Waste Segregation using IOT and Deep Learning Classification: An Extensive Review

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Abstract
"According to the World Bank, estimates state that by 2050, the world will generate 3.88 billion tonnes (3,880,000,000,000 kilograms!) of waste each year – an alarming increase of 73% from 2020." [1, 2]. With the recent rise in population, the generation of waste and garbage has significantly increased. Ineffective waste management practices can result in significant environmental impacts like pollution, wildlife impact, climate change, human health hazards like the spread of diseases and respiratory issues, and even aesthetic and tourism impacts resulting in economic costs. This has resulted in the need for better and more efficient waste management practices. Currently, several well-organized waste management systems are functional. However, they require human intervention, which might be a health hazard for sanitation workers. This has drawn the attention of scientists and engineers. With the alarming increase in waste, there has also been a good increase in the studies conducted on waste management and its automation. In this paper, we survey many such researches. We find that many attempts have been made to automate the process of waste segregation and sometimes the entire waste management process. A lot of ideas propose the effective use of IoT for this purpose. These projects proposed using different sensors to detect the dampness in the waste and then segregate them into wet or dry wastes. However, due to hardcoded thresholding, this might be inefficient. To counter that, many other projects ideate using deep learning algorithms along with IoT devices and provide comprehensive evaluations of these algorithms. The literature review indicated that immense attention is paid to this issue, and research has been conducted to mitigate the problems in this domain effectively. Despite that, this domain could still use unique approaches to resolve major open questions.

Keywords: Waste management, Waste segregation, Waste sorting, Internet of Things (IoT)-based waste management, Deep learning-based waste management, CNN-based waste classification, Smart bins, Automated waste management, Edge computing in waste management, Image-based waste sorting, Sustainable waste management, Waste detection, Cloud Computing in waste management.

1. Introduction

Waste segregation identifies and separates garbage and waste products to dispose of or recycle materials effectively based on their characteristics. To segregate waste appropriately, correctly determining the garbage generated class is essential. Waste is generally segregated at source as dry and wet.

Waste categories are created based on how they will be disposed of, leading to characteristic-based segregation. This reduces landfills' large-scale impact on nature and declines contagious diseases. It is also essential for several reasons, including Cost savings, Resource Conservation, and a Sustainable Future. Due to such intricacies in waste segregation, manual segregation can be ineffective.

This has attracted the application of the Internet of Things (IoT) and Machine Learning (ML) systems for real-time monitoring and automated segregation. IoT devices are interconnected appliances, often through the Internet or Wi-Fi. These devices have various sensors, such as temperature and gas sensors, cameras, and others, that collect real-time data for monitoring.

As the name suggests, machine learning attempts to make the machine learn the patterns in the study environment without manual work. Machine learning is a large part of the larger artificially intelligent (AI) systems that perform data analytics without explicit instructions. These algorithms learn manually extracted patterns from massive training samples and generalize them to predict relationships between newer, unseen examples. ML systems improve with data. They extract useful information from raw data processing, which helps in decision-making. Due to this, Machine learning has found immense applications in fraud detection, cyber-security, and recommendation engines.

A newer, fast-developing field that is a subdomain of Machine Learning called Deep learning (DL) works on an architecture that precisely tries to replicate human learning. It does so by imitating the neural networks in the human brain. These neural networks contain neurons interconnected to each other. These neurons constitute hidden layers that pick up patterns abstracted at various levels in the study environment. Deep learning algorithms are structured to exploit patterns from environments where humans cannot find any. This is sometimes a pro, sometimes a con.

Initially, self-pattern recognition was impossible for computer systems. So, feature extraction techniques were used for that purpose. These techniques were used to manually extract patterns from the study environment and feed them to the algorithms for learning. However, Deep Learning algorithms can learn these patterns without human intervention. In the process of waste segregation, the pixels of the waste object are learned with better accuracy compared to hand-extracted features, given optimized training time.

In particular, deep learning has intensely impacted historically difficult areas of comprehension for machine learning, such as human-level image classification, speech recognition, and handwriting transcription, and improved self-driving cars. These are not the only domains impacted by Deep Learning. Convolutional Neural Networks (CNNs) are modified deep learning architectures to suit image classification and classify waste into different categories. They have become a significant area of study in waste management automation.

