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IoT-Based Waste Segregation with Location Tracking and Air Quality Monitoring for Smart Cities

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Abstract: Massive human population, coupled with rapid urbanization, results in a substantial amount of garbage that requires daily collection. In urban areas, garbage often accumulates around dustbins without proper disposal at regular intervals, creating an unsanitary environment for humans, plants, and animals. This situation significantly degrades the environment. To address this problem, a Smart Waste Management System is introduced in this paper, employing machine learning techniques for air quality level classification. Furthermore, this system safeguards garbage collectors from severe health issues caused by inhaling harmful gases emitted from the waste. The proposed system not only proves cost-effective but also enhances waste management productivity by categorizing waste into three types: wet, dry, and metallic. Ultimately, by leveraging machine learning techniques, we can classify air quality levels and garbage weight into distinct categories. This system is beneficial for improving the well-being of individuals residing in close proximity to dustbins, as it enables constant monitoring and reporting of air quality to relevant city authorities.

Keywords: air quality; garbage segregation; IoT; location tracking; smart cities; ThingSpeak

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1. Introduction

India has made significant efforts to keep its cities, roads, and streets clean and has become a clean and healthy country with proper waste management [1]. However, the improper disposal of waste in open spaces has resulted in air emissions that may cause health problems, such as headaches, eye and throat irritation, breathing difficulties, stomach pain, vomiting, diarrhea, etc., due to the harmful substances in organic and non-organic chemicals, including high levels of ammonium hydrogen sulphide [2]. Waste pickers, who manually segregate garbage also may suffer from severe skin problems. Improper management of waste, particularly from households and communities, can pose serious threats to human health and the environment over time. Hospital and medical waste containing harmful micro-organisms and toxic or radioactive industrial waste can pollute rivers, air, and soil, threatening the earth's ecosystem [3,4]. In rural areas, poor waste management can endanger plants and animals, as garbage present in open dustbins is consumed by animals, resulting in lethal injuries and damage to the animals' digestive tracts, leading to starvation, ulceration, reduced fitness, growth problems, and premature death of animals, caused by plastic, glass, metals, chemicals, and other materials [5–7]. Contaminated soil also poses a serious threat to both flora and fauna, as toxic substances can enter the food chain and harm them indirectly. The harmful impact of contaminated soil is not limited to plants and animals, as humans can also be negatively affected by ingesting, inhaling, or coming into contact with it [8].

In this paper, we propose a smart waste segregation and management IoT system that not only helps to alleviate the negative effects of contaminated soil, but also aims to raise awareness among different segments of society about the importance of proper waste disposal. Administrative authorities in various cities have implemented waste segregation processes, and these efforts are often combined with awareness programs aimed at educating citizens about the different types of waste and their harmful effects on healt [9]. However, it can always be challenging to ensure that people always throw garbage in the correct bin, as they may not have the time or inclination to observe which bin they should use. Additionally, most current waste management systems require human effort for waste segregation, which can have a hazardous impact on the health of those involved in these tasks. Furthermore, the use of five different bins (blue for paper, green for glass, yellow for metals and plastics, brown for biowaste, and black for mixed waste) could be ineffective, as dry waste can include a variety of materials such as plastic, glass, wood, metal, and cloth [10]. Therefore, more systematic garbage segregation requires additional human effort and could pose a health hazard to those involved in the waste segregation processes.

The system uses electronic sensors and IoT applications to detect and segregate waste into three categories: wet, dry, and metallic waste, with the help of appropriate sensors deployed in each bin. The real-time monitoring of the garbage level and air quality around the bins, along with their GPS-based location tracking, allows for efficient management and timely disposal of the waste. In addition to its waste management capabilities, the system also has security features. The metal sensors in the bins can detect and identify any dangerous metal explosives, which can be helpful for police and intelligence agencies in preventing terrorist attacks. Moreover, by tracking the weight of the garbage collected from specific regions, municipality officials can evaluate the efficiency of the waste management process in those areas. The system also incorporates machine learning to classify the air quality levels and garbage weight into different categories, thus allowing for more accurate and precise analysis of the waste management data. Overall, the IoT-based system presented in this paper could be a promising solution for efficient waste segregation and management, aiming to enhance the health and well-being of citizens while also minimizing the environmental impact of waste.

The structure of the paper is well-organized and covers important aspects of research. In Section 2, the related works in the recent literature are reviewed, providing the necessary background and context for the proposed approach. In Section 3, the proposed approach is described in detail, including the processing steps involved. Section 4 presents the experimental findings and discussion and includes the results obtained from the experiments as well as a detailed analysis of the results. Finally, Section 5 concludes the paper with the conclusions and future research work.

2. Related Work

Effective and efficient methods for waste collection and segregation at the domestic level are presented in [11]. The waste is classified based on its composition, such as metal, plastic, and biodegradable materials, and stored accordingly in their designated segments of the dustbin. This approach aims to improve waste management and promote recycling by ensuring that each type of waste is disposed of in the most appropriate manner. Garbage-First is a server-style garbage collector, targeted for multi-processors with large memories, that meets a soft real-time goal with high probability, while achieving high throughput [12]. Whole-heap operations, such as global marking, are performed concurrently with mutation, to prevent interruptions proportional to heap or live-data size. Concurrent marking both provides collection "completeness" and identifies regions ripe for reclamation via compacting evacuation. This evacuation is performed in parallel on multiprocessors, to increase throughput.

A smart waste segregation and management IoT system is presented at the source-level/community level [13]. The system uses a GPS-module to monitor garbage dustbins in real-time, ensuring that they are replaced once they are filled with waste. By utilizing IoT applications and electronic sensors, the proposed system contributes to the creation of a clean and healthy environment for nearby residents and also reduces the workload of garbage pickers [14]. The purpose of the system is to operate like an "Electronic Dustbin" that uses IoT devices and sensors to monitor the garbage level, bin location, and air quality in real-time. Such a cost-effective solution can help to improve waste management efficiency and also may reduce the reliance on human involvement in waste segregation and management [15].

Khan et al. [16] proposed a smart bin system that uses an ultrasonic sensor [17], an Arduino microcontroller, a Wi-Fi Module, and an Android App for waste management. The ultrasonic sensor is installed at the top of the dustbin, and it detects when the garbage reaches the maximum level, sending signals to the microcontroller. The microcontroller, in turn, uses the Wi-Fi module to send data to the mobile app, which informs the administration that the dustbin is full and needs attention. While this system offers the advantage of real-time monitoring of dustbin levels, it has limitations when it comes to waste segregation and recycling. All types of garbage are dumped together in the bin, with no segregation for recycling purposes. Additionally, the location of the dustbin is not available to direct garbage collectors, who have to physically inspect and remove the garbage, resulting in inefficiencies in the waste collection process.

