Uncollected Solid Waste Detection and Reporting Using Machine-learning and Geotagging

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Abstract: Uncollected solid waste has become an ever-growing threat to our livelihoods, posing many problems that span health risks, environmental pollution, and unpleasant aesthetics. Traditional methods of reporting uncollected solid waste have proven ineffective and we struggle to keep pace in addressing the growing volumes of waste. This study focused on developing a solid waste detection and reporting system based on machine learning and geotagging. The developed system sought to enable solid waste management entities to obtain verified solid waste reports and accurate location details of the uncollected waste instances. A ResNet model was trained on commonly used solid waste image datasets from online sources. The model achieved a provisional accuracy beforescore of seventy percent (70%) though this statistic can be improved by adjusting model parameters. A rapid iterative design approach was employed to facilitate the development of the crowdsourcing app. This enabled the researchers to swiftly build, evaluate, and refine functional prototypes of the system before finalization. The resulting system receives solid waste images together with their location data and verifies the correct image reports using the trained model, before finally visualizing the reports on a map. Overall, the system provides a platform for the general public to collaborate with solid waste management bodies in combatting uncollected solid waste. In the future, the system may be diversified to allow reporting other amenity issues besides uncollected solid waste.

Keywords: Solid waste detection, Solid waste reporting, Geotagging, ResNet, Machine learning

1. Introduction

The growing use of technology has not spared the solid waste management sphere as a growing number of studies have sought to develop smart systems based on emerging technologies to aid in waste management in cities (Mihai et al, 2019). The Swachh Bharat Mission launched in India has also driven the development of solid waste reporting systems. The mission launched the Swachh Technology Challenge, a competition that encourages entrepreneurs and innovators to develop new technologies for waste management (Anitha et al, 2022). This has led to the exploration of multiple avenues and resulted in the emergence of innovative solutions focusing on waste management. The annual volume of solid waste generated in sub-Saharan Africa is pegged at one hundred and seventy-four million (174 000 000) tonnes as of 2019 and only forty-four percent (44%) of it is collected (Adedara, 2023). The volume of solid waste produced is expected to triple by 2030 while the percentage of solid waste collected drops. Uncollected Solid Waste refers to waste that is generated but which remains uncollected due to lack of collection services (Mas, 2019)

In 2021, the World Health Organization underscored the significant health hazards associated with uncollected solid waste and indicated the seriousness of the issue. These included gastrointestinal infections with symptoms such as diarrhoea and vomiting stemming from the consumption of contamination of food and water, respiratory conditions induced by toxic pollutants released by burning solid waste, and vector-borne diseases like malaria and dengue fever-transmitted disease vectors like mosquitoes and flies. Local governments are obligated to facilitate the collection of both solid waste in bins and isolated waste, however since most of this waste is dumped in discrete areas, local municipals rely on citizens' reports to know about these areas. Taggio et al. (2022) allude that existing systems for citizen reports are ineffective in that they fail to provide meaningful location details of reported waste instances and there is no metric to guide what is worth reporting and what is not. The goal of this research, therefore, is to create a crowdsourcing mobile app that can be used to detect and report uncollected solid waste. To do this the following objectives were formulated:

Objectives

- To capture and submit images of uncollected solid waste
- To filter out valid submissions using a machine-learning model

- Tag and display the location of valid reported solid waste instances

According to Njiru & Takeuchi (2018), Sustainable Development Goal (SDG) 11 focuses on making cities and human settlements sustainable, while Target 11.6 specifically aims to reduce the adverse per capita environmental impact of cities by improving the management of municipal and other waste effectively by 2030. By providing details for reporting uncollected solid waste, the application supports waste collection leading to cleaner, healthier, and more resilient urban environments. The crowdsourcing approach particularly leverages the power of community involvement as the app ensures comprehensive coverage and timely reporting of waste accumulation and reduces its environmental impact on communities and cities. Ultimately, the system intends to simplify the reporting process, enable prompt waste collection, and eventually support more effective waste management strategies.

2. Literature Review

This section looks at the commonly used machine learning algorithms, datasets used to train models, and commonly used techniques for collecting uncollected waste.

2.1 Commonly Used Machine Learning Algorithms

Convolutional Neural Networks (CNN) are a type of machine learning neural network that is suited for image recognition and classification tasks and have gained adoption in the detection and classification of waste in images (Majchrowska et al, 2021). Across the reviewed studies, three types of pre-built CNN models were used for solid waste detection, and from their findings, each had its trade-offs which are explored below.

