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Technical solutions for waste classification and management: A mini-review

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Abstract

The massive growth of population coupled with urbanization over the years has created a significant challenge of increase in waste generation. India has achieved massive developmental growth in economic and social areas but still lacks a proper waste management system. The lack of knowledge about segregation of waste into different categories and proper disposal techniques in a country like India with an accelerated population growth is a critical issue. Since trash has different disposal techniques, according to its type, segregating waste through an automated process at the point of collection will streamline the process and result in effective waste management and utilization. The mini-review article evaluates the recent literature on technologies used for municipal waste segregation and management, with the motive of providing critical information for advancement in current research. This article reviews the use of various convolutional neural network architectures for waste classification and describes in detail as to why image processing methods are preferred over sensors for segregation into respective categories. It is also important to have an efficient waste monitoring and management system for proper disposal. A comprehensive mini-review was undertaken to understand internet of things-based models proposing efficient waste handling, from the perspective of reduced costs, collection time and optimized routes. The proposed systems were compared and evaluated based on the sensors used monitoring, microcontrollers and communication protocols such as Long Range, Global System for Mobile Communication, Zigbee and Wi-Fi, which are employed for the secure and efficient data transmission.

Keywords

Waste management, waste segregation, convolutional neural networks, internet of things, communication protocols, sensors

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Introduction

India with its population of 1.3 billion, 62 million tonnes of waste is generated every year. In this only 43 million tonnes are collected, out of which 31 million tonnes are dumped in landfill sites. With the recent trends of economic growth, an estimated growth of up to 165 million tonnes is expected by 2030 in urban cities.

India has a number of regulated categories of waste-like solid, hazardous, biomedical, electronic, construction and demolition, plastic, lead acid batteries (UNCRD, 2017). In these categories, municipal solid waste (MSW) and industrial hazardous waste are becoming a burden on densely populated major cities. The top 10 populous cities are having an increase in the per capita MSW generation. Even Surat, a city with only a population of 7.2 million has a 2172% growth rate of MSW. This raises concern over a mismatch in the population increase and capacity to increase the waste processing in metropolitan cities (Kumar and Agrawal, 2020). India has the most unorganized process of filling the landfills with MSW. In the current scenario, landfills are no longer being used for reducing the contact between humans and environments created by toxic wastes, but rather they are being used for dumping the waste without following any sanitary protocols. These chaotic landfills may cross the saturation point and no longer be able to take the heat due to the pilling up of waste and catch fire anytime. The emissions from the landfills cause a variety of problems like asthma, elevated cardiovascular risks and other infections specially to rag pickers who are exposed to the chemicals the most (Indian Landfill, 2020). The diversity in the forms of different religious groups, cultures and traditions which is prevalent in our country makes sustainable waste management more difficult. If the waste dumping without treatment is continued at this rate, 1240 hectares of land per year will be needed by 2031.

In 2016, solid waste management (SWM) rules were inaugurated. Waste segregation at source was made mandatory. Households are expected to segregate waste in three categories, organic or biodegradable, dry and domestic hazardous waste.

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Even bulk waste generators like hotels and hospitals are required to treat waste in collaboration with urban local bodies. The national policy took into account the informal sector, municipalities have been directed to include waste and rag pickers which comprise 1.5 million of the population for the first time in the formal waste management sector. Fast-Moving Consumer Goods (FMCG) manufacturers were directed to collect non-biodegradable packaging generated during production (Vikaspedia). However, waste segregation and management are still a very prevalent problem despite these rules and regulations. The massive population of India and its accumulation of waste is the biggest barrier towards manual waste segregation. Apart from an authority, regulations and enforcements, training and capacity building at every level is needed to bring improvements. India has a current literacy rate of 74.04% and hence it becomes very important to educate people about the different categories of waste. The lack of knowledge about the segregation of waste in different groups is another concern in SWM and another reason which renders manual segregation techniques ineffective.

Irregular management of waste also has several environmental consequences. If biodegradable wastes are decomposed under anaerobic conditions, it leads to the release of methane gas. Apart from being a major contributor of global warming, methane also causes open fires and explosions. Another issue faced is with respect to the odour, especially during the summer season. Smog and a large number of respiratory diseases are caused due to uncontrollable waste burning. Inflammation, bacterial infections, anaemia, reduced immunity, allergies and asthma are some of the other problems faced because of poor waste management (Kumar et al., 2017).

Despite the phase 2 of the Clean India Mission, a countrywide campaign initiated by the Government of India being implemented in order to reduce open defecation, it is still a strain (The Wire, 2021). The barrier in SWM is the lack of sustainable methods for waste collection and disposal. Littering of waste on the streets of India is a problem which impacts public health. An availability of a lack of training in SWM and insufficient budgets with municipal authorities is another barrier. A regulation for SWM is a need for India.

Information about the future quantities and characterization of waste is needed to determine the waste treatment plans. The wise use of technology can help the waste management scenario to a great extent as waste can be segregated prior to collection. Effective services of waste management and planning can be implemented if accurate projections about the type and total amount of waste generated is made. Monitoring of the bin conditions could help devise a waste collection schedule and save costs as well. Automating the entire waste collection system can be a long-term solution and help in increasing the efficiency. The following sections contain a detailed review on image-based models for classification of waste, different sensors and communication protocols used for waste bin monitoring and finally the route optimization models that help reduce the time and money spent in collection of waste.

Waste classification

According to the SWM rules of India (2016), MSW can be broadly classified into one of three categories as shown in Figure 1 (CERC-ENVIS, 2016): organic waste (biodegradable), recyclable waste (non-biodegradable) and other domestic hazardous/toxic waste (non-biodegradable).

The following are some of the items that fall into each waste category:

a) Organic: Kitchen waste, fruits/vegetable peels, meat, leaves, dust
b) Recyclable: Metals, paper, glass, cardboard, recyclable plastics
c) Domestic Hazardous: Batteries, other e-waste, hospital waste, spray cans

When it comes to e-waste, people generally do not dispose larger electronic products in the bin, and SWM guidelines suggest that it should not be mixed with organic or recyclable waste. Larger electronic devices are mostly disposed of or recycled by the unorganized sector, which is both dangerous and ineffective. Chargers, cables, batteries and earphones are among the most common e-waste products thrown away in bins; as a result, they must be separated from the other categories at the source and disposed of appropriately. Medicine and e-waste fall into the category of toxic waste, but they are not disposed together or have the same treatment methods.