Ishak et al. proposed a system in [18] which is designed to segregate garbage into biodegradable and non-biodegradable waste using an IR sensor, an Arduino microcontroller, and a robotic arm operated by four servo motors. The IR sensor detects when the dustbin is overfilled and sends a signal to the Arduino, which activates the servo motors to direct the robotic arm to segregate the garbage and place it in their respective dustbins. The advantage of this system is that it efficiently segregates different types of garbage with the help of a robotic arm. However, the system lacks the ability to track the location of the dustbin using a GPS module. Additionally, the system does not monitor air quality, which is crucial for taking necessary actions to improve the surrounding environment and reduce pollution.

Gaikwad et al. [19] proposed a Smart-Bin system that not only alerts administrative authorities about garbage collection but also segregates the garbage when it is thrown into the bins. The system comprises an ultrasonic sensor, a PIR sensor, a moisture sensor, an Arduino microcontroller, and a NodeMCU. The ultrasonic sensor detects the garbage level, the moisture sensor detects wet and dry wastes, and the PIR sensor detects the movement of rodents. The collected data from different sensors is passed to the Arduino controller, which passes it to NodeMCU. NodeMCU sends the collected data to the cloud for data analysis and future forecasting. This system efficiently manages garbage levels and segregates wet and dry garbage based on the moisture level. Additionally, rodent movements can also be tracked. However, the system does not track the location of the dustbin using a GPS module, as in the previous system. Moreover, the air quality is not monitored, which could have helped to take actions to improve the surrounding air quality.

Channe et al. proposed a system in [20] that is designed with an ultrasonic sensor, an Arduino microcontroller, an LCD screen, a Wi-Fi modem, and a buzzer to monitor the level of garbage in the bin. The ultrasonic sensor measures the garbage level, which is displayed on the LCD screen. The buzzer provides a notification when the garbage in the bin reaches its maximum capacity. The Arduino microcontroller transmits the data collected by the sensor to the system webpage via the Wi-Fi modem. When the dustbin becomes full, an alert message is sent to the relevant authority. Although this system efficiently monitors the garbage level and alerts the authority when the bin is full, the location of the dustbin is not tracked using a GPS module. Also, the system does not monitor the air quality in the surrounding area, which could provide valuable data for improving air quality. Moreover, the system does not facilitate the segregation of different types of garbage, and all types of garbage are dumped together, which hinders recycling efforts.

In [21], an IoT system was proposed to evaluate the level of garbage collected in dustbins using a sonar sensor that measures distances from two centimetres to four hundred centimetres with three millimetre accuracy. The system records and transfers the collected data to the relevant authorities. The system is designed to learn from experience and make predictions on future waste generation, traffic congestion, and garbage level. The recorded data can be stored in a MySQL database, and a routing algorithm has been developed to find the shortest and most efficient route to the dustbin. The system's advantage is that it efficiently manages the garbage disposal in the dustbin and provides data for future analysis. However, as with the previous systems, all types of garbage are dumped together, and there is no scope to segregate them. Additionally, the location of the dustbins is not available to direct garbage collectors who need to arrive and empty them.

The system proposed in [22] consists of a network of dustbins that are connected in a master-slave configuration. The master dustbin is equipped with a microcontroller, such as Arduino UNO [23], and the slave dustbins communicate with their corresponding master dustbin. Each dustbin has three types of sensors: a load sensor to measure the weight of the garbage, a level sensor to monitor the garbage level, and a humidity sensor to record the humidity in the surrounding area. The location of the dustbin is sent to Google Maps through the microcontroller to help direct garbage trucks to the dustbin's location for efficient garbage pickup. This system monitors the load and level of garbage and the humidity levels in the area surrounding the dustbins. The location of the dustbins is also tracked and shared with the concerned city's authorities. However, air quality in the surrounding area is not monitored.

Vishnupriya et al. [24] proposed a system that categorizes waste into three different types: biodegradable waste, metallic waste, and plastic waste. Once waste is dumped into a dustbin, it is segregated using a combination of a moisture sensor, an inductive sensor, and a capacitive sensor. The moisture sensor detects the moisture level, the inductive sensor detects metallic items, and the capacitive sensor tracks plastic items. Sub-dustbins are attached with sensors that detect microbe levels, and corrective measures are taken based on the readings. This system efficiently segregates different types of garbage with the help of specific sensors, and corrective measures are taken based on the readings from the microbe level sensors. However, the locations of dustbins are not tracked in this system.

The system proposed in [25] is another garbage classification system that combines IoT and Artificial Intelligence. This system uses IoT devices and smartphones to process image-related information in real-time. After the recognition of the garbage type, the system interacts with the user via text or voice. AI-based robot vacuums [26] can also be used to classify indoor obstacles and to automatically clean indoor floors. In [27], the authors proposed "GarbageNet", another novel system that uses AI techniques, particularly the Transfer Learning machine learning method, to address the garbage classification problem. GarbageNet was evaluated using real-world garbage data, which showed better performance compared to other methods.

As far as existing research on air quality monitoring with IoT devices is concerned, the aim of the work presented in [28] was to provide a thorough analysis of the state-of-the-art for Internet of Things-based indoor air quality monitoring devices. This review study highlighted that the main limitation of most existing systems is the use of calibrated sensors. The accuracy of monitoring systems is an important requirement and this review recommended the need to focus on more adequate calibration arrangements.

Regarding the detection and analysis of outdoor air quality there are also many research studies in the relevant literature. For example, the research presented in [29] was intended to examine the spatial and temporal variation of air quality in areas at North China. The researchers monitored the Air Quality Index (AQI), which is a complete indicator that concurrently encompasses and incorporates various pollutants and can also represent the overall state of ambient air quality. The results of this study can help government and administrative authorities to design and implement regionally differentiated policies regarding air pollution.

When detecting ambient air contaminants, water vapour presents another significant challenge. The experimental setup for target gas recovery as well as water vapour reduction through corresponding devices were recommended in [30]. In this approach, the rate of target gas recovery and the elimination of water vapour were analysed. It was discovered that the KPASS (Key-compound PASSer) devices can remove water at a rate that was roughly 60% greater than the Cooler's. The Chiller devices demonstrated poorer target analysis recovery rates compared to the ones provided by the KPASS in all instances of concern.

In another research work, four sites in Florence's urban area were examined to gather numerous samples of outdoor air [31]. The findings of this research showed that the examined regions had higher concentrations of formaldehyde, acetaldehyde, and acetone than other carbonyl compounds (CCs). The gathered data were examined in light of each CC's particle-to-gas ratio. The character and volume of traffic passing by the sampling locations were tangentially linked to the pollution picture of CCs that was acquired.

