquisition. The average mAP of the model obtained from the test images is 86.2%. While real-time waste detection, the average accuracy of metal, plastic and paper is 86.7%, 96.3%, and 82.3% respectively. With an average accuracy of 82.3%, the threshold accuracy rate is defined at 80% by adding tolerance to the lowest accuracy level so that the model can be more flexible with waste detection performance

4.2 Flow Chart

Once the acquisition graph is received, it is sent to the Raspberry Pi for waste detection and identification. Hosting will be prioritized on a flexible platform to make waste detection using a pre-made measurement graph. After the waste phase has been identified, the removable lid of a particular waste area will be processed and opened by a servo vehicle. After that, the retractable platform will be lowered to allow the waste with the help of gravity to fall into a particular dump room. The ultrasonic sensor is used to detect the presence of debris inside the discharge chamber by comparing the distance before and after the presence of debris. For example, the total distance traveled by an ultrasonic audio radio is 0.50m when the room is empty (measured by the length of the waste room). If there is a presence of debris in the waste collection room, the total distance traveled by the ultrasonic sound wave will be reduced as shown above the sewage. At the same time, the Pi camera always takes pictures of the waste and sends them to the Raspberry Pi to do the segmentation. If the type of waste is not in one of the categories (metal, plastic, or paper), then the waste is unknown and the system will classify it as standard waste based on the information obtained by the ultrasonic sensor for detecting waste.

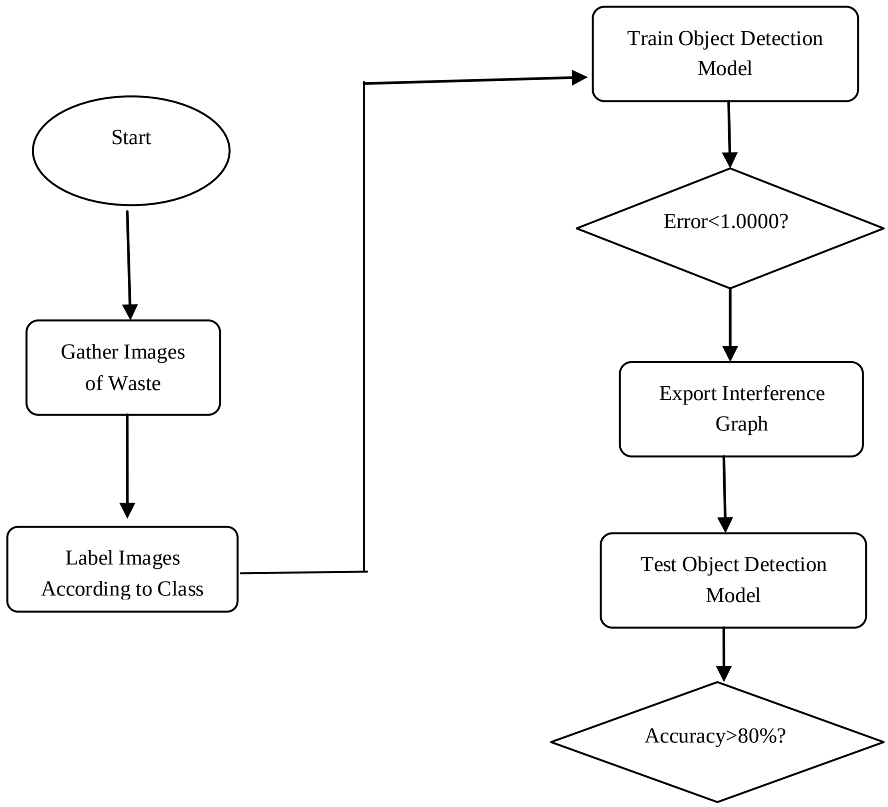


Figure 4: *Flow chart of Obtaining Object Detection Model*

4.3 Algorithm

Algorithm for how to find trash waste.
1: Put garbage on a reclining platform
2: Ultrasonic Sensor 1 detect the presence of waste
3: Camera snapshot and send it to Raspberry Pi
4: The Raspberry Pi performs waste image classification using inference graph.
if garbage = paper **then**
  Open the removable paper closet lid; Open a reclining platform
Elseif waste = metal then
  Open the removable metal door lid; Open a reclining platform
Elseif waste = plastic **then**
  Open the removable lid of the plastic room; Open a reclining platform
Else
  Open a reclining platform
End
5: Close the retrospective cover and retrospective speaker

Algorithm describes the operation of the drum. The ultrasonic sensor is used to detect the presence of debris inside the discharge chamber by comparing the distance before and after the presence of debris. For example, the total distance traveled by an ultrasonic audio radio is 0.50m when the room is empty (measured by the length of the waste room). If there is a presence of debris in the waste collection room, the total distance traveled by the ultrasonic sound wave will be reduced as shown above the sewage. At the same time, the Pi camera always takes pictures of the waste and sends them to the Raspberry Pi to do the segmentation. If the type of waste is not in one of the categories (metal, plastic, or paper), then the waste is unknown and the system will classify it as standard waste based on the information obtained by the ultrasonic sensor for detecting waste. These measures are taken to reduce the amount of training databases needed to train the waste disposal model by eliminating the need to prepare a standard waste training database and to reduce computer costs. The system is designed and trained to separate and dispose of waste according to the image of garbage. The waste image database is organized with different recording angles, lighting conditions, and backgrounds. Thus, the system is able to distinguish waste thrown into different areas and positions. However, if the waste is covered with an external material such as a garbage bag, it will be identified as standard waste.

5 Conclusion

We introduce a smart waste management system using sensors to monitor the condition of the drum. Lora's low-power communication protocol and long-distance data transfer, and TensorFlow-based object detection to perform waste identification and segregation. The pre-trained acquisition model is able to work well on the Raspberry Pi 3 Model B + due to its lightweight nature. The model was able to identify and classify waste into categories such as metal, plastic and paper. However, the accuracy of the model can be improved by increasing the number of training details in this case, the number of trash screens and by increasing the training time.

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