With rapid urbanization and population growth, MSW generation in India is estimated to reach 300 million tons by 2030 (Tiseo, 2021). As a result, if a proper management system is not implemented, the landfills will be further exploited, as only a small proportion of waste is treated. The existing system in India disregards waste segregation and instead majorly focuses on collection of mixed, unsegregated waste. To limit the amount of garbage disposed in landfills, the process of waste management must begin with waste segregation at the source and then treatment of various waste categories using appropriate procedures. Since biodegradable trash accounts for more than 50% of MSW generated in India, it can be treated by composting or bio-methanation, reducing the amount transferred to landfills if segregated at the source (Ahluwalia and Patel, 2018). Similarly, recyclable waste can be sent to recycling plants, and other non-biodegradable trash can be processed using methods such as incineration. Primary segregation (at source) is preferred over secondary segregation at central facilities because of the low output product quality and contamination of wet waste. The following are a few significant benefits of waste separation at the source (NITI Aayog, 2021):

a) Reduces capital intensive secondary segregation units
b) Low probability of waste contamination and pre-treatment for recycling
c) Reduction in transportation footprint and green-house gas emissions
d) Increased longevity of landfills and promotes decentralized treatment centres

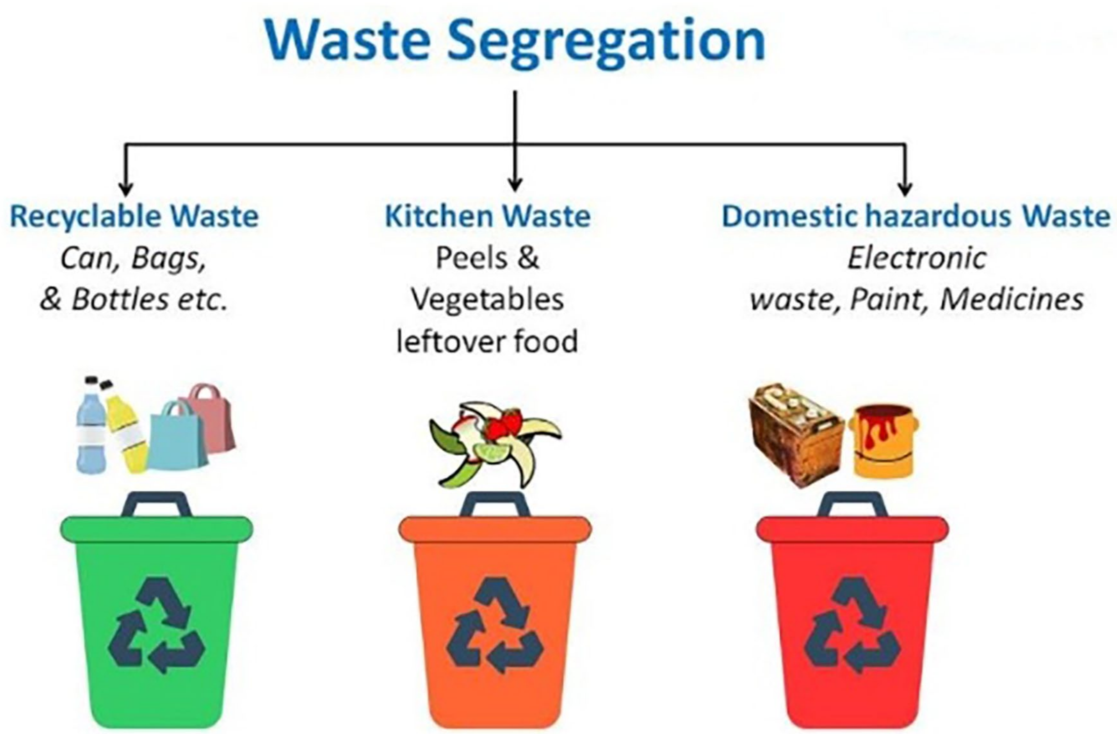

Figure 1. Waste segregation according to solid waste management rules 2016 (Teachoo, 2020).

Despite the existence of an unorganized and informal sector in India for collecting recyclable materials from households, it remains a weaker market as only saleable waste is collected. Given the necessity of sorting garbage into standard categories at the source, the role of technology in this process is crucial, as manual segregation by waste pickers is both inefficient and hazardous. The subsections that follow will explain in detail about the published works on the use of sensors and deep learning algorithms for efficient and accurate waste classification.

Waste classification using sensors

Sensor is a device that produces an output signal which contains information about a certain phenomenon, as a response to an input. It has widespread applications across various industries and is being deeply penetrated into an individual's daily life through the advent of internet of things (IoT). Similarly, sensors can be employed in systems to classify incoming waste into its respective category (Chandramohan et al., 2014). Although policies emphasize manual segregation of daily trash at home, it is unreasonable to ignore the behavioural differences among humans that make this task appear to be a choice rather than a necessity. Technological trash classification solutions, which can be placed in areas like apartments or collection centres on the street, provide a more systematic and accurate segregation than manual or secondary facilities classification.

In the study of Namratha et al. (2021), the authors aim to segregate waste broadly into two categories (dry and wet waste) using moisture sensor integrated with Arduino. If moisture content of the waste, measured by the medium's dielectric permittivity is above a fixed threshold, it is classified as wet waste. The system also monitors other parameters of the bin and sends the data to the cloud using NodeMCU for further processing. This methodology of classification is not efficient due to the reliance on only one sensor and a prefixed threshold level. Since metallic waste is also an important class to consider for classification, there is a need for using additional sensors. Proximity sensors, which detect objects by the emission and reception of electromagnetic radiation, can be used to distinguish between metallic and dry waste. Inductive proximity sensors are used to identify metal waste, whereas capacitive proximity sensor can detect dry waste such as paper and plastic based on permittivity value (Agarwal et al., 2020). On similar lines, authors (Chandramohan et al., 2014) present an economic waste segregator system that uses a parallel resonance impedance sensing mechanism (inductive coil with LC circuit and LDC1000 converter) to identify metallic items and capacitive sensors to differentiate dry and wet waste. A major drawback of this system is in terms of scalability for classifying a larger variety of waste as the whole mechanism is based on relative dielectric constant.

Amongst the large class of non-biodegradable waste, it is equally important to identify items than can be recycled and segregate them according to their type (metal, plastic, glass, cardboard, paper), as they have different treatment methods. In the study of Norhafiza et al. (2018), an automated system is presented where the incoming recyclable trash (metal, plastic, paper) is isolated into the respective compartment of the bin using sensors and motors. The effectiveness of the electronic system placed in the bin is measured using the time required to

Table 1. Sensors for waste segregation.

Reference	Sensor type	Waste category
Namratha et al. (2021)	Moisture	Differentiate dry and wet waste
Agarwal et al. (2020)	Inductive proximity	Metallic waste
	Capacitive proximity	Dry waste (paper, plastic)
Chandramohan et al. (2014)	Impedance sensing mechanism	Metallic waste
	Capacitive	Differentiate dry and wet waste
Norhafiza et al. (2018)	Photoelectric	Paper
	Inductive	Plastic
	Capacitive	Metal

classify the recyclable item using sensor readings. The time response is defined as the time gap between inserting the material and falling into the respective compartment. Capacitive, inductive and photoelectric sensors are used to identify metal, plastic and paper, respectively. After experimentation, the authors report that the time response differs with the physical condition, colour and transparency of recyclable items which result in a slight delay for classification. Refer Table 1 for the list of sensors used.