The conclusion of all these research works emphasizes that the use of real-time air quality monitoring tools should be encouraged and adopted by smart city initiatives to identify, resolve and restore unfavourable environmental situations, so as to achieve improved living environments for the people who inhabit them [32–34].

3. The Proposed System

3.1. System Technologies

The proposed system in this paper is designed to segregate waste thrown out by people into dry, wet, and metal waste using corresponding sensors such as a moisture sensor and a metal sensor. This segregation allows for efficient waste management, where each type of waste can be handled and disposed of properly. Additionally, when a dustbin becomes filled with garbage, its location is sent along with a corresponding message to the Blynk app to inform the concerned authority. This feature can aid in timely and effective waste collection, ensuring that the dustbins are not overflowing and causing unhygienic conditions. A graphical representation of the Blynk app is depicted in Figure 1.

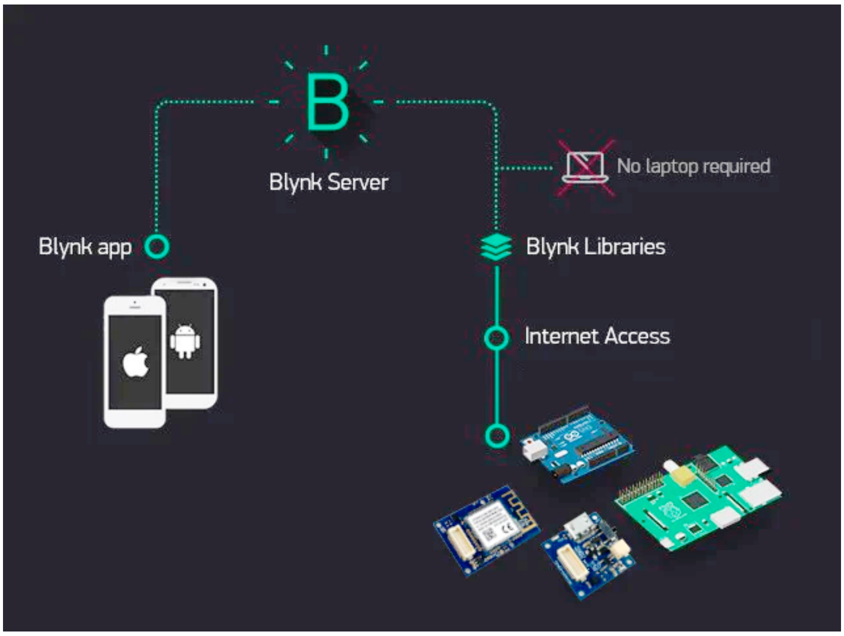


Figure 1. Blynk Application.

Moreover, unlike some earlier, similar systems that only sent messages to concerned authorities, this proposed system takes a photo of the person throwing away the garbage.

This feature can act as a deterrent to those who might try to litter, as their actions will be captured and recorded. This can lead to improved civic behavior and cleaner public spaces.

The proposed system also monitors and analyzes the air quality surrounding the dustbin using sensors. The collected data are then passed to the cloud where the administration authorities can perform machine learning and compare the latest air quality with the past to predict future trends. This feature can help the authorities to make informed decisions and take action to improve air quality in areas where it is poor. Additionally, the weight of the garbage collected in a dustbin is monitored and this data can be submitted to the cloud for analysis and future predictions. This feature can aid in optimizing the waste collection process, where the authorities can plan and allocate resources efficiently based on the data.

Furthermore, the garbage level is also recorded and analyzed to understand how frequently the dustbin is getting full. This information can aid in scheduling waste collection, where the authorities can plan for timely collection based on the fill-level of the dustbin, ensuring that the dustbins are not overflowing and causing unhygienic conditions.

The system framework incorporates a range of integrated technologies, including the following:

1. The Raspberry Pi is a small, single-board computer that is used for computing and programming tasks and can be easily connected to a computer or TV monitor.
2. NodeMCU (Node Microcontroller Unit) is an open-source development environment based on the ESP8266 system-on-a-chip (SoC) [35] that is inexpensive and widely used for IoT projects.
3. The ultrasonic sensor is used to measure the level of garbage in the bin, utilizing ultrasonic sound waves to calculate the distance.
4. The inductive proximity sensor can detect metal and is used to segregate metallic waste.
5. The raindrop sensor is utilized to sense the moisture in the garbage and distinguish wet waste.
6. The Pi camera captures the image of the person throwing the garbage, which can be used as evidence in case of any illegal activities near the garbage bins.
7. The GPS module is used to track the location of the dustbins so that the garbage can be disposed of quickly when it reaches maximum capacity.
8. The IR sensor is used to detect when a user is near the dustbin by detecting Infrared Radiations (IR).
9. The air quality sensor (MQ135) measures the air quality near the garbage bins to protect the health of people living in the area.
10. The load cell sensor measures the weight of the garbage in each bin, which can be used to determine the ideal time for garbage disposal.
11. The servo motor rotates the circular disk containing the dustbins and the circular flap on which garbage is placed.
12. ThingSpeak is an IoT platform service that analyzes live data streams and is used to monitor air quality and garbage weight readings sent by the NodeMCU.
13. Blynk is an IoT platform that allows for quick interface development to control and monitor electronic devices and sensors. The Blynk app in the proposed system sends notifications to administrators when the dustbins are full, along with their exact location, to facilitate quick garbage disposal.

3.2. System Architecture and Implementation

The proposed Smart Waste Management System employs several integrated technologies to manage garbage efficiently, as shown in Figure 2. When a user throws garbage into the dustbin, the raindrop sensor and metal sensor detect the moisture level and whether the garbage is metallic or not, respectively. These sensors send their outputs to the Raspberry Pi, which then rotates the circular disk containing the three dustbins to a specific angle, ensuring that the garbage falls into its appropriate dustbin. The type of garbage detected is recorded, and this information is sent to the cloud for analysis. The data collected can be used to identify the majority type of garbage that has been thrown away, which can be helpful in planning waste management strategies.

As the garbage level in the dustbin increases, it is constantly monitored by the ultrasonic sensor. When the garbage level reaches below 10cm, the ultrasonic sensor sends its reading to the NodeMCU, along with the dustbin's location sent by the GPS module. This information is useful in ensuring that garbage disposal is done on a fast-track basis, reducing the chances of garbage overflow. Moreover, the air quality sensor continuously monitors the quality of air in the area surrounding the garbage. This information is crucial in identifying areas where the air quality is poor due to the presence of garbage, which can adversely affect the health of nearby residents. The load cell sensor measures the weight of the garbage contained in each dustbin, which can be used to determine the optimum time for garbage collection.

