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ORIGINAL ARTICLE

Waste management in urban localities: an IoT and machine learning solution

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Abstract In recent history a lot of importance has been given to the management of waste as the amount of waste generated has seen a drastic increase. Proper segregation of waste for proper disposal has been hard to monitor due to the lack of the right infrastructure and human error. This research aims at providing a solution for waste management, specifically in urban localities where the most amount of waste is generated. In this research, design and implement an efficient 'smart waste management system' is carried out and in doing so it used various technologies like machine learning for classification of waste during collection, Internet of Things (IoT) for monitoring the bin, and making the process of disposal of this waste collected systematic and structured, and cloud to store the various types of data collected. This research has integrated these technologies successfully through our 'Smart Bin' model and has obtained promising results. The prototype obtained with this research, can be implemented in regions like malls, supermarkets, shopping complexes, and other urban settings similar to these, where there is a lot of foot traffic which is directly proportional to the amount of waste generated. The designed prototype running with machine learning is exactly classifying the waste materials and placing them in the designated bins. The results of this model shown in result section along with 3D models. With the implementation of emerging technologies in this research made this prototype more efficient and reliable.

Keywords Deep Learning · Machine Learning · IoT · Cloud · CNN · Raspberry Pi

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1 Introduction

Waste management has been a major problem across the world, especially in India. Due to India's large population and high density of population per square kilometer, there is a lot of waste that is generated by the country. In 30 years, our overall waste generation has doubled. The rate at which waste generation is increasing doesn't seem to reduce anytime in the years to come. With this amount of waste being generated it has become hard for us to tackle the problem of waste segregation. A lot of non-biodegradable waste makes its way to landfills and has adverse effects on the environment as these substances aren't decomposed by nature leading to them affecting the land and marine life around them.

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Non-biodegradable waste isn't just affecting the environment but also the quality of life of people. In Deonar dumping grounds as the trucks come to dump waste a lot of ragpickers, typically from the age group 14–18 line up to pick the non-biodegradable wastes like plastic, cardboard, etc. This is exposing them to high levels of toxicity. The Indian government and the different local governments have taken the initiative to deal with this problem of waste management but there is a long way to go for us to educate our population regarding this and make sure the waste is disposed of properly.

Traditional methods, which are characterized by ineffective resource allocation and rigid collection schedules, frequently lead to overflowing bins, higher operating expenses, and environmental risks. Innovative approaches that make use of cutting-edge technologies for effective decision-making, predictive analytics, and real-time monitoring are needed to address these problems (Olawade, et al. 2024). Such a typical waste management system is as shown in Fig. 1. One revolutionary strategy to alter urban trash management systems is the combination of machine learning and the Internet of Things (IoT). IoT makes it possible to install smart sensors and gadgets for data gathering in real time, bin waste level monitoring, and waste generator-collector connection. This data is processed concurrently by machine learning algorithms to forecast garbage creation trends, optimize collection routes, and boost recycling effectiveness. This collaboration promotes the creation of sustainable urban settings, improves resource usage, and lowers greenhouse gas emissions (Ikram, et al. 2023; Venigandla et al. 2024).

To build such efficient and intelligent system supposed to focus on creating a framework powered by data that integrates predictive analytics, efficient collection logistics, and

Fig. 1 Basic flow of waste management system

real-time trash monitoring (Wang, et al. 2021). A centralized cloud platform, communication networks, and sensor-enabled smart bins make up the IoT-based architecture used in the recommended system are briefed as follows. *Smart Bins*: Featuring ultrasonic sensors to gauge garbage concentrations and identify bin occupancy. *Communication Networks*: Effective data transfer from bins to a central hub is achieved by using low-power edge devices which has Wi-Fi features. *For data collection and preprocessing*: Waste levels, timestamps, and geolocation are among the real-time data obtained by smart bins. To guarantee consistent analytics, data preparation entails addressing missing values, standardizing sensor inputs, and filtering out noise. *Trash Classification*: Recycling facilities utilize deep learning models, such as Convolutional Neural Networks (CNNs), for image-based trash sorting. Evaluation metrics including trash collection efficiency, cost savings, route optimization accuracy, and environmental effect (e.g., decrease in carbon emissions) are used to assess the system's success. *Integration of technology and its challenges*: The approach tackles issues including sensor accuracy, data interoperability, and communication network scalability. IoT network dependability is ensured by security measures including data encryption and safe communication protocols (Wu, et al. , 2023; Yang et al. 2021).