In the real world, a variety of waste material is present and it is always not limited to the three broad categories that the above papers generalise on. The chance of misclassification is high when the moisture content of an organic waste is low and when differentiating between recyclable and non-recyclable waste. A downside towards the use of sensor-based system for waste classification is the reliance on only sensors, which increases the risk of errors due to degradation overtime, higher probability of misclassification, dependency on prefixed thresholds and increase in the maintenance cost.

Although existing publications majorly focus on classifying waste either as dry, wet or metallic using sensors, the economic value of waste is best realized only when it is segregated according to the SWM rules (2016). When waste is segregated as biodegradable, recyclable and other non-biodegradable at the source, the cost of secondary segregation units is reduced, less waste is dumped in landfills and more value is obtained by disposing these categories accordingly. This combined with a proper waste management system powered by IoT will substantially reduce the maintenance and transportation cost incurred for MSW management. To classify the wide range of waste items available accurately while also overcoming the drawbacks of sensor-based systems, led to more research works on the use of deep learning algorithms for waste classification.

Waste classification using CNN

Detection or classification of waste from an image is not an easy task for a processor to perform due to the complexity involved. The algorithm must focus on the object and distinguish it from other classes using the features extracted. It is a simple visual task for humans, but the processor sees only a three-dimensional matrix of pixels (0–255). Thus, a handcrafted, simple rule-based model would not be effective in this case. There are too many probable variations to hard code. This is where deep learning and specifically convolutional neural networks (CNNs) come into use.

Deep learning has become the most widely used computational approach in the field of machine learning as it successfully addresses a wide range of applications and achieves remarkable results on several complex cognitive tasks (Alzubaidi et al., 2021). It requires large-labelled datasets to train and predict unseen data. In recent years, CNNs are used for various image classification tasks, and have shown to be effective when compared to traditional methods (Wang et al., 2019). Simple neural networks like multilayer perceptron are not preferred for images classification tasks because it converts the two-dimensional image array of pixels into one-dimensional vector and this results in loss of spatial relationships between pixels. CNN appeared as the most suitable algorithm as it learns the spatial relationship between pixels. The following subsections will focus more on the use of CNN architectures and transfer learning approach for image-based waste classification.

CNN architecture

MNIST is a large database that consists of images of handwritten digits and it is widely used for image processing tasks. The CNN architecture used for digits classification on the MNIST dataset is shown in Figure 2. A CNN contains two parts: the convolutional layers in the front and the fully connected (a.k.a. Dense) layers in the back.

The significance of each layer is briefly outlined below:

Input. During training, the input to the CNN network are images. These images must be of the same size, and a smaller dimension is preferred to reduce the complexity and training time. Square images as input are preferred and the number of channels depends on whether it is Greyscale or RGB.

Convolutional layers. This layer is the backbone of CNN architecture as it performs feature extraction from the images through convolutional operation. It essentially comprises of a matrix of weights (kernel/filter) that is convolved with the input, after which a bias is added. The resultant output matrix is termed as feature map as it represents the features extracted. In a single convolutional layer, multiple such filters can be applied on the single image and the output from each filter is stacked. The filter

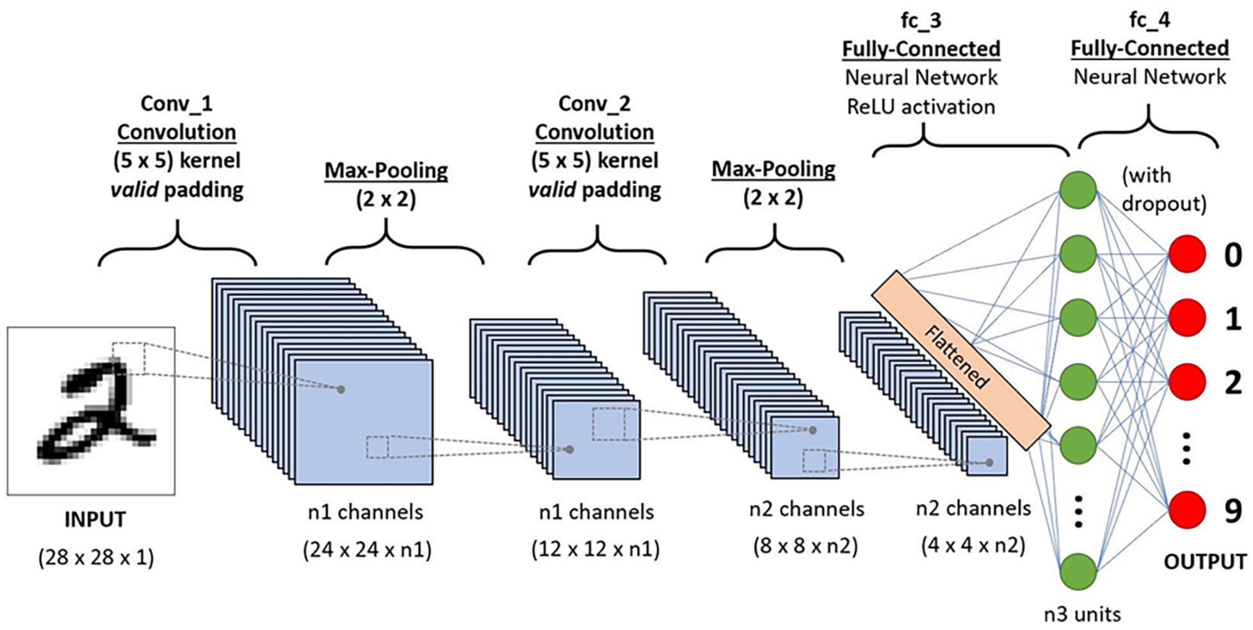

Figure 2. Example of CNN architecture (Kundathil, 2020).
CNN: convolutional neural network.

and bias are trainable parameters; hence their values keep updating so that the network's output is close to the actual. The output dimension of a convolution layer will be:

$$[m,m,c]\times[f,f,n_f]=\left[\frac{m+2p-f}{s}+1,\frac{m+2p-f}{s}+1,n_f\right]$$

m: input size, f: filter size, s: stride, p: padding, nf: number of filters.

Pooling layers. These are majorly used to down-sample the output from a convolutional layer (feature maps). The feature map will contain information about which parts of the image is focused more on and these pooling layers discard the unnecessary things and extract only the useful information. These feature maps are sensitive regarding the location of objects, hence pooling layers aid in achieving translational invariance and reduce overfitting by generalizing features. Three most commonly used pooling layers are: Max, Min and Average. An example of max pooling with stride 2 is shown below:

$$\begin{bmatrix}2&1&3&4\\7&3&3&8\\8&9&2&1\\1&1&5&6\end{bmatrix}\rightarrow \text{Max pooling } (2\times 2 \text{ filter})\rightarrow\begin{bmatrix}7&8\\9&6\end{bmatrix}$$

The output dimension of a pooling layer will be of the form:

$$n_{\text{out}}=\left[\frac{n_{\text{in}}+2p-f}{s}\right]+1$$

Where, f (filter size), p (padding), s (stride) and n (input size) are the parameters. Padding is an operation of extending input dimension by adding zeros so that all pixel values are concentrated.