Additionally, the IR sensor detects the user's presence near the dustbin and sends a signal to the Raspberry Pi to rotate the circular flap on which garbage will be initially placed by the people. This mechanism helps to maintain the hygiene of the dustbin and prevent contamination by ensuring that the flap remains closed when not in use. Finally, the proposed system utilizes two IoT platforms: Blynk and ThingSpeak. The Blynk app sends notifications to the administrators whenever the dustbins get filled up with garbage along with their exact location. On the other hand, ThingSpeak is an IoT platform used to analyze live data streams and monitor the readings of air quality and garbage weight sent by the NodeMCU on a regular basis. The data collected can be used to identify patterns and trends that can help in developing more efficient waste management strategies.

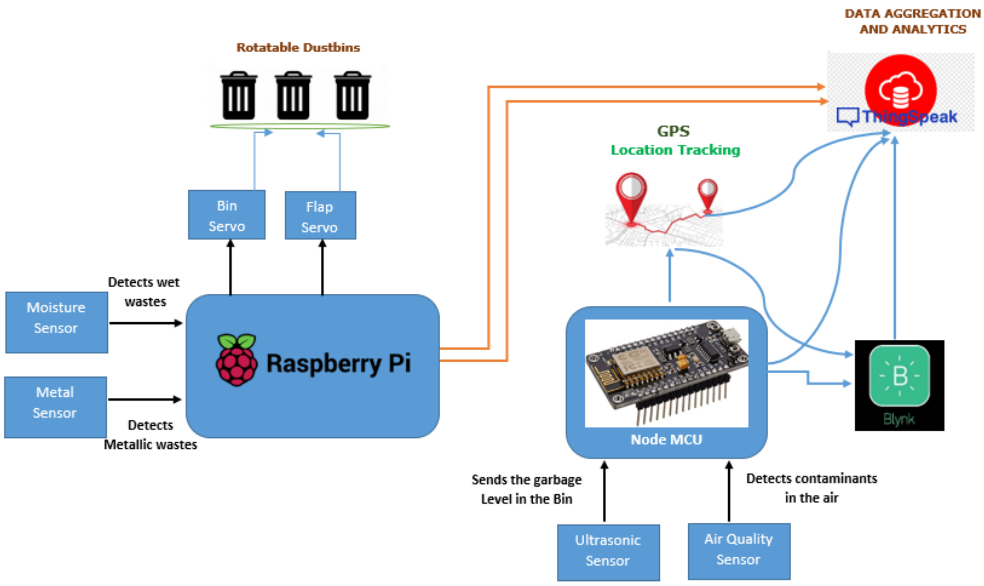


Figure 2. System Architecture of Automatic Waste Segregation.

The NodeMCU, a Wi-Fi enabled microcontroller, plays a critical role in the proposed system. It receives the ultrasonic sensor readings that monitor the garbage level in the dustbin, and when the level goes below 10 cm, it sends an alert to the Blynk app, which notifies the administration that the dustbin has reached its maximum capacity. The NodeMCU also sends the dustbin's GPS location to the Blynk app, which shows it on a map, enabling easy identification of the dustbin from which the notification is being sent. The system also monitors the air quality around the dustbins using an air quality sensor. The NodeMCU sends the obtained air quality readings in parts per million (PPM) to ThingSpeak, an IoT platform for collecting, analyzing, and visualizing data, for further analysis. The amount of garbage thrown into each dustbin is also recorded using a load cell sensor connected to the NodeMCU, which sends the weight readings to ThingSpeak.

ThingSpeak uses the air quality and load cell readings to create a dataset for the classification of PPM levels into different categories. For this purpose, an application was developed in the Orange open-source data visualization, machine learning, and data-mining package [36]. The Orange application uses the air quality dataset available in the ThingSpeak cloud to determine the best machine learning model for the classification task. Once the model is selected, it is trained using the training dataset, and the predictions are made for the testing dataset. The garbage level in each dustbin is also constantly tracked and sent to ThingSpeak for classification purposes.

In summary, the proposed system is a comprehensive and integrated solution for efficient waste management. It uses a range of sensors, microcontrollers, and cloud-based platforms to monitor the garbage level, type, and air quality in and around the dustbins. The data collected is analyzed using machine learning techniques to enable effective decision-making and resource allocation.

4. Results and Discussion

The proposed system is designed to not only detect the type of garbage, but also to monitor the garbage level of the dustbins to ensure effective disposal when the maximum holding capacity is reached. Additionally, it monitors the air quality of the surrounding area to maintain the health of the people. The recorded data are analyzed and classified using the Orange open-source data visualization, machine learning, and data-mining package. Real-time recordings provided by ThingSpeak cloud notify the administrative authorities when the air quality surpasses the acceptable limit. Moreover, the system tracks the garbage level, which can be used to monitor the frequency of garbage thrown away in a specific locality by the residents. The system provides a comprehensive solution to the problem of effective waste management and promotes sustainable development by encouraging proper waste segregation and disposal.

Figure 3 displays a graph of the PPM levels recorded by the air quality sensor over time. The red dots in the graph represent the PPM values recorded at various timestamps. The sensor constantly monitors the air quality near the dustbin by measuring the concentration of pollutants such as carbon monoxide, nitrogen dioxide, and particulate matter. The PPM level is measured at regular intervals to ensure that the air quality remains within the acceptable limits.