The proposed approach overcomes several shortcomings in the current waste management systems by making use of cutting-edge technology like cloud computing, deep learning, and the internet of things. The following information demonstrates how this strategy outperforms conventional techniques. *(i).Improved categorization of trash using convolution neural networks (CNN)*: The sensor-based systems utilized in the current methodologies have poor precision when it comes to differentiating between dry, moist, and plastic waste kinds. The suggested approach uses CNN to improve categorization, achieving high levels of picture recognition accuracy. This will make recycling more effective. *(ii). Real-time trash level monitoring:* Current garbage collection techniques frequently adhere to set timetables, which leads to inefficiencies like overflowing bins or needless journeys to underfilled bins. The suggested method uses a cloud platform (ThingSpeak) to update the garbage amounts in bins in real time. This guarantees prompt collection, prevents overflows, and lowers operating expenses. *(iii). Automated alerts using the If This Then That (IFTTT) protocol:* Currently, waste management authorities and collection teams usually communicate by manual reporting, which causes reaction delays and inadequate coordination. However, the suggested solution, which uses the IFTTT protocol, automatically sends out email warnings when the bins are full. This facilitates communication and enables prompt action. *(iv). Using the cloud to visualize waste status:* Data-driven decision-making is challenging in current systems. Better planning, transparency, and accountability are ensured by the cloud platform's real-time dashboard that shows bin status, including fill levels, in the proposed work. *(v). Better operational and environmental results:* Ineffective garbage collection with current techniques raises carbon emissions by causing needless trips and delaying the resolution of overflow. The suggested solution reduces greenhouse gas emissions and fuel consumption, which helps to create a cleaner urban environment. It also optimizes collection schedules that are prompted by real-time monitoring.

The main goal of the proposed work is to build a framework for smart waste management where machine learning, IoT, and Cloud are seamlessly integrated with one another. The following are the main objectives of the proposed work.

i). *Creating a Convolutional Neural Network Model for Classification of waste into three classes, PET plastics, metals and other recyclables.* The first step in order to create an efficient convolutional neural network model is to have a good dataset i.e., good number of images of all types of waste that we plan to categorize in all aspects, shape, size, color etc.

Next step is the creation of a machine learning model which can classify the waste given into one of three types, namely PET plastics, other recyclables and metals. It is aimed to make use of convolutional neural network model and achieve an accuracy as high as possible.

Creating a machine learning model involves a proper understanding of training and the classification process. A convolutional neural network model is a machine learning model which is capable of classifying images with the help of a process known as feature extraction. Many Image classification models were created based on the convolutional neural network model architecture and are capable of classifying images with great accuracy. These image classification models use many functions and features to classify the images. It is aimed on integrating the functions of these models for the creation of own convolutional neural network model. One model which we will draw features from is the Xception model.

To monitor and actuate the Smart bin, the model will be equipped with sensors which are interfaced to the Raspberry Pi 3 A + board.

ii). *Designing an efficient model of "Smart Bin" for seamless integration of the Classification and the Monitoring system.* The final objective is to create a Smart Bin infrastructure which can showcase the above objectives is the best way possible. This bin must have the classification model i.e., the machine learning trained model loaded on to a processor present on the smart bin, which is also capable of connecting to a network enabling it to connect to cloud platform. Overall, the classification model and monitoring system must work in collaboration in order to ensure smooth working of the model, also keeping in mind the amount of memory and RAM available for the program.