Fully connected layers. As shown in the architecture above, the input to the fully connected layers at the end is the output from the flatten layer. This layer consists of a set of neurons that have two parameters: weights and biases. The weights are multiplied to the input to the layer (matrix multiplication), and the biases are added to them. After this linear operation, activation functions are applied. These layers determine the relationship between the position of features in the image and its corresponding class. The output layer will then give the final output; in the case of Softmax activation the probabilistic distribution of each class is returned.

Activation functions. Activation functions are mathematical functions that introduce nonlinearity to the network, enabling it to learn complex mappings between its input and the output by limiting the output range. Rectified linear unit (ReLU) is a piecewise linear function that is widely adopted in recent times as it makes the model easier to train. If the input is a negative value, output from ReLU will be zero. Softmax is another activation function that is employed in the output layer of a network. The output will be the probabilistic distribution of each neuron in the final layer.

In CNN as we go deeper into the network, the layers focus on more sophisticated parts of the image. The initial layers may start with detecting edge features, and it gets deeper, the layers extract groups of pixels to entire objects. The CNN architecture, which consists of millions of trainable parameters, have their values constantly updated during training. This happens through the process known as back-propagation. Based on the loss associated during training, the optimizer which focuses on minimizing it, updates trainable parameters such as filter weights, weights of neurons and associated biases. As a result of this process, the algorithm learns to predict each class accurately and certain layers are added to the network to prevent it from overfitting the training dataset. Thus, improving the training method or optimizing the network enhances the image classification result.

Transfer learning for CNN

Deep neural networks with large amount of data takes a lot of calculation and time to train the model and optimize the parameters. Through transfer learning, a previously well-trained model can be used to perform a task, by making small modifications to the architecture and achieve good results even with a smaller dataset. Thus, the convolutional layers operate on the images as usual, while the extracted features are handled by other fully connected layers, depending on the objective. Hussain et al. (2019) intend to analyse the performance of Inception-v3 network for transfer learning. Inception is one of the most accurate CNN architectures developed by Google for image classification, trained on the ImageNet dataset. It is evaluated by testing and comparing existing networks on two distinct datasets. It was inferred that the accuracy improves as the number of epochs and training images increase, and that image quality is also important.

When it comes to training a CNN model using transfer learning approach, there are numerous networks available to experiment on. The Keras framework provides a variety of applications, wherein the pre-trained weights can be accessed by instantiating it. The underlying principle of the most commonly used transfer learning architectures is explained in brief below.

- *VGG*: VGG is a simple architecture, which came into existence as a solution to the problems faced by AlexNet architecture. It was proposed based on the principle of 'deeper the better', has more layers than AlexNet and utilizes smaller convolutional filters. VGG16 is a 16-layer (13 convolutional and 3 fully connected layers) VGG network. It uses 3×3 filters with better depth in its convolutional layers and it leads to an effective receptive field rather than using larger filters. The depth of the network, that is, the number of filters increases as the image size reduces. The blocks of convolutional layers followed by a ReLU activation causes nonlinear succession of layers, thereby leading to better discrimination.
- *MobileNet*: In order to deploy deep learning algorithms on edge devices with low computational power, a lightweight network named as MobileNet was introduced. MobileNetv2 is an advancement of the initial MobileNet architecture, which further reduced the number of parameters.
- *Residual Network (ResNet)*: It was identified that going deeper into the layers resulted in decrease in generalizability of a model and the gradient reaches a very low value, thereby resulting in no improvement in training. The ResNet network attempts to solve the problem of vanishing gradients and comes under the category of architectural engineering of layers, as it modifies the internal structure of it. The underlying principle of ResNet is the presence of skip connections and original input is added to the output of convolutional block.

Table 2. Confusion matrix for binary classification.

***P*↓*A*→**	**CLASS 0**	Class 1
Class 0	TP	FP
Class 1	FN	TN

True Positive (TP): Number of predictions (*P*) and actual (*A*) values of Class 0 that match.
True Negative (TN): Number of predictions and actual values of Class 1 that match.
False Positive (FP): Number of images predicted as Class 0 but belongs to Class 1.
False Negative (FN): Number of images predicted as Class 1 but belongs to Class 0.

- *DenseNet*: This network attempts to solve a problem in ResNet, that is, summation leads to impeding the information flow. The layers are directly connected to each other by concatenation which results in the reuse of features thereby reducing the parameters. Now each layer will have access of gradients of others and this will solve the problem of vanishing gradients.
- *Inception*: The inception network uses different convolutional filters and pooling layers, and the bottleneck layer shrinks the representation. The auxiliary classifier (Softmax output from hidden layers) present has a regularizing effect and can tackle vanishing gradients. Inceptionv3 network focuses on breaking larger filters to smaller ones to reduce the parameters. For example, 5×5 filter is split into two 3×3 filters which is further split into 1×3 and 3×1 (asymmetric convolution).

Performance evaluation using confusion matrix

Confusion matrix is a two-dimensional representation of actual and predicted values of each class in a dataset. It is widely used to assess the performance of a classification algorithm as it summarizes the correct and in-correction predictions of an algorithm. Table 2 is an example of confusion matrix of a binary classification problem.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

Accuracy reports how many predictions are correct out of the total. The percentage of correct predictions on data allocated for the training phase of an algorithm is known as training accuracy. The accuracy achieved on dataset that the model has not encountered during training is known as test accuracy.

Dataset for waste classification

For waste classification using deep learning algorithms such as CNN, the dataset used is predominantly the most important aspect to focus on before model building. The dataset varies depending on the classification objective, and model performance is influenced by the architecture used, number of classes, type and count of images in each class. The performance of classification models varies with dataset, and there is a lack of large

Table 3. TrashNet dataset by Gary Thung and Mindy Yang.

Class	Types of waste	Count of images
Cardboard	Carton box Food packaging box	403
Glass	Tumblers Glass jars Beer bottles Wine bottles	501
Metal	Foil Juice tins Food cans/tins	410
Paper	Newspapers Magazines Letters Pamphlets	594
Plastic	Box and containers Bottles	482
Trash	Wrappers Toothpaste Plastic covers Used cups	137

dataset for training a waste classifier. Despite the lack of a big dataset for classifying trash, particularly into groups according to SWM rules, research on the TrashNet dataset has progressed. The TrashNet dataset (Thung et al., 2016) was created by Gary Thung and Mindy Yang for recyclable waste classification using CNN. It comprises of six classes and 2527 images in total as shown in Table 3, all captured on a white background as shown in Figure 3. This dataset can be expanded by adding a new class or increasing the number of images in each category. The works published on the TrashNet dataset for waste classification using CNN are described in detail in the next subsection.