The first type, *AlexNet* was used by Susanth et al (2021) to identify solid waste objects and detect the type of waste from images while Majchrowska et al. (2021) used it to detect and classify waste in images. Findings from both studies concur that the *AlexNet* model performs fairly well in both detection and classification but is outperformed by other models. Its lightweight model makes it suitable for use in limited processing resources. The second, *ResNet* was proposed as a solution to challenges faced by the increase of convolutional layers in VGG Ziouzios et al.(2020). Rajakumaran et al.(2023) leveraged it for real-time identification of solid waste by a drone camera. They obtained a 95% accuracy score while Susanth et al.(2021) obtained a 93.5% score when using *ResNet50* to detect and map out solid waste in drone-captured and satellite images. Both studies concur that the model performs well with poor-quality images, is computationally efficient, and has a small memory footprint. This poses ResNet as an ideal image detection algorithm to be used on a solid waste detection mobile application. Majchrowska et al. (2021) compared our third type, *EffiecientNet,* with *AlexNet* and *ResNet* and they elucidated that it was more adopted for solid waste detection tasks while the other two are optimized for waste classification. This is contradictory to the findings of Mudemfu & Wayne (2023) who argue that this model is suited for image classification tasks. This contradiction might be due to the different scholars focusing on a different task as the first study focused on detection tasks while the second focused on classification tasks. Their contradictory findings may also be an indication that *EfficientNet* is well suited for both tasks. Mudemfu & Wayne (2023) compared it with *VGG, AlexNet, ResNet*, and *DenseNe*t and concluded that this is the best model to implement as it can be altered to outperform any other CNN-based model in any metric. By allowing the alterations to its architecture to achieve the desired balance between computational resources and detection accuracy, EfficientNet also becomes another prebuilt model that may be used in solid waste detection mobile applications although its performance may be greatly affected by the limited processing resources on mobile devices.

2.2 Datasets Used to Train Models

In all the studies reviewed, none created a new solid waste image dataset as all the studies used pre-created solid waste image datasets. Niu et al. (2023); Rajakumaran et al. (2023); Taggio et al. (2022; Ulloa-Torrealba (2023) used the *Trashnet* dataset to train CNN-based models in tasks of solid waste detection in aerial images. These studies managed to obtain acceptable performance metrics with this dataset that is suited for solid waste image classification though they hinted that different datasets could have guaranteed better performance. It is more suited for classification tasks as it spans six classes: glass, paper, cardboard, plastic, metal, and trash; this explains why Ma et al. (2020) obtained higher performance scores than all other waste detection studies as they used the *Trashnet* dataset for classification tasks. Majchrowska et al. (2021); and Mudemfu & Wayne (2023) created their custom datasets by extracting images from various public image datasets including *Trashnet, Open Litter Map, "Wassste", and TACO-Trash-Dataset*. According to Mudemfu & Wayne (2023), combining images from different settings helped reduce overfitting. This poses the practice of merging different datasets as a possible solution to obtaining a reliable dataset for training a solid waste image detection model.

2.3 Commonly Used Techniques for Reporting Uncollected Solid Waste

Verma et al. (2022) , and Torres & Fraternali (2023) developed uncollected solid waste reporting systems based on images captured from an aerial flying craft that included drones and satellites. The architecture of these systems was similar to that of Wang et al. (2020) though it harnesses images captured from mobile phones in place of drones, in this architecture, the device capturing images acts as a client while the facility carrying the model acts as a server. Shahab & Anjum (2022) attempted to deploy both client and server on a mobile device and they reported that the algorithms required great processing power while mobile devices have limited processing power. To counter this, a choice has to be made between either scaling down the algorithm and reducing performance levels in the process or simply deploying the algorithm on the web end. This ultimately puts the former architecture ahead of the latter as the architecture of choice in solid waste reporting systems

To successfully add location details to images in their systems they integrated Map APIs. Wang et al.(2020) used a *Gaode API* which is presented fully in the Mandarin language making it unusable in non-Mandarin speaking regions. The other three studies used *Google Maps API* and they pointed out that it is easier to use and has a wide range of features compared to *OpenStreetMap API*. Ndlovu et al. (2023) used the Google Maps API to mark locations of reported potholes in a pothole reporting system and highlighted that it displays different levels of detail about reported potholes based on the zoom level used. Another added advantage of using Google Map API is that it allows free access to all features as long as the project is not yet commercialized. With this in mind, Google Map API can be utilized to locate uncollected solid waste