2 Literature survey

In implementing new techniques in waste management, to ensure a more efficient, safer, and eco- friendly way of segregation and logistics in this work, we have reviewed papers that deal with the concepts of waste management, consisting of different methods.

In the paper, Efficient IoT Based Smart Bin for Clean Environment (Murugaanandam et al. 2018), we see that the method followed here recognizes the fullness of a bin, which reports readings and updates the status of the bin to the nearest corporation office and these factors can be monitored through the internet. The paper also specifies the use of ultrasonic sensors to detect the level of the bin, with features like locking the bin door during the rainy period.

In continuation to the above paper, another paper, Waste Management System for Bangladesh (Failed 2021), shows us an infrastructural setup, where the bins are equipped with a GSM module that gets connected to the main center and provides information about the status of the bin asking the garbage trucks to clear them, which in turn reduces the time taken for collection of waste once the bin is full.

In the paper, Material Classification of Recyclable Waste using the Weight and Size of waste (Rahmad et al. 2018), we see a different type of approach to segregation of waste through ultrasonic sensors and load cells, here dry waste is classified into different sections of recyclables in categories paper, glass, plastic, and metal. The concept of this paper revolves around categorizing recyclable waste.

While talking about segregation and categorizing of waste, the paper, Automatic Waste Segregation (Gupta et al. 2018), This paper talks about the method they have used to implement segregation using capacitive sensors, and parallel resonance impedance systems. Here they have used conveyor belts and a segregator bin which has various sensors for detecting the type of waste.

In the paper, A Deep Learning Model for Odour Classification Using Deep Neural Network (Failed 2019), here the paper talks about different ways of classifying odor and determining the cause or the source.

In the publication, "An IoT-Based Architecture for Waste Management" (Aleyadeh and Taha 2018), we come across two ideologies in this publication, one being how the smart bin is monitors the waste level, content inside the waste bin as well as the bin's environment. The second is followed by scheduling and routing of waste collection vehicles based on the relayed information from the bins.

To better understand the application of IoT in smart bins we also reviewed, Smart garbage management system for a sustainable urban life: An IoT-based application (Minhaz Uddin Sohag 2020), proposed a system that aims at minimizing the issue of waste overflowing in community bins by notifying the staff assigned for collection using a mobile application, they will also monitor the day of the week and the period of time during the day (morning, afternoon, evening or night). We also come across a simple diagram for the structure and build of the smart bin.

"IoT Based Smart Bin for Smart City Application" (Mithinti et al. 2019), in this paper IoT is based on a smart bin for smart application here the bins are equipped with an ESP32 CAM Wi-Fi module and a sensor that senses the fullness of the bin and sends the status to the corporation office, this paper also talks about implementing the shortest path algorithm for collection of waste.

To study the cloud implementation in forming a network of smart bins we referred to "Cloud-Based Architecture for Solid Waste Garbage Monitoring and Processing" (Rashmi et al. 2019). This paper has a goal at providing a cloud-based solution to monitor and condemn solid waste odors in crowded cities. It uses AWS kinesis to understand the pollutants in solid waste, contributing to air pollution.

For the implementation of a reliable monitoring system, we reviewed the paper, Odour and Air Quality Detection and Mapping in a Dynamic Environment (Srinath et al. 2021). This is a model wherein a system is fitted to a moving vehicle, and it consists of a series of sensors that detect a foul smell, it puts up the level of toxicity and location using GPS on the map, and this data is sent to the local authorities in priority to clean up the contaminated area.

For the ML approach to waste segregation, we reviewed the "Classification of TrashNet Dataset Based on Deep Learning Models" (Aral et al. 2018). In this paper, the publisher uses Deep Learning to classify the TrashNet dataset. Well known datasets like Densenet121, DenseNet169, Inception v4, ResnetV2, MobileNet, Xception architectures were used. Inception V4 Model was found to have the best test accuracy among the others, with an accuracy of 89% among 500 test cases.