This paper reviews many ideas and projects that implement automated waste management or segregation using different tech stacks, including Internet of Things devices and Deep Learning algorithms, individually or in complement to each other.

2. IoT-based waste segregation systems:

A unique take on the automated waste management and segregation project was proposed, based solely on IoT. Such an approach utilizes moisture or rain sensors to sense the waste's moisture content when placed on it. Based on the moisture levels detected, the waste is then segregated into the respective bins using a relay and a servo motor [3, 4, 5].

A moisture sensor was used to detect the waste’s wetness, and an MQ sensor was used to detect gas and temperature intensity in the waste to segregate hazardous wastes. An Arduino Uno microcontroller controls all these components. It also proposes an alert system that notifies the concerned authority about the bin status through the cloud [3].

A dry and wet waste segregator, the "Spontaneous Waste Segregator (SWS)," uses a rain sensor, an ultrasonic sensor, and a servo motor to classify the wet and dry waste into the bin. It also uses an IR sensor and a GSM module to alert if the bin is filled [4].

Another project that does classification based solely on IoT uses an MSP430 microcontroller with a moisture sensor and a rain sensor to detect moisture. An inductive proximity sensor was also used to detect metal, an ultrasonic sensor to measure the bin's fullness, and motors to drive the conveyor belt onto which the waste is placed. The project also incorporates the essence of Do-it-Yourself (DIY) by encouraging users to build the model themselves [5].

Despite this unique approach, implementing it in real-time is challenging as people randomly throw away waste instead of placing it on the sensor. In addition, the thresholds are manually set for the moisture, rain, and MQ sensors. Instead, machine learning models might be a better choice as they gradually pick up valid features.

With that motivation, many papers attempted to incorporate machine-learning models, particularly deep-learning models, to classify wastes. Convolutional Neural Networks were mainly used for this purpose.

3. IoT and Deep Learning based waste segregation systems:

A model was proposed that contains four waste compartments with retractable lids for the entry and exit of different wastes. TensorFlow-built deep learning model – SSD MobileNetV2 is used to make an intelligent waste management system with an auxiliary LoRa communication protocol. A frozen inference graph of the model is used for object detection using a camera associated with a Raspberry Pi 3 Model B+ as the central processing unit. It uses five ultrasonic sensors to monitor waste levels and detect waste, and servo motors operate the lids to segregate waste. A waste detection platform is used to classify the waste before opening it into its respective waste compartment. The model has achieved an accuracy of 86.7%, 96.3%, and 82.3%, respectively, for metal, plastic, and paper [6].

This model works well for outdoor public bins. However, using Wi-Fi over the LoRa communication protocol for in-house bins and waste processing sites will improve efficiency and allow mass access without needing a separate LoRa network.

Another model uses the Raspberry Pi 3 module as the microcontroller equipped with a Pi camera module. A CNN trained on Lobe - a Microsoft tool for building deep learning models for edge devices, is used. The trained CNN model is deployed on the edge device - Raspberry Pi module. The camera captures the image of the waste based on the output from an IR sensor, sends it to the microcontroller, and classifies the image into dry or wet waste. A servo motor then sorts the waste [7].

Another idea that implements a CNN proposes a unique approach toward waste segregation. It provides a diagrammatic architecture and idea for implementing a smart robotic arm that detects and classifies wastes in the surroundings into dry and wet waste, picks them, and puts them into the respective bin. It utilizes a Raspberry Pi 3B+ module as the CPU for the robotic arm, a CNN classifier, and the Sony camera. The CNN classifier here is trained using "edge impulse," another software used to train AI models for edge devices such as Raspberry Pi 3B+ used here. The author claims the model has an accuracy of 84.96% [8].

Although unique in its method, this project might find a better application in collecting littered waste rather than dry and wet waste classification, which the author seems to have failed to mention.
Another exceptional approach to waste segregation utilizes the computational power available on mobile devices and a simple mobile app— “DeepWaste.” The computation for waste segregation here is restricted only to mobile devices. The author has tested this on several CNN models, like InceptionV3 and others. The Resnet50 achieved the highest average precision of 88.1%. It is an exciting approach to giving the public a means by which they can classify confusing and complex wastes [9].