3. Methodology

The Rapid Application Development (RAD) methodology was chosen for the development of the uncollected solid waste detection and reporting system. Its focus on building and testing functional prototypes in short, iterative cycles aligns perfectly with this approach (Sooni, 2023). Each iteration concentrates on a specific component of the system, such as the mobile application's user interface or the server-side image detection model. This allows for independent testing and refinement of each component, ensuring optimal functionality before integration with the entire system.

3.1 Tools and Technologies Required to Develop the System Were Also Identified

Table 1: Required Tools

	Tool	Use Case
1	Python	Programming language for training the solid waste detection model.
2	Google Collab	Development environment for training and testing the solid waste detection model.
3	React Native	JavaScript framework for mobile app interface development.
4	Google Maps API	Map service for geotagging identified solid waste instances
5	SQLite	

3.2 Data Collection and Preprocessing

Using a pre-created solid waste image dataset, the study leveraged *Trashnet, "Wassste", and TACO-Trash-Dataset* datasets. The resulting dataset was then meticulously annotated and split into training, validation, and test sets. During the preprocessing phase, images were resized, normalized, and augmented to improve the model's robustness.

3.3 Selected Model

A *ResNet* pre-trained model was adopted as it yielded a good balance between accuracy and efficiency in five (5) previous studies reviewed in the literature review. In the developed system, the *ResNet* model would be trained in solid waste image detection rather than classification tasks as the system focuses on uncollected solid waste. The model's architecture comprises 50 layers, enabling it to capture intricate features within images. It uses residual blocks as its core building blocks as they ensure information flow throughout the network by adding the input directly to the output of convolutional layers. The pre-trained model comes with weights already learned on a massive dataset for image classification, necessitating adjusting to enable object detection tasks.

3.4 System Design

The design was constructed as the blueprint of the developed system, defining the structure and interactions between different system components.

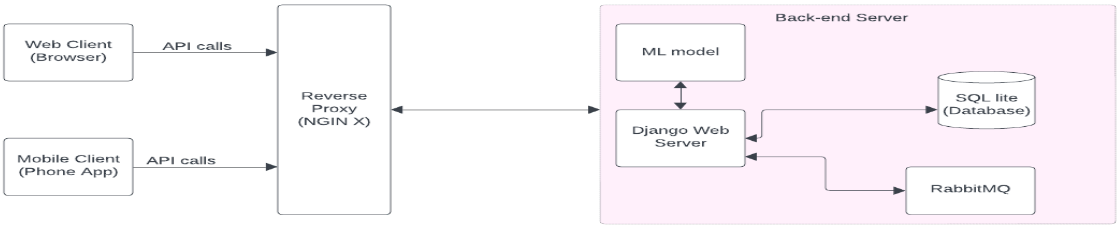

Figure 1: System Architecture

From the system design, the system would have two possible points of interaction with the back-end services; the Web Client, for use by the system administrators, and the Mobile Client for use by general users as highlighted in Figure 1. This was to ensure that the mobile end (for the contributing public) remains minimalistic and uncluttered to foster usability and hence boost adoption rates.