Classification on TrashNet dataset

Hulyalkar et al. (2018) use only four classes of the TrashNet dataset (metal, glass, paper and plastic) for the CNN-based waste sorting model. The architecture used consists of three convolutional layers, each of which is followed by 2×2 max-pooling filter, and two fully-connected layers in the end. After 50 epochs, the model's accuracy was estimated to be around 84%. In order to reduce the prediction time, the authors (Bircanoğlu et al., 2018) propose RecycleNet, an optimized CNN model for recyclable material classification, by altering the dense block thereby reducing the parameters. Although the number of parameters reduced from seven million to three million, it was able to achieve a test accuracy of only 81% on the TrashNet dataset. The test accuracy was obtained from the randomly sampled 431 single-object images of the TrashNet dataset.

To deal with low classification accuracy and longer running time in the existing models for waste classification, a multilayer hybrid convolution neural network (MLH-CNN) is proposed that achieves an accuracy up to 92.6% when experimented on the TrashNet dataset (Shi et al., 2021). 20% of the images in TrashNet dataset was allocated by under-sampling for testing the performance of the proposed architecture. The architecture is similar to that of VGG Network, but less complex, as a smaller convolution kernel (3×3) with stride and maximum pool layer is used to reduce the network parameters. The input image is of dimension $64 \times 64 \times 3$. To further reduce the parameters and training time, SGDM+Nesterov is chosen as the optimizer. The authors report an improvement in the classification accuracy of MLH-CNN when compared with other architectures.

Aral et al. (2018) test the performance of deep learning architectures such as DenseNet, MobileNet, Xception and InceptionResnetV2 on the TrashNet dataset, for waste classification using transfer learning approach. The networks were trained over a large number of epochs after data augmentation, with Adam as the base optimizer. The test accuracy for each architecture with and without fine tuning was reported, and the DenseNet fared significantly better than the others, with an accuracy of 95% obtained on the test set (17% of TrashNet dataset).

ResNet has emerged to be a better transfer learning model in terms of performance when compared with its alternatives for waste classification. ResNet is a 34-layer CNN architecture that uses skip connections to solve vanishing gradients problem in deep networks. In the study of Adedeji and Wang (2019), the authors used ResNet-50 architecture for feature extraction on TrashNet dataset, after which support vector machine (SVM) algorithm classifies the type of waste. This architecture achieved an accuracy of 87% on the TrashNet dataset after training for 12 epochs. The Inception-ResNet architecture introduced by Szegedy increases the network while also avoiding vanishing gradients. To compare the performance of this model on the TrashNet dataset, Ruiz et al. (2019) experimented with several other CNN architectures such as VGG, Inception and ResNet. The performance of ResNet and Inception-ResNet architectures was almost similar, and a mean accuracy of 88.66% was achieved along with lower standard deviation. The mean accuracy was obtained after five runs on the test set.

A novel model DNN-TC, based on ResNeXt architecture is proposed in the study of Vo et al. (2019), wherein to the ResNeXt-101 network, two fully connected layers are added and log-softmax is used in the end to compute the confidence for each class. The performance of DNN-TC architecture on the TrashNet and VN-Trash dataset (organic, inorganic and medical) is compared with other CNN architectures such as Densenet121_Aral, RecycleNet, ResNet_Ruiz and ResNext-10 network. It achieves a test accuracy of 94% on the TrashNet dataset and 98% on the VN-Trash dataset. Class-wise prediction is also analysed through the confusion matrix. Refer Table 4 for performance comparison among different architectures on the TrashNet dataset.

Other recyclable waste classification algorithms

To improve the utilization of recyclable resources, a novel deep learning algorithm to classify recyclable garbage accurately is presented (Huiyu et al., 2019). The dataset consists of

Figure 3. Sample images from each class of TrashNet dataset.

Table 4. Performance of various CNN architectures on TrashNet dataset.

Reference	Classes used from TrashNet	Architecture	Accuracy reported (%)
Hulyalkar et al. (2018)	Metal, glass, paper, plastic	3 convolutional layers with max-pooling, 2 fully connected layers	84
Bircanoğlu et al. (2018)	All classes	RecycleNet	81
Shi et al. (2021)	All classes	MLH-CNN	92.6
Aral et al. (2018)	All classes	MobileNet	84
		Xception	82
		Inceptionv4	94
		DenseNet	95
Adedeji and Wang (2019)	Metal, glass, paper, plastic	ResNet50 + SVM	87
Ruiz et al. (2019)	All classes	VGG-19	79.3
		Inception	87.71
		ResNet	88.66
Vo et al. (2019)	All classes	Densenet121_Aral	91
		ResNext-10	90
		RecycleNet	68
		ResNet_Ruiz	72
		DNN-TC	94

CNN: convolutional neural network; MLH-CNN: multilayer hybrid convolution neural network; SVM: support vector machine.

600 images of recyclable objects such as paper, plastic, glass, metal and others, out of which 120 images were allocated for test set. The recognition rate (83.87%), which is inversely proportional to the loss rate, was used to assess the model's performance. Not experimenting with better CNN architectures and the lack of sufficient training data are the evident drawbacks. Similarly, in the study of Huh et al. (2021), the incoming trash is classified into one of following categories of recyclable waste: paper, glass, plastic, vinyl and can. The process begins with the capture of an image of the trash and then label recognition; if the label is not recognized, it is fed into spectroscopic and image classification algorithms for identifying the class it belongs to. This system focusses on the separation of recyclable and non-recyclable trash, but a disadvantage is that, it creates a need for label in each item as otherwise classification time is increased.

During the training phase of image processing algorithm such as CNN, the features extracted for images of metal and non-metal such as plastic may not be distinct in a few cases as both categories resemble the same in images. To tackle this problem, Gondal et al. (2021) use multilayer perceptron to classify the waste into metal or non-metal and CNN identifies the class of the non-metal waste (food, paper, plastic and general waste). The model is trained using 1241 images, tested with 349 images and are analysed based on various classification metrics. A visible drawback of this approach includes the usage of very few training-sample for a multi-class classification thereby reducing the flexibility

Sheng et al. (2020) intend to propose a better waste management system based on IoT and AI, as a replacement for the traditional methods. The image of incoming waste is captured and classified into one of the categories (metal, plastic, paper and general) by the Tensorflow based pre-trained SSDMobilnetV2 architecture deployed in the Raspberry Pi 3. The model's performance is analysed with respect to the mean average precision (86.23%) and error during training is evaluated to prevent overfitting. The authors suggest increasing the number of images and waste categories in order for improving the flexibility of the system.