However, incorporating this into bins can be difficult due to the involvement of mobile phones. In addition, the projects above tried to install the deep learning models onto the edge devices. Although these mobile architectures are fast and efficient, they can impact the model’s accuracy. This is due to the techniques used, like model compression, to make the models edge-friendly.

To experiment with trade-offs between speed and accuracy, a few papers used separate processing units to run the model inference.

4. Full-fledged CNNs as the classification units:

An architecture and code implementation of a sophisticated system that integrates a CNN-YOLOv8 and IoT devices, specifically Arduino UNO and a servo motor, where the CNN detects and identifies the type of waste and the IoT devices sort the trash into the respective bins. It also implements a web app for real-time monitoring of the waste levels. The paper claims full implementation of the idea and provides code snippets backing it up [10].

Another architecture and implementation of an autonomous waste sorting machine that leverages transfer learning on Faster RCNN-based inceptionv3 model, a funnel to separate and drop the waste onto a conveyor belt controlled by a motor and flaps to classify the wastes into different categories. Inductive proximity sensors were used to classify metallic wastes. The confidence levels of each waste classified were high. Also, CNN training logs were visualized in the paper [11]. Since the dataset was small and manually collected, the accuracy of the above CNN model could have been affected. They could have instead utilized a standard dataset to train the model.

In addition, neither of the above papers evaluated the model's overall accuracy or other metrics. Accuracies and other metrics could have been used to show the model's performance. Instead of using a single model like YOLOv8, a comprehensive comparison of multiple deep learning models could have been shown, summarizing the performance of different models on a standard dataset.

In that essence, another project involving a conveyor belt that segregates the wastes uses ATMega2560 AVR as the microcontroller. Waste is placed on the conveyor belt and detected by an ultrasonic sensor, which prompts the camera to take an image and send it to a processing unit for classification. The processing unit runs an Inception-Resnet V2-based CNN with few additional inputs and dense layers at the top. Based on the output of the CNN, the respective servo motor is activated to push the waste to the respective bin. The author claims that this CNN achieves a state-of-the-art accuracy of 98.3% and compares it with other models [12]. A GSM module is used for the alert system here. Using a GSM module for the alert system is undoubtedly an improvement from the previous version. However, with the advent of the internet, utilizing Wi-Fi-enabled devices for sophisticated alerts could've also been an alternative.

Another paper proposes a similar project that utilizes a "roller" - a conveyor belt that carries the waste and also measures the load using a load measurement sensor. A camera captures an image of the waste being carried on the roller, and then the image is processed using a CNN model. Based on its output, the microcontroller-ESP8266 sends control instructions to the roller to carry the waste to the respective servo motor. The servo motor then segregates the waste. The author has also efficiently leveraged Wi-Fi, Bluetooth, the Cloud, and an Android application for real-time data monitoring. The paper explores different CNNs like AlexNet, VGGNet, Resnet50, and Resnet34 to compare their performances and provides a detailed metrics analysis [13].

As we can see, there has been a common trend to use conveyor belts to carry the wastes to the respective bins, each slightly different in its implementation. Another paper implements a conveyor belt and rotating bins controlled by the Renesas microcontroller. A camera captures an image and sends it to a processor for CNN classification. Based on its result, the rotating bins are aligned so the conveyor belt's waste falls into the respective bin [14]. However, the exact type of CNN used here isn't mentioned, and the rotation of the bins using a DC motor might consume more power.

The proposed conveyor belt models are efficient for waste processing sites, but scaling down to in-house waste segregation can be difficult.

With each project focusing on adopting CNNs for garbage classification, an independent evaluation of CNNs exclusively for waste classification can help assess their performance. This is due to the inherent characteristics of waste images, such as inter-class similarity and intraclass variance.

5. Assessment of CNNs for garbage classification:

Particular research comprehensively evaluates YOLOv5 and YOLOv7 models on the standard TACO dataset by incorporating metrics like f1-score, precision, recall, and confidence scores. This paper visualizes metrics like f1 vs. confidence, precision vs. recall, and others that depict the model's performance. It also visualizes the training logs of the model to depict training progress over time [15]. Along with the complete comprehensive evaluation of the models YOLOv5 and v7, the author could have also included YOLOv8, one of the state-of-the-art models for object detection and classification, completing the comparative evaluations of the models of the YOLO family.