Solid Waste Reporting Sequence

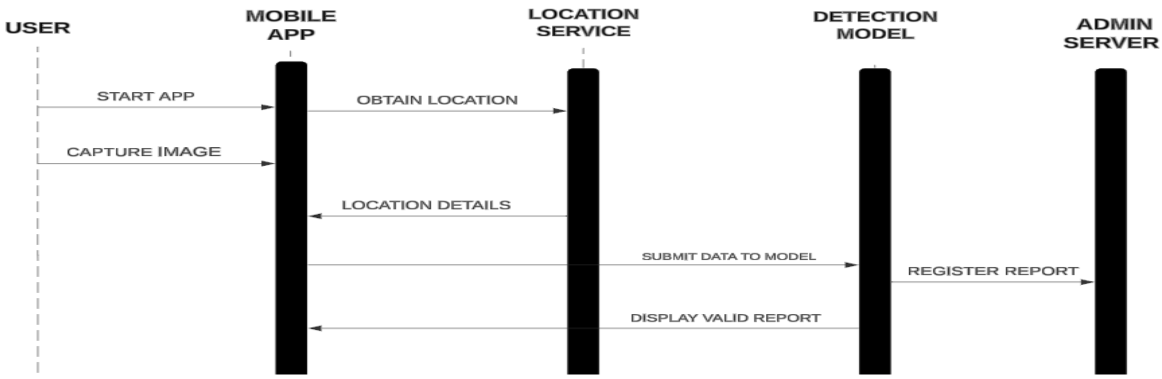

Figure 2: Solid waste reporting sequence diagram

Users initiate the solid waste image reporting process by launching the Mobile App, which allows them to capture an image of the solid waste they encounter together with the device's location and timestamp. Users are then prompted to fill in their details including their email address for purposes of user identity and future messages as highlighted in Figure 2. The is bundled together with the user's email address and sent to a central Django Web Server. The server then invokes the pre-trained *ResNet* algorithm and runs the image through the algorithm to detect any waste present in the image. If the reported image is detected to have solid waste, the server extracts the submitted location data (latitude and longitude). It makes a *Google Maps API* Call, that is, the server makes a request to the *Google Maps API* using the extracted location, and the API plots a point (marker) on the map at the specified location, visually representing the waste sighting.

4. Results and Discussion

The following section discusses the completed system that was achieved following the system architecture outlined in the previous section and also sheds details on the ResNet model.

4.1 Model Performance Statistics

Matplotlib and Pyplot tools (sub-modules of Matplotlib) were used for visualizing and analyzing the performance of the machine learning model's accuracy during the testing phase. It is important to note that this model was trained and deployed as an incremental learning model. This means it is a type of machine-learning model that can continuously learn and improve as it receives new data.

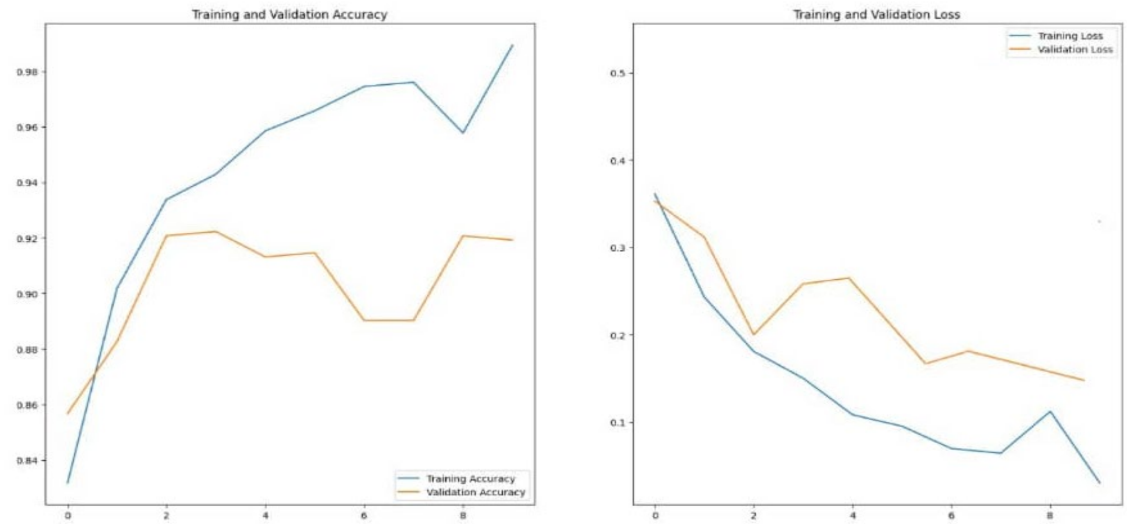

Figure 3: Training and Validation Accuracy Graph (left), Training and Validation Loss Graph (right)

The *training accuracy* increases steadily across epochs, indicating the model is progressively learning to classify images during training correctly. Ideally, this value should reach a high plateau (close to 1) as training progresses. The *validation accuracy* also increases thus indicating that the model is generalizing well and is not simply memorizing the training data. The *training loss* generally decreases across epochs, which is a positive sign as this indicates that the model is learning to reduce its errors and improve its performance on the training data. The *validation loss* generally decreases thus depicting that the model is generalizing well and is not overfitting to the training data. Overall, the metrics shown in these graphs indicate that the *ResNet* model is likely performing well during training.