The performance of classification models varies with dataset and there is a lack of large dataset for training a waste classifier. In the study of Guang-Li et al. (2020), a combination model based on three pre-trained CNN architectures, VGG19, DenseNet169 and NASNetLarge as the candidate classifiers, is proposed. The optimal prediction from these three classifiers is chosen as the final result. This architecture's performance is then tested using two different datasets and the classification accuracy is reportedly increased by 6–10% when compared with existing solutions. A major drawback of this model is the significant delay in waste classification result when implemented in real-time systems such as Raspberry Pi.

Apart from CNN, machine learning algorithms such as SVM classifiers can also be used for image processing tasks and the classifier is built after dimensionality reduction of the features extracted by transforming images. In the study of Sakr et al. (2016), the authors use CNN and SVM algorithms for classifying waste as plastic, paper or metal (2000 images in total). The images for the dataset were captured by placing the trash items on a chamber with lights and 20% of the images were allocated for the test set. Although the test accuracy obtained using SVM (94.8%) is higher than that of AlexNet (83%), CNN will be favoured as it reduces the overfitting observed in SVM. The average classification time was estimated to be 0.1 second with a standard deviation of 0.005 second.

Classification of plastics

After biodegradable waste, plastics makes up a substantial amount of the waste thrown in landfills, and it is critical to recycle it properly because it can be toxic when burned or dumped. Distinguishing plastic from non-plastic product is an easy task for humans, but it is not the case for image processing algorithms as it solely depends on the training data. Sreelakshmi et al. (2019) propose Capsule-Net, a novel CNN network for plastic or non-plastic classification that consists of nested neural layers. Capsule-Net outperformed standard CNN architectures for binary classification, with an accuracy of 96.3% on the first dataset and 95.7% on the second dataset of same type but distinct origin. The drop of information in pooling layers is reduced thereby making them efficient even for smaller training data.

Not all plastics have the same chemical composition, therefore the recycling mechanism and its output value differs for each type of plastic. In the study of Bobulski and Kubanek (2019), a CNN model is proposed to sort plastic trash into four categories: polyethylene terephthalate, high-density polyethylene, polypropylene (PP) and polystyrene. A 15-layer and a 23-layer CNN network, which differed in terms of convolution filter size and number, was trained using the WaDaBa dataset (images of plastic waste). The 15-layer network with a small input resolution achieved a better accuracy in a shorter training time when compared to the rest.

Classification of e-waste

According to the Central Pollution Control Board Report of 2020, although India being one of the biggest e-waste contributors in the world, only a small proportion was collected through the organized chain, meaning that most of the e-waste management process is handled by the informal sector like in many other countries. The trash bins mostly contain smaller e-waste products like earphones, cables, whereas larger products such as laptops and television are disposed through the informal sector. To tap into this market, a deep learning-based e-waste collection system is proposed (Nowakowski and Pamuła, 2020). Prior to the physical collection, the type and dimension of the equipment is identified to allocate collection vehicles and plan routes efficiently. The network was trained using 180 images of washing machine, refrigerator and television, and the test accuracy of the CNN model after experimenting with various filter size was 96.7%. A faster region-based CNN model was also implemented as it can identify both, the class and size of the object, but the test accuracy was lower than the best CNN. The fundamental disadvantage of the network is the fewer training data samples.

Summary of classification using CNN

Through this section, it is evident that the flexibility of systems using CNN for waste segregation is higher than that of sensors, as it overcomes the shortcomings of sensor-based system. The following are some of the advantages of adopting image-based waste classification over sensors:

- Higher accuracy and efficiency
- Lower classification time
- Completely dependent on training data and not prefixed thresholds

- Can cover a wide range of waste items
- Can differentiate between recyclable and non-recyclable waste accurately

A major disadvantage of using CNN is that, there is no specific rule to follow to reach the best model for a given dataset. Thus, it necessitates extensive experimentation by modifying various parameters of the network such as input size, batch size, filter size, number of filters, activation function, layers and optimizers. Although dataset samples are minimal, data augmentation is employed to increase the diversity of the images used.

Most of the literature revolved around the use of transfer learning approach for classification as the number of training samples in each dataset was limited, yet the performance was superior compared to standard CNN architectures. The choice of CNN architecture for transfer learning-based model varies with purpose, but the most sought-after networks are MobileNet, Inceptionv3, ResNet, VGG and DenseNet. Apart from accuracy, reduced classification time, prevention of overfitting using regularization and lower model size are key factors to be considered before real-time deployment of waste classification algorithms. It is also important to note that the training data can be modified for CNN according to the use case, therefore it is possible to accurately segregate waste according to SWM rules of India.

Waste monitoring

The rising population has a direct impact on the level of trash generated and the lack of proper infrastructure to monitor and manage it leads to several complications affecting the day to day lives of the citizens. The current waste management or monitoring systems may not be flawed but can definitely be improved. Given the technology advancements, the ways to monitor, collect and dispose of garbage can be made more efficient. A thorough review of existing IoT systems focused on waste monitoring and alerting is presented in this section along with drawbacks of one over the other.

Sensors

Sensors play a vital role in an IoT infrastructure as it is considered to be the source of all data generated. Various sensors have proven to be useful in determining the status of the bin and also to keep a check on the environment around the bin. Overflowing or unattended bins lead to bad smell and release of toxic gases causing inconvenience to the people living in the area. MQ2 and MQ3 sensors help detect the presence of toxic gases and foul smell and hence can help monitor the bin's condition at all times (Manjunath et al., 2019). An IR sensor has the capacity to measure distance and proximity and is one of the preferred sensors to detect the level of trash in the bin (Manjunath et al., 2019, Satyamanikanta et al., 2017). It contains an IR LED that emits radiation which when falls on an object gets reflected back. The change in resistance of the photo-electric diode (IR receiver) with respect to the portion of IR light received when put in the equation can help detect the distance between the sensor and the object. A smart bin proposed in (Sreejith et al., 2018) monitors the level of the waste and automatically moves to the garbage collecting area, to dispose of the waste. The controller is connected to the IR sensor, gas sensor and rain sensor. The IR sensor will close the top door of the bin once the threshold is reached. The bin is then moved to the collection area with the help of a two-axis robot.

IR sensors can also be placed at different heights to keep track of the fill status of the bin. The authors in (Navghane et al., 2016) propose a simple model consisting of three IR sensors placed at three levels to indicate the level of garbage in the bin. The first IR sensor when triggered indicates less than 50% fill of the bin, the second IR sensor indicates 50% fill level and the third would indicate the bin to be full and hence trigger a notification through the microcontroller to a mobile web browser using Wireless Fidelity (Wi-Fi). A similar system was defined in (Abhimanyu et al., 2016) where four IR obstacle line sensors were used to gather real time data from waste bins. Although IR sensors seem just fine when used to monitor the level of trash in the bin, Ultrasonic sensors take the upper hand as they have a longer range and are not affected by external factors (Mdukaza et al., 2018).