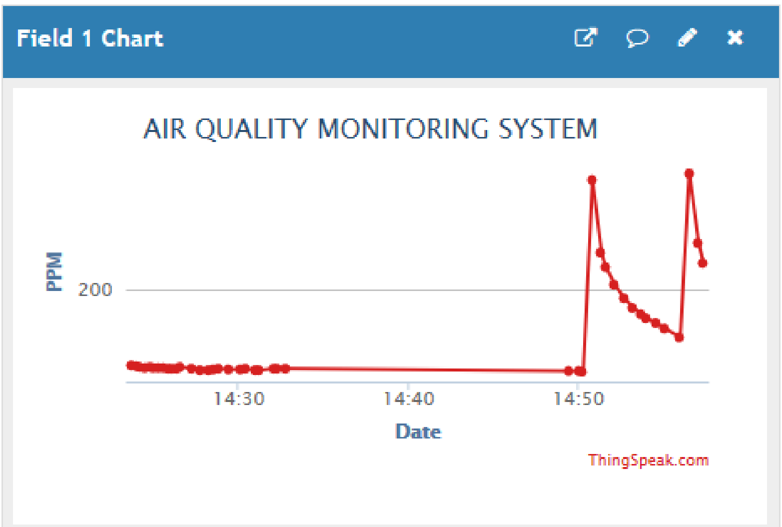
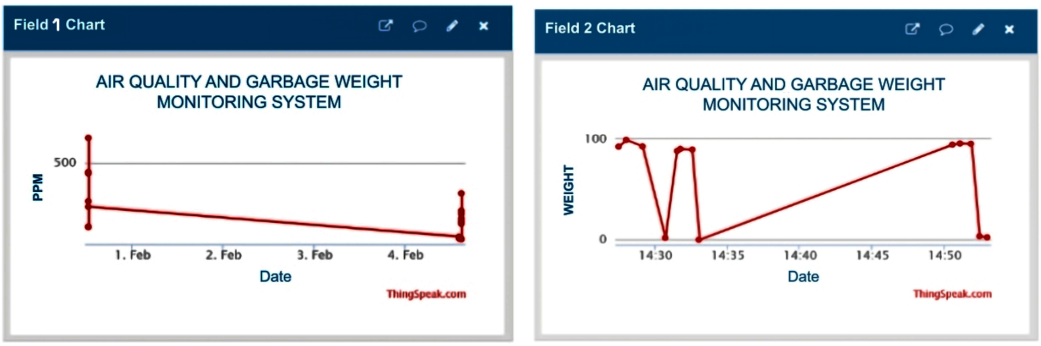


Figure 3. Air Quality Monitoring-PPM Level.

The x-axis of the graph indicates the time at which the air quality status was last updated. If the apparatus is working continuously, the x-axis shows the time of the most recent PPM reading. However, if the apparatus is turned off due to a power failure or any other reason, the x-axis shows the date on which the air quality sensor's status was last updated. The air quality data collected by the sensor are sent to ThingSpeak for further analysis and classification. If the PPM level exceeds the acceptable limit, the system can notify the administrative authorities in real-time, enabling them to take appropriate measures to maintain the health and safety of people living in the nearby areas.

The load cell sensor plays a crucial role in monitoring the amount of garbage thrown in the dustbins. This sensor measures the weight of the garbage in the dustbins and sends the readings to the NodeMCU at regular intervals. These readings are then displayed in the form of a graph, as shown in Figure 4. By analyzing this graph, the authorities can get an idea of the amount of garbage that is thrown into each dustbin on a daily basis, and can plan accordingly for its disposal. Moreover, the load cell sensor's readings can help in estimating the required size for the dustbins based on the amount of garbage thrown away every day. This information can be used to optimize the waste management process by deploying dustbins of the appropriate size in different locations based on the amount of garbage generated in those areas. Additionally, by tracking the weight of the garbage in real-time, the city's authorities can identify if a particular dustbin is being overfilled and, consequently, can take appropriate action to prevent littering and maintain cleanliness in the surroundings. This helps to ensure that the waste management process is efficient and effective, and helps to maintain a clean and healthy environment.



(**a**) Field 1 (**b**) Field 2

Figure 4. AirQuality and Garbage Weight Monitoring using Load Cell.

To provide more details, the process of machine learning classification using the air quality dataset recorded in ThingSpeak can be broken down into several steps, as illustrated in Figure 5. Firstly, the air quality dataset (i.e., the training dataset) is preprocessed to remove any missing or irrelevant data, and to transform the data into a suitable format for the machine learning models.

Next, the preprocessed dataset is passed to the Test and Score widget, which is a tool in the Orange open-source data visualization, machine learning and data mining package. The Test and Score widget evaluates the performance of different machine learning models on the dataset and provides scores for various metrics such as accuracy, precision, recall, and F1-score. In this case, three different machine learning models-Random Forest, Decision Tree, and Naive Bayes-were selected and attached to the Test and Score widget. The widget can be used to compare the performance of these models on the training dataset and it also displays their scores on the different metrics.

Based on the scores provided by the Test and Score widget, the analyst can select the best machine learning model for the classification task. Once the model is selected, it is trained on the training dataset using the selected algorithm. Finally, the trained model is applied to a separate dataset (i.e., the testing dataset) to evaluate its performance on new and unseen data. The results of the classification can be used by the authorities to monitor the air quality around the dustbins and take necessary action to maintain the health of nearby residents.

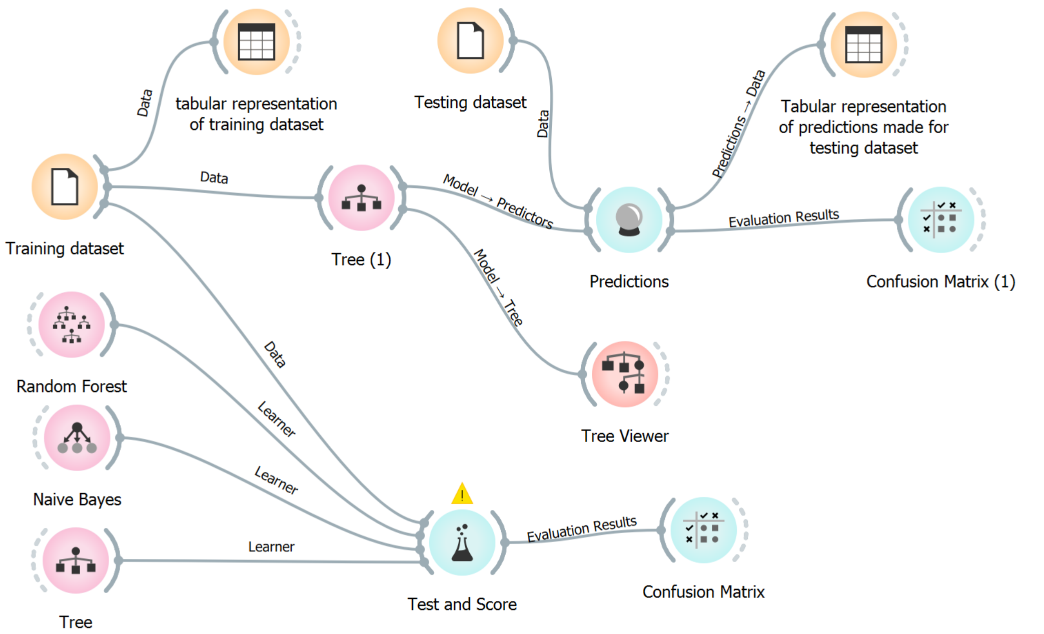


Figure 5. Machine Learning Models for Air Quality Monitoring.