The training accuracy is increasing, and the training loss is decreasing, indicating that the model is learning to classify images correctly. Throughout the training process, we monitored the model's performance on the validation set and made necessary adjustments. To measure the accuracy of our model, we employed early stopping. This technique involves halting the training process once the model's performance on the validation set ceases to improve, thereby avoiding overfitting and ensuring that the model generalizes well to unseen data. As a result of these efforts, our ResNet model achieved a significant milestone, attaining a 70 percent accuracy rate in detecting solid waste. This accomplishment marked a major step forward in the development and effectiveness of our image detection system.

4.2 Mobile App Interface

The app interface is simplified to guarantee usability for the general public who might have limited digital literacy skills. The app is solely for submitting solid waste reports without requiring user accounts which simplifies the user experience significantly. Users can simply open the app, capture and submit images of uncollected solid waste, and fill out their necessary details hassle-free. Since there are no user accounts involved, there's no need for users to remember login credentials or go through a registration process, making it more accessible to a wider audience. Additionally, this approach potentially encourages more people to report waste, as it removes barriers to entry such as account creation.

Mobile App Upload Flow:

1. The user clicks "Gets Started" and opens the mobile app camera
2. The user is prompted to grant access to the device location
3. User captures an image of suspected waste and
4. To complete the report the user is prompted to fill in their details (name, surname, email address, phone number)
5. Report is submitted for processing
6. App displays the validity of the report

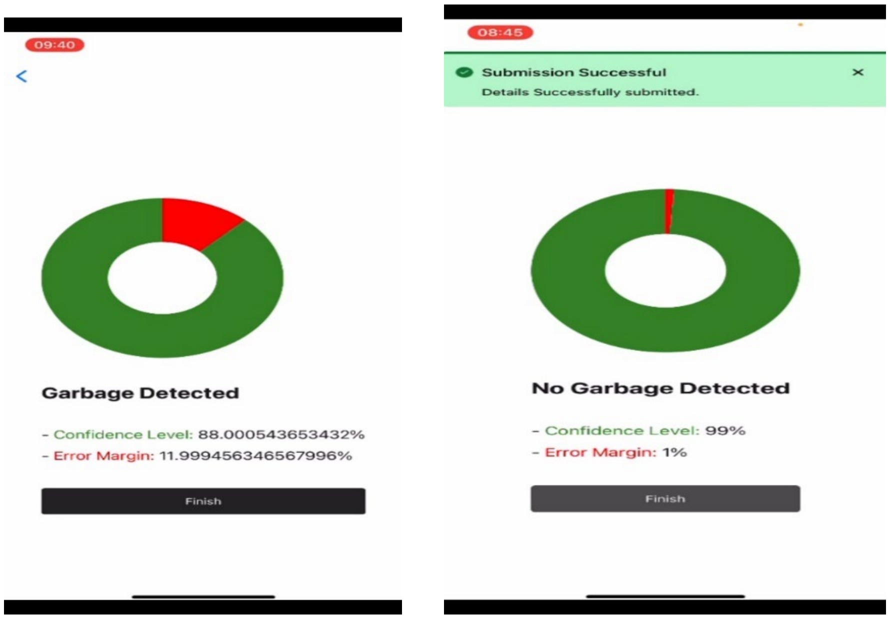

Figure 4: Solid Waste Detection Status, Garbage Detected (left) No Garbage Detected (right)

Upon submission, the image is relayed to a web server which then runs the ResNet model to detect the presence of solid waste in the image. The resulting status together with the waste detection model's confidence level and error margins metrics are displayed to the user. The *confidence level* in an image detection model indicates the likelihood that the model's prediction is correct. *The error margin*, also known as the margin of error, quantifies the uncertainty or potential inaccuracy in the model's prediction. It is also often expressed as a percentage. Showing these metrics helps build trust with users by providing transparency about the detection process. Users can see how confident the system is in its detections, which can help them understand and trust the app's decisions. Using the two metrics developers can identify specific types of waste or scenarios where the model struggles, benchmark the model's performance over time, and a whole lot of aspects that need to be revised to improve the model.