IR sensors are best used to detect the presence of the object and ultrasonic sensors are used to accurately predict the distance to the object. Unlike IR sensors, ultrasonic sensors are not affected by external light conditions as they use sound waves to detect the distance to the object (Burnett, 2017). The authors of (Kumari et al., 2018) describe the bin monitoring system as a three-layer architecture where the data gathering layer contains the HY-SRC05 sensor to measure the level of trash in the bin. Ultrasonic sensors can either be used to trigger an alarm when the bin is completely full or can help detect the level of trash at different heights of the bin: test case 1: bin is empty; test case 2: 50% of bin is full; test case 3: the bin is 90% full; test case 4: the bin is completely full and test case 5: the bin is overflowing (Yerraboina et al., 2018). While monitoring the level of trash in the bins is one way to make sure they are cleaned in time, there are situations when the bin may not be completely full and hence left unattended. In such cases there is a chance of bad odour and release of toxic gases from the waste which can cause a lot of inconvenience. Hence a system to notify the authorities about bins that may not be full but have been storing garbage for up to 3 days was proposed in (Susila et al., 2018).

Microcontrollers

Although sensors play an important role in the data gathering process, microcontrollers help process the data and take necessary actions based on the data gathered. This section introduces some of the most used microcontrollers in a waste monitoring system. ArduinoUNO is one of the easiest to use microcontrollers that when coupled with an ESP8266 module can send data to cloud services for further visualization (Sandeep et al., 2017). Raspberry Pi on the other hand is a minicomputer with inbuilt

Wi-Fi capabilities which makes it more ideal to use in an IoT network. PIC controller is a cost efficient, easy to use microcontroller that has an EEPROM chip to retain information. It can be used as the main component that collects data from the ultrasonic sensor about the level of trash in the bin and sends it to a web browser for visualization with the help of an ESP8266 module (Karthik et al., 2021).

NodeMCU is a controller known for its high performance, low power consumption that has predefined libraries which help program the microcontroller easily. An ultrasonic sensor when connected to it can detect the level of trash in the bin and if it is found to be greater than 90%, the NodeMCU model is programmed to send the data to a web GUI for display using its inbuilt Wi-Fi capabilities (Zavare et al., 2017). Intel Galileo and Intel Galileo Gen 2 boards are the first initiative by Intel which are compatible with Arduino headers and reference APIs. These boards are open source and hardware which means that the hardware schematics and source codes are available online free to download and modify. A system that employs Intel Galileo Gen 2 Microcontroller was defined in (Parkash and Prabu, 2016). A transmitter section that contains an ultrasonic sensor to detect the level of trash in a bin is connected to an 8051 microcontroller that gets the sensor data, processes it and sends it to the central server using an RF transmitter. The receiver section contains a RF receiver to get the information of the bins and feed it to the Intel Galileo Gen 2 Microcontroller that runs the web browser to display the information. The web browser contains information like the level of trash and status of each bin along with the bin Id.

Communication protocols

IoT is the interconnection of devices where smart devices communicate with each other to share data and perform tasks without human intervention. For devices to share information, some protocols are used to enhance the security and efficiency of data transmission. Protocols such as Bluetooth, Wi-Fi, Z-Wave, Zigbee, RFID, Cellular and Ethernet are known as communication protocols. They are used to connect IoT devices and establish communication between them (Types of Communications in IoT, 2021).

Wireless Fidelity

Wi-Fi or Wireless Fidelity belongs to the IEEE 802.11 communications standard and is commonly used in homes and offices spaces to connect devices to the internet. The Wireless router sends a radio signal to a device which then converts it into readable data (Brain and Homer, 2021). ArduinoUNO as discussed before is an easy-to-use microcontroller but it lacks internet capabilities that can help transmit data from the sensor end to a cloud service. An ESP8266 Wi-Fi module is commonly used with an Arduino controller to enable it with the internet. A similar setup was discussed in the study of Sandeep et al. (2017) wherein an Arduino with the help of an ESP8266 module sends data to a web server that displays the status of the bins in a graphical view with colours indicating the fill level of the bin.

ATMega16 Microcontroller is a 40 pin, 8-bit microcontroller that like the Arduino lacks inbuilt Wi-Fi capabilities and hence makes use of an ESP8266 module to connect to the internet and transmit data (Nathrani et al., 2018). Tabassum et al. (2021) point out the drawback of using Wi-Fi when a NodeMCU model connected to an ESP8266 module was used to transmit sensor values to the IoT Server. Due to its low range, it was suggested to use a routing protocol for low power and lossy network. Vishnu et al. (2021) tackled the issue of low range of Wi-Fi by using a hybrid system to monitor both home-based bins and public trash cans. The system architecture consisted of two microcontroller-based sensor end nodes: Public Bin Level Monitoring Unit (PBLMU) and Home Bin Level Monitoring Unit (HBLMU) with ultrasonic sensors to measure the fill-level along with Global Positioning System (GPS) module to determine location of the bins and transmit the data to a central station for further analysis. The PBLMUs (for public places) were employed with LoRa for long range data transmission, whereas the HBLMUs (in home) used Wi-Fi module. An intelligent GUI was designed to monitor the trash bin status and the authors also estimate the life expectancy of the PBLMU to be 70 days when fully charged.

Zigbee

Zigbee is a high-level protocol standard that uses less power (which allows longer battery life) and ad hoc mesh network to provide long distance transmission. The most popular Zigbee Module manufactured by Digi International is called the XBee which can be configured using the X-CTU Software. This software allows for a digital representation of the formed network thus helping in monitoring and detection of any remote node/network failure (Ghate and Kurundkar, 2016).

Ghate and Kurundkar (2016) describe a system wherein each bin is fitted with an ultrasonic sensor and Zigbee module connected to an Arduino. The Zigbee on the bins send the sensor data to the receiver end Zigbee which further feeds it to the Arduino for processing. The GUI displays information such as the bin fill level, location of bin, bin ID and contact information of authorities. Zigbee technology is also known for its remote control and sensor applications under harsh isolated radio environments (Singhvi et al., 2019).

Global System for Mobile Communication

GSM or Global System for Mobile Communication developed by the European Telecommunications Standards Institute is a default standard for mobile communications providing 2G/3G/4G digital Cellular network for mobile phones.

A GSM module is a circuit used to establish communication between a mobile or computer and a GSM system. Many surveillance systems use microcontrollers, GPRS/GSM and cloud technology to monitor the overflow of the garbage and deliver the information to the concerned authorities (Kirti et al., 2020). The

Table 5. Comparison of communication protocols.