To provide more details, a confusion matrix is a tool used to evaluate the performance of a machine learning model. It is a table that summarizes the predictions made by the model against the actual values. Figure 6 shows the confusion matrix obtained for the Decision Tree model applied to the air quality dataset. The matrix displays the number of instances of different PPM levels that were correctly classified as well as the number of instances that were misclassified. The diagonal elements of the matrix represent the number of instances that were correctly classified, while the off-diagonal elements represent the misclassified instances. The confusion matrix provides useful information for evaluating the accuracy, precision, recall, and F1 score of the model. It can also help in identifying the areas where the model needs improvement. In this case, the confusion matrix helps in evaluating the performance of the Decision Tree model for classifying different PPM levels of air quality.

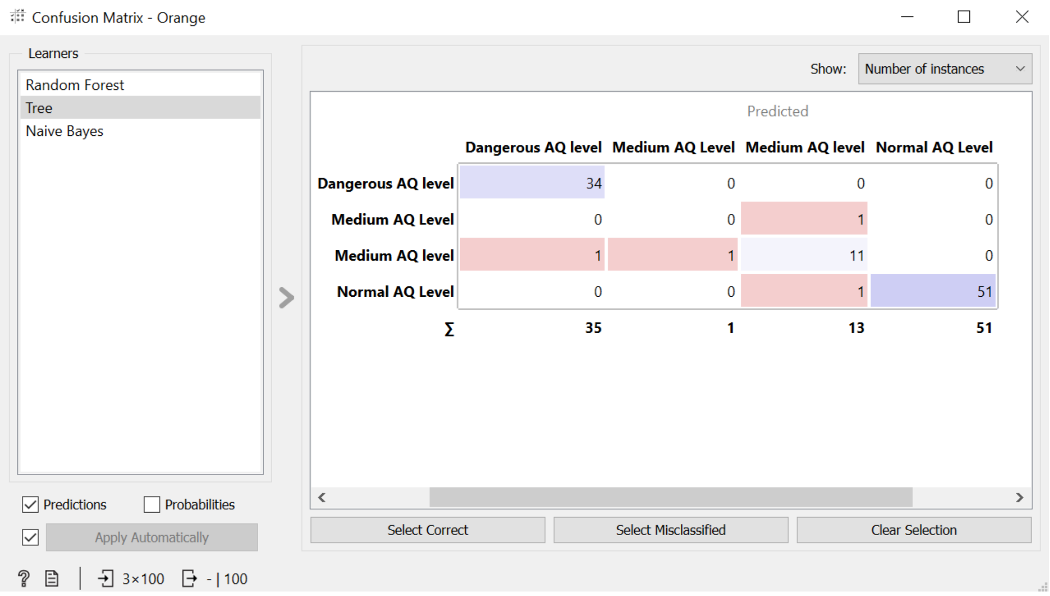


Figure 6. Confusion Matrix for Instances between the Predicted and Actual Class based on the PPM Level by Applying the Decision Tree Model.

Figure 7 shows a comparison between the actual classification categories and the predicted classification categories using the Decision Tree model. The results confirm that the model has accurately classified the PPM levels into their respective categories, as the actual and predicted categories match exactly. This suggests that the Decision Tree model is effective in classifying air quality levels based on PPM readings. The accuracy of the model can be further analyzed by examining other metrics such as precision, recall, and F1 score, and thus providing a more comprehensive evaluation of the model's performance.

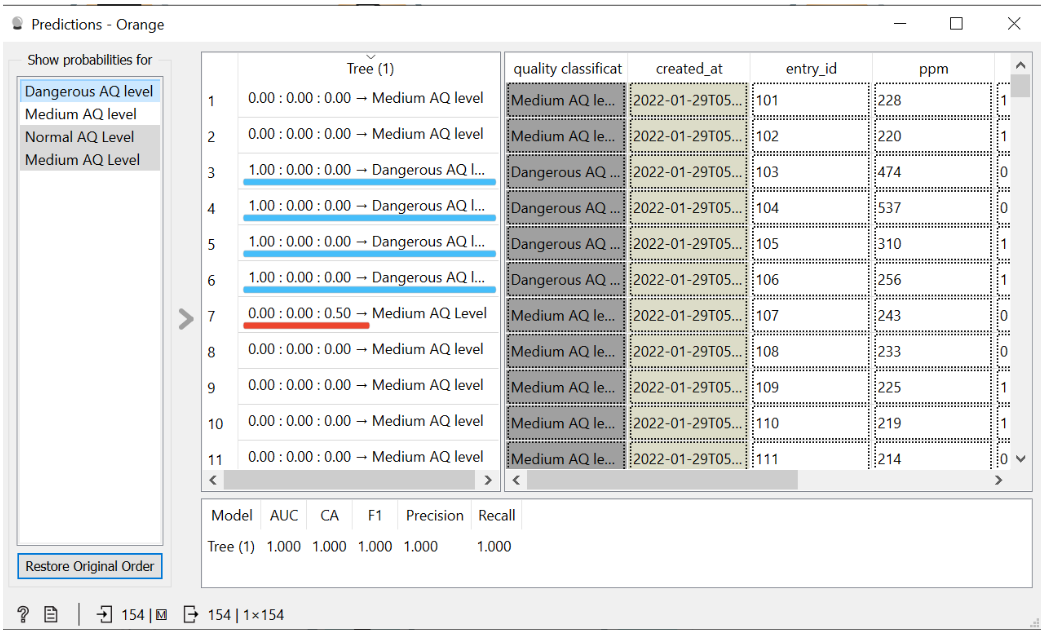
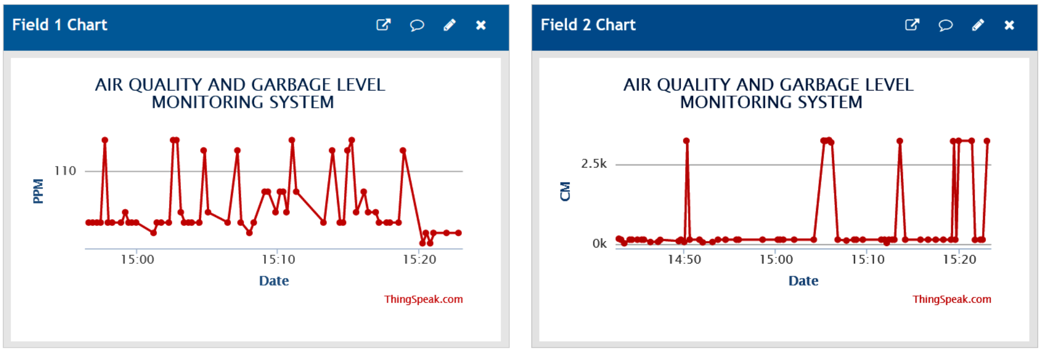


Figure 7. Comparison of Actual Air Quality Classification and Predicted Classification by the Decision Tree Model based on the PPM Level.