Another comprehensive study and evaluation of different AIML methodologies on garbage classification into six categories. The author compares HOG+SVM, a simple CNN, resnet50, resnet50 without residual connections, and a

HOG+CNN architecture that combines handcrafted features with CNN convolution features. The author compares these results with other projects implementing classification using the same dataset [16].

Both the above studies focus on evaluating the performance of existing CNNs and methods. However, they don't emphasize altering the current methods by introducing newer methodologies.

6. Experimenting alterations to CNNs:

Two papers try to present newer methodologies. One paper explores the use of pixel-distributed learning for garbage classification. The author has focussed on addressing the inherent vulnerabilities in CNNs. This study explores training a VggNet CNN on the standard Kaggle dataset of wastes in 6 different categories. The training of the model is done on the original images, then on augmented images, and then on "patch-shuffled images." The paper mentions steps towards how the patches were created and shuffled. The patch shuffle images with a patch size 4x4 have shown the highest test accuracy of 82.4% on the original images [17].

Another paper explores using a "Depth-wise separable convolution attention module" for garbage classification, which is explained in detail in the paper. The author has focused on addressing the inherent characteristics in garbage images, such as inter-class similarity and others that are generally ignored in CNN classifications. This is secured by including the channel and spatial attention. This study explores training a Resnet50 equipped with DSCAM. The use of Resnet50 as the backbone has also been justified. The DSCAM model was trained on the datasets created by Huawei Cloud and Baidu AI Studio. This model was also compared against other popular CNN models and seems to have obtained state-of-the-art accuracy [18].

An author has also given an intriguing approach towards in-house dustbins with waste segregation capabilities. Despite the dustbins being equipped with such capabilities, the computation time required for classification is reduced due to "computation offloading" to the cloud. The tech stack used involves a Raspberry Pi module with a Sony camera to capture an image of the waste when it is thrown into the dustbin. This image is then securely transferred to the "Information system" on the cloud, where classification is done by a Deep CNN-Resnet50. which utilizes shortcut connections to behave as a shallow network. The images are also stored in a MySQL database on the cloud, which the bin users can access. Based on the information system results, the bin's waste is classified. The author also claims to have tested the bin in real-time by deployment in a few houses. The CNN model used is claimed to have an accuracy of 93.4% [19].

Even though the author claims this implementation is cost-efficient, the exact costs were not mentioned. Also, the author did not address the cloud's pay-as-you-go model, where users are billed monthly or yearly. An estimate for a specific population could have given a good idea about the project's long-term cost-effectiveness. Also, the purpose of storing the data on the cloud's MySQL service is not mentioned.

7. Discussion

From all the conducted and ongoing research, we see that each attempt tries to build on the previous one, either by newer additions or experimentations involving replacing existing mechanisms. Experimenting with CNNs instead of moisture sensors and the addition of technologies like "pixel distributed learning" or "DSCAM" to the CNN models all complimented the previous analysis of the CNNs [17, 18]. Different studies were conducted to test the robustness of varied algorithms and mechanisms in the domain of waste segregation and management. Each study presented proposed unique insights into the specific procedures studied. However, implementing such an automated system is still far-fetched due to the expensive approaches. Mechanisms like conveyor belts used in a lot of the studies might be a good choice for large waste processing sites and hence cost-efficient as well [5, 11, 12, 13, 14]. However, the working principles of many of the conveyor belt systems are not functionally complete since all the different types of waste start at the same spot. Separating them as they go can be a challenging task. Even though several papers propose good ideas on how it can be done, those aren't good enough. Many times, for the CNN to run the inference on the waste or for sensors to pick values, the conveyor belt has to stop, making the process inefficient and or placing the waste exactly on the sensors for better detection. These conveyor belts also cannot be scaled down to in-house bins. A potential challenge in this field would be to attempt a solution for the physical segregation systems outside the conventional bounds.

8. Conclusion

Starting with IoT and incorporating machine learning, automated waste management has come a long way today. Classification and separation can be efficiently done today with the help of high accuracy in garbage categorization achieved using CNNs and advanced microcontrollers, with early techniques using sensors as the foundation. Even as it stands, there are still problems with cloud connectivity, and the problem of randomness in the distribution of waste points out areas that can be improved. Future research aimed at creating real-life implementations in numerous urban environments could resolve real-world challenges and improve model designs, specifically for internal systems.

9. References

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