Characteristic	Wi-Fi	Zigbee	GSM	LoRa
Max end devices	Depends on number of IP addresses	More than 64,000	To the registered phone numbers	More than 5000
Peak current consumption	100 mA	30 mA	400–500 mA	17 mA
Range	100 m	10–100 m	3 km in city	More than 15 km
Data rate	54 Mbps	250 Mbps	64 kbps–120 Mbps	290 bps–50 kbps

LoRa: Long Range; GSM: Global System for Mobile Communication; Wi-Fi: Wireless Fidelity.

system in PP Singhvi et al. (2019) makes use of a GSM module connected to an Arduino to send real-time sensor data to the website and short message service (SMS) notifications when any irregular activity is recorded by the sensors. They also provide a facility for citizens to voice their complaints regarding any waste disposal or management-related issue through the webpage. A similar system was defined in (Malapur et al., 2017) wherein the data from the bin end is then sent to the server side using the GSM/GPRS. The level of garbage is indicated through dashed lines and a buzzer is activated when the garbage bin is full. The percentage of garbage level is sent through SMS using the GSM shield and the information is stored in a MySQL database.

A GSM modem is a dedicated device with a USB port or Bluetooth connection facility. The difference between the module and modem is that the former can be integrated within an equipment and the latter is an external equipment. The GSM modem has a SIM card slot and operates over the subscription to the mobile operator similar to a mobile phone. When the modem is connected to a computer through a USB cable, the computer can connect to the internet and communicate over the mobile network. This modem when connected to a microcontroller can help send the sensor values to a GUI developed using MATLAB or any cloud service (Morajkar et al., 2015). The authors also mention the advantage of using GSM over Zigbee Technology by stating that the latter has a shorter range and low data rate in comparison to the former. Putra et al. (2019) tested their smart garbage monitoring system using GSM modem under three network technologies: Edge Network, High Speed Packet Access (HSPA) and LTE. It was found that LTE showed the least amount of delay while sending message alerts to the app when compared to Edge and HSPA.

Long Range

Wi-Fi, Bluetooth and Cellular networks are some of the most used wireless communication networks but most of the time they are bound to be susceptible to noise, external interference, network lag and so on, which reduces the efficiency of data transfer. Some other drawbacks as mentioned by Mdukaza et al. (2018) are reduced sensing accuracy due to temperature changes, bandwidth lag in GSM, short range of Wi-Fi and unauthorized access in Zigbee technology.

As its name suggests, Long Range (LoRa) is widely known for its long-range communication (up to 10 km) while consuming the least power among most of the other communication protocols (Sheng et al., 2020). It has the capability to handle millions of messages per station and hence is considered ideal for a public network setup.

Sheng et al. (2020) employ LoRa communication protocol for LoRa data transmission of the real-time location and fill level of the bin using GPS and ultrasonic sensor, respectively, to the Wasp mote gateway. This protocol is preferred over the others for its low power consumption and higher transmission range. In a similar system, the fill level of the bin, presence of harmful gases and weight of the bin are all measured using IR sensors, gas sensor and load cell, respectively. This data is then transferred to the gateway using LoRa communication protocol, which is considered secure for long distance transmission (Bharadwaj et al., 2016). The energy efficient waste management system proposed by Cerchecci et al. (2018) makes use of a single-chip microcontroller, an ultrasonic sensor to measure the fill levels and LoRa Low Power Wide Area Network technology. The work focuses on power optimization and network architecture. It allows wide area transmission in urban-areas by using single or few access points and also makes use of star topology. Table 5 shows a summary of all communication protocols discussed.

Route optimization

Waste monitoring and data analysis help understand when and where bins need to be cleaned and maintained but this isn't enough for a system to be completely efficient. Along with data about which bin needs to be cleaned, if an optimized route to effectively collect trash from all bins was also available, it would help reduce time and fuel consumption to a great extent.

Even now, solid waste collection is done without analysing the demand and the routes for collection are left to the drivers (Beliën et al., 2012). With growing urbanization, we can only expect more and more waste to be generated in the coming years and hence an efficient route optimization system needs to be put in place that takes into account the cost, number of vehicles available, route length and so on. Beliën et al. (2012) specify collection of waste as a vehicle routing problem that takes into account the set of vehicles, number of stops and depots. They also mention the possibility of solving the optimal routing problem by applying different types of models like linear programming, hierarchical methods and so on.

Apart from the number of vehicles and stops, priority should also be given to the level of trash in each bin. A system developed by Khan et al. (2021) makes use of a mobile application that can track the truck movements and also provide an optimized route to efficiently collect trash from all the bins. The sensors attached to the bins help find the priority of one dustbin over the other which when synchronized with Google Map API can direct the collection trucks along the best route from a high priority location to a lower one. Another way of figuring out the ideal route is by the use of Dijkstra's Algorithm. The bin data from the IoT system collected over time can be really helpful for the development of smart cities as analytical insights can be gained from sensory data by forecasting a location's filling levels. A cost–benefit analysis was also conducted by Misra et al. (2018) by utilizing Dijkstra's algorithm to determine the ideal waste collection route.

Conclusion

The existing waste management system, which majorly focuses on collection and transport of mixed unsegregated waste is ineffective. This not only fills up the landfills, but also reduces the scope of recycling which has a higher output value. In order to reduce the amount of waste dumped in landfills and effectively utilise waste treatment centres established; the waste generated must be segregated at the source in accordance with the SWM rules. The importance of technology in this process cannot be overstated, as it can cut down the operation costs and boost resource profitability by adopting an effective management system. This paper reviewed the use of sensor-based system and image processing techniques to segregate incoming trash. The shortcomings of using sensors for segregation is the dependence on prefixed threshold, higher maintenance cost and scalability concerns. There is a lack of a large dataset for waste classification, hence most works reviewed uses transfer learning approach. The findings of CNN-based classification algorithms on the TrashNet dataset show that image processing is preferable than sensors for waste segregation since classification time is lowered without sacrificing accuracy, and the system can be scaled to cover a large range of waste categories.

After segregating the waste into its respective category, it is equally important to have a robust monitoring system powered by IoT. Waste bin monitoring systems are smart systems built on an IoT architecture that includes sensors to monitor the bin conditions, microcontrollers to process the data and finally a cloud platform to visualize the sensor data. Research based on the type of sensors used for bin monitoring suggests that ultrasonic sensors are preferred over IR sensors to monitor the level of trash in the bin for the sole reason that the latter is affected by external light and is better off when detecting the presence of an object rather than distance. Sensors like MQ2 and MQ3 are often used to identify the presence of toxic gases like ammonia that is released when garbage is left unattended for several days. Microcontrollers like ArduinoUNO, Raspberry Pi seem to be the first choice when it comes to monitoring systems like these but controllers like PIC, NodeMCU, Intel Galileo Gen 2, 8051 are also being used to process bin data despite being less advanced. Comparisons drawn between communication protocols such as Wi-Fi, Zigbee, GSM and LoRa showed that GSM is a widely used network to connect to the web servers and also send alert notifications to the registered users via SMS. On the other hand, LoRa is widely known for its long-range communication (up to 10 km) while consuming the least power among most of the other communication protocols. The efficiency of waste collection in terms of time could be improved by optimizing the route taken by the truck drivers while considering factors like prioritizing bins based on level of waste, number of trucks and so on.

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