Figure 8 is a plot that shows both the PPM level recorded by the air quality sensor and the readings for the ultrasonic sensor sent by the NodeMCU. The red dots in the plot indicate PPM values along with their timestamps, and as long as the apparatus is in working mode, the PPM level is picked up at regular short intervals to monitor the quality of the air near the dustbin filled with garbage. The x-axis of the plot shows the time at which the air quality status was last updated when the apparatus is working for some duration of time. However, when the apparatus is turned off due to power failure for a substantial amount of time, such as several days, the x-axis shows the date at which the air quality sensor's status was last updated.

Furthermore, the plot displays the readings for the ultrasonic sensor sent by the NodeMCU, which measures the distance between the top of the garbage in the dustbin and the ultrasonic sensor. By analyzing these data, the authorities can estimate the frequency at which the dustbins are becoming full on a daily basis. This information can be used to plan the cleaning and waste disposal schedules and ensure that the dustbins are emptied before they overflow, causing littering and unhygienic conditions. Additionally, the ultrasonic sensor readings can also help estimate the size of the population staying in the nearby area based on the amount of garbage generated in the locality. This information can be used to optimize the waste management process by deploying dustbins of the appropriate size in different localities based on the amount of garbage generated in those areas.



(**a**) Field 1 (**b**) Field 2

Figure 8. Air Quality and Garbage Level Monitoring using Air Quality and Ultrasonic Sensor.

Figure 9 illustrates how machine learning models can be used for classification based on the garbage level dataset. More specifically, the garbage level dataset (i.e., the training dataset) is first passed to the Test and Score widget. Then, three machine learning models, namely Random Forest, Decision Tree and Naive Bayes, were selected and attached to the Test and Score widget. The models were trained on the dataset and their performance was evaluated based on certain parameters such as accuracy, precision, recall, and F1-score. The results of this evaluation are displayed in the Test and Score widget, which helps the analyst in deciding the model that will be best suited for conducting machine learning on the given dataset. This process potentially enables a city's authorities to analyze the garbage level data and predict the filling status of dustbins, which may in turn aid in optimizing waste management operations.

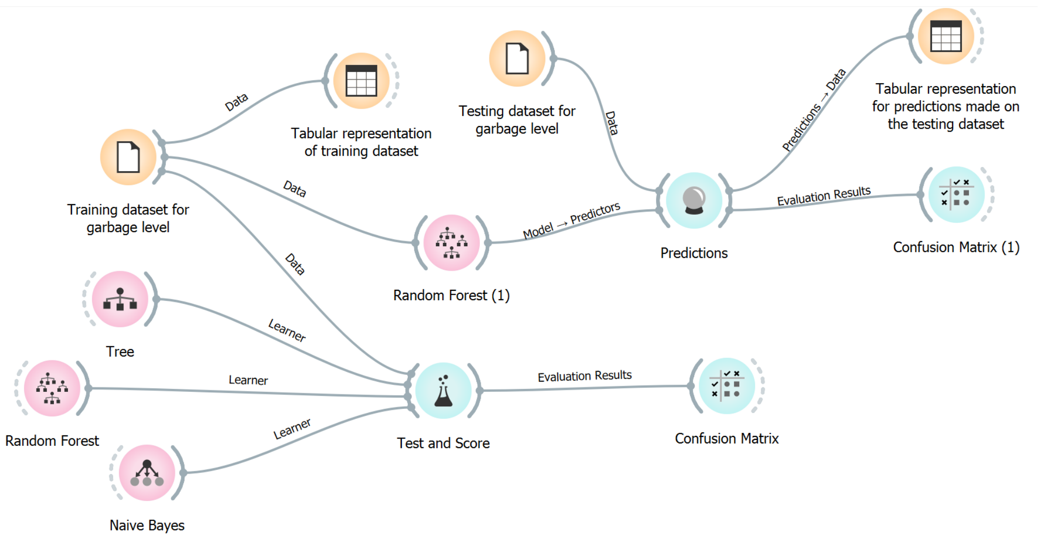


Figure 9. Machine Learning Models for Garbage Level Monitoring.

Figure 10 displays the Confusion Matrix obtained by passing the training dataset through the Random Forest model, which predicts the classification category of the garbage level in centimetres. The matrix presents the numbers of instances when the garbage level was either correctly classified or misclassified. The result obtained from the Random Forest model is then passed to the Prediction widget, which predicts the classification category for the testing dataset based on the analysis of the training dataset. It is worth noting that transfer learning techniques such as Multi-Modal Multitask (MMMT) Learning [37,38] can be applied to improve the generalization ability of the machine learning model used.

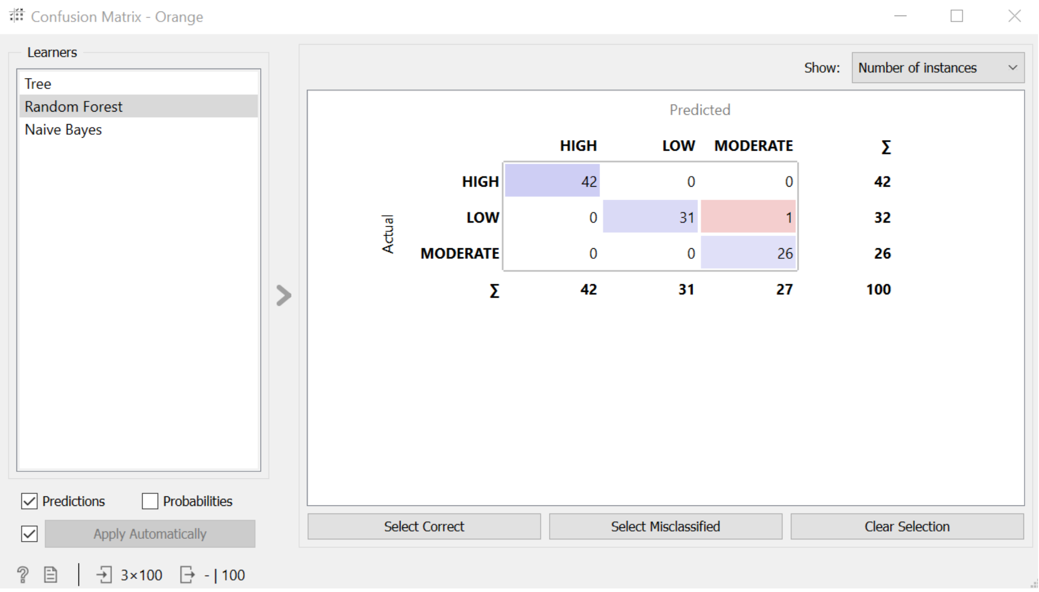


Figure 10. Confusion Matrix for Instances between the Predicted and Actual Class based on the Garbage Level by Applying the Random Forest Model.