4.3 Map of Reported Uncollected Solid Waste Instances

Only admin users on the web-side interface can access the valid submitted solid waste reports and their location details. This page displays a map showing the accurate location(s) of the reported uncollected solid waste reports. This allows the waste collection entities to traverse to the exact points where uncollected solid waste has been reported and conduct clean-ups. The accurate locations are obtained when the user submits an image of suspected solid waste. The map is facilitated by a Google Maps API. Once a report has been attended to, the admin notifies the user. The email addresses submitted by contributing users are used for real-time notifications whereby the users about informed about the progress of their reports. This fosters transparency and trust in the system.

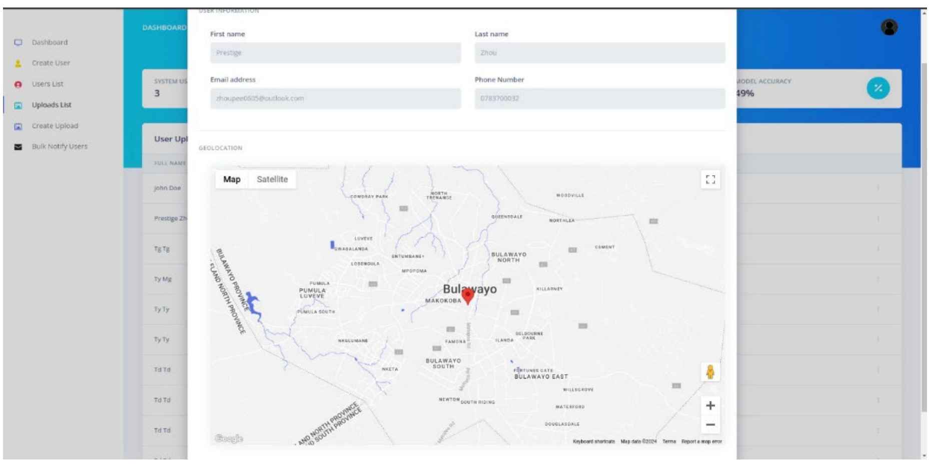

Figure 5: Map showing the location of a reported uncollected waste instance

4.4 Proposed Improvements

Zimbabwe, like other global counterparts, is grappling with the challenges posed by electronic waste (e-waste) in an increasingly digital world (Tsiko S, 2024) . Future improvements for the app could involve expanding its functionality to include the detection and reporting of electronic waste (e-waste). The ResNet model could be trained on e-waste datasets to enhance the app's capability to accurately identify various types of e-waste from user-submitted images, ensuring precise classification and appropriate handling of electronic devices. This would streamline the e-waste management process, allowing for more efficient and sustainable handling of electronic waste. Integrating gamification into the uncollected solid waste reporting app could affect its usability but has the potential to significantly enhance user engagement. Gamification features like points, levels, and leaderboards incentivize users to actively participate in waste reporting and community clean-up efforts. Challenges and badges further motivate users to contribute positively to environmental conservation, while virtual rewards offer recognition for their contributions. By combining these elements, the app transforms waste reporting into an engaging and rewarding experience, driving greater community involvement and fostering a culture of environmental responsibility.

5. Conclusion

This research explored the development of a crowdsourcing mobile application for solid waste detection and reporting based on machine learning and geotagging. The application aimed to address the growing challenge of neglecting solid waste by providing a user-friendly tool for waste identification and reporting. From this research, it can be concluded that machine learning models, particularly Convolutional Neural Network models, are effective for solid waste detection in images. By leveraging a binary classification pre-trained model, ResNet50, the application achieved high accuracy in identifying various types of solid waste in their natural environments. This backs all prior work conducted by scholars in the same field. Another takeaway point of note is the need to achieve a balance between model accuracy and computational efficiency. While complex models can offer higher accuracy, they might not be suitable for mobile devices with limited processing power. This research utilized a mid-range model and achieved good accuracy while maintaining efficiency for mobile deployment. Finally, in developing a system for use by the general public, user-friendly design principles should be adopted to achieve widespread adoption. This influenced the creation of two separate interfaces for the contributing users and for system admins to keep the interfaces clean, minimalistic, and uncluttered. To foster use, the app requires no sign-up for one to capture and upload an image but requires user details after the successful upload of a report. This research successfully demonstrated the feasibility of developing a crowdsourcing mobile application for solid waste detection and reporting using machine learning and geotagging. The application has the potential to empower citizens to participate in waste management efforts by facilitating waste identification and reporting.

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