Finally, Figure 11 shows that the Random Forest model has accurately predicted the classification category based on the garbage level. The plot compares the actual classification category from the training dataset with the predicted classification categories using the Random Forest model. It can be observed that actual and predicted categories match exactly, indicating that the model has correctly classified the garbage level. These results demonstrate the effectiveness of the Random Forest model in predicting the classification category based on the garbage level.

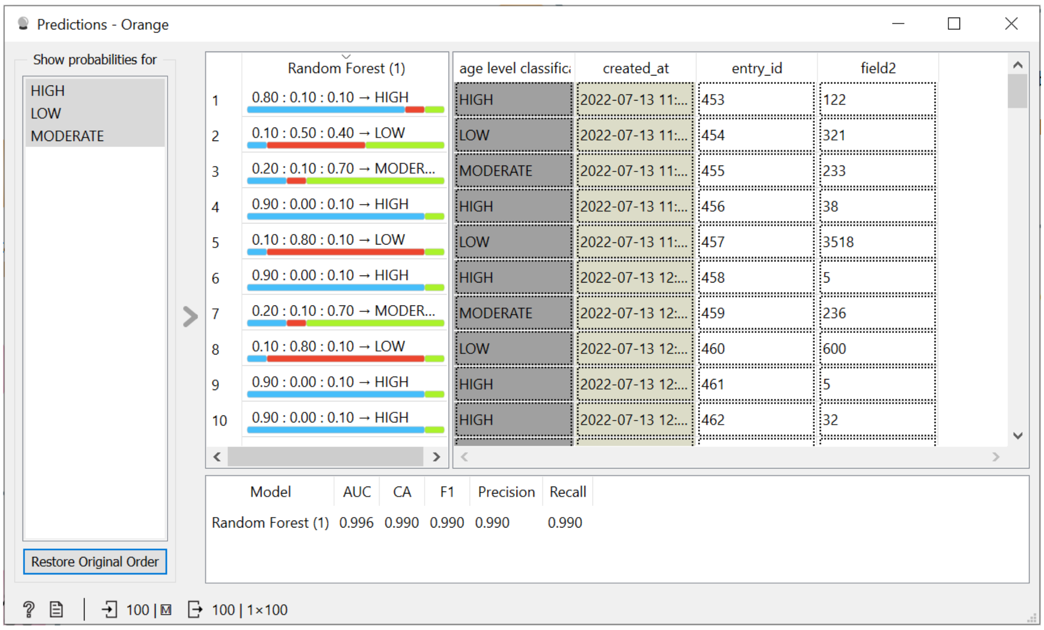


Figure 11. Comparison of Actual Garbage Level Classification and Predicted Classification by the Random Forest Model based on the Garbage Level.

Discussion

The proposed system utilizes IoT technology for automatic segregation of garbage with location tracking and surrounding air quality monitoring. Metal sensors incorporated into the system can efficiently identify dangerous metal explosives, which can be beneficial for intelligence agencies. Additionally, the weight of the garbage collector is tracked, enabling municipal officials to evaluate how much garbage is being collected from specific regions. Machine learning algorithms classify the air quality levels and garbage weight into different categories, thereby improving the health of people staying nearby dustbins as air quality is continuously monitored and reported to concerned authorities.

Improper waste management results in serious problems for both health and the environment. The proposed Smart Waste Management System helps in the efficient segregation of disposed waste at the source-level/community level, reducing dependency on humans for effective waste segregation and management. Garbage dustbins are monitored in real-time using GPS, ensuring that they are replaced when filled with waste. The system incorporates IoT applications and electronic sensors, creating a clean and healthy environment for people residing in nearby areas while easing the workload of garbage collectors. Overall, this system provides a feasible solution for the challenges posed by improper waste management.

5. Conclusions and Future Work

The system presented in this paper provides an efficient solution to maintain a clean and hygienic environment, while it also utilizes IoT technology to connect electronic devices for communication and data sharing. However, the suggested solution requires a reasonable investment for initial system setup and deployment. In addition, the personnel managing the system's configuration and deployment must have a high level of expertise and understanding of its functionalities and operations. The system ensures that waste does not accumulate in dustbins by notifying concerned staff when a dustbin is filled and needs to be disposed of quickly. Additionally, the system segregates waste based on its type, allowing proper disposal in the fastest manner possible, and it also encourages recycling of non-biodegradable waste, thereby preventing soil pollution. Moreover, the proposed system utilizes a Pi camera, potentially helping to prevent criminal offenses by capturing images of people throwing objects in dustbins, which have become frequent targets of terrorists and criminals. Overall, the system offers an effective solution to waste management and contributes to the cleanliness and hygiene of a city's environment.

Whenever the garbage bin reaches its capacity, the system will automatically send its location along with a notification to the Blynk app to inform the concerned authority. This research work presents a more feasible solution by utilizing IoT devices and ML techniques, along with integrated technologies, to develop an Electric Dumpster. The main objective of this system is to monitor the garbage level, location, and air quality in real-time, with greater efficiency and cost-effectiveness.

As a future direction, the functionality of the system can be further extended by adding more features and capabilities. For example, machine learning techniques can be applied to the collected data to predict waste generation patterns and provide insights into the effectiveness of waste management policies. Additionally, the system can be enhanced by incorporating more sensors to monitor factors such as temperature and humidity, which can affect the rate of waste decomposition and odour control. Moreover, the proposed system can be integrated with other smart city initiatives to create a more holistic approach to waste management. For instance, the system can be connected with smart traffic management systems to optimize garbage collection routes and schedules based on real-time traffic information. Furthermore, the system can be used to promote public awareness and education about the importance of proper waste disposal and recycling, through various media and outreach programs.

Another future work is research towards the sustainability analysis of the proposed system by adopting a systematic approach for waste management, such as the one presented in [39] where authors take a holistic view of sustainable construction waste management. They review the sustainability issues of construction companies, contractors, government sectors, and materials manufacturers in Australia's construction industry from economic, social, and environmental perspectives. In our approach, it would be similarly interesting to analyse the motivation of involved stakeholders (such city's authorities) in adopting sustainable waste management practices and also to explore the role of positive and negative incentives, goal setting, and the hierarchy of needs theory.

In terms of scalability, the proposed system can be deployed in various settings, such as public places, residential areas, and industrial zones. The system can also be customized to suit the specific needs of different locations and communities. Furthermore, the system can be integrated with existing waste management infrastructure and facilities to provide a more comprehensive and integrated waste management solution. Overall, the proposed system has the potential to revolutionize the waste management industry and contribute to creating a cleaner and healthier environment.

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