GIS or Geographical Information System could be used to a great extent in the field of waste segregation. "Remote Sensing in its Applications" (Qiong et al. 2006) Calls GIS a system which is able to make effective decisions by manipulating data to stimulate alternatives. "Solid Waste Management Planning using GIS and Remote Sensing Technologies Case study Aurangabad City Bangalore" (Landscape and Urban Planning, 2006) talks about how a geographical information system can be used as a major tool for effective planning waste management. Since each city in India (and World Wide) face unique problems with respect to waste management, the gains of using such tools cannot be understated. Waste management issues of the surveyed cities were considered to solve some of the present situation problems like proper allocation, relocation an maintenance of waste bins, identification of optimal waste bin placing.

Another Usable approach is to use a combination of Sensors to detect waste. In "Automatic Waste Segregator and Monitoring System" (Ahmed and Muhammad 2006), a sensor based waste segregator is designed which can sort the waste into three categories which are metallic, organic and plastic. The sensors named are an inductive proximity sensor, a capacitive proximity sensor and a moisture sensor. The inductive proximity sensor (an electromagnetic sensor) will be able to segregate metallic waste while the capacitive sensor (an electic field detecting sensor) can be used to identify plastics or other similar materials. This model uses the principal that organic wastes contain a fair amount of moisture to be detected by the moisture sensor.

Another Sensor based model is seen in Automatic Waste Segregation and Management (Narkhede et al. 2020). This model also segregates wastes into 3 categories: wet, metal and dry. Sensors are installed to classify the waste coming through the conveyor belt. A deflection mechanism is used in order to fill the waste in its respective bin.

Similar to the Machine Learning approach, Sensors can also be integrated with Robots in a effort for Waste Segregation. An Example of this is "Automatic Waste Segregator Bin using Robotic Arms" (Agarwal et al. 2020). This study aims to create system which uses Robotic arms and sensors together in an effort to make an optimal automatic segregating bin. The segregation of wastes are done using various sensor. The sensors used here are a moisture and metal sensors for segregation and an IR sensor for path detection. The system will then program the robotic arms to pick and place the waste into the correct bin, also uses the IR sensor to define the path taken to throw the waste into the bin. Once the waste has been appropriately segregated, the status of the bin will be updated with the help of an LCD display. This system can find great usage in urban localities with an immense amount of waste like malls, theatres and schools.

Looking at sensor-based waste classification methods, there are several papers that focus on this methodology. Waste segregation by the metal detection system and capacitive sensing module is a methodology used to segregate metal waste and wet waste, respectively. Here the metal detection system induces current to metallic objects when it is in close proximity. The capacitive sensing module measures the relative dielectric constant that is present in between the plates since wet waste has a higher dielectric constant due to the presence of wet content in the waste. This way segregation of wet and dry waste takes place (Gupta et al. 2018; Failed 2018).

One of the most common sensors used for the detection of waste itself is the IR sensor which is used to detect the level of the bins in many cases. Another way of segregating wet waste is using the moisture sensor at its highest sensitivity to detect the presence of moisture in the waste, the waste which is classified is then directed to the respective category, like using a rotating platform (Rajkamal et al. 2014).

3 Methodology

The methodology followed in this research is represented through the Swimlane diagram as shown in Fig. 2. Each of the steps involved in the methodology diagram are briefly elaborated to make it more insightful and give a better understanding of the working flow of our smart bin model. The following steps elucidate each transaction that takes places throughout the model to give us the desired functionality as an output:

Step 1 User approaches bin

The User approaches the bin with an object to throw. The object can be in three forms, them being metal, PET plastics and other recyclables. The waste the user wants to dispose of is placed in the bin individually.

Step 2 Segregator bin opens

When the user approaches the bin, an ultrasonic sensor will be used to detect the individual. The segregator bin will open using motors and the person will be able to drop the object into the bin.

Step 3 Clicking the image of waste for classification

Once the waste has been placed in the bin, the camera gets activated through a switch. We use the raspberry pi camera here, which will be mounted on top of the segregator bin. The segregator bin will be lit up using LED lights in order to obtain an accurate image with which the machine learning model can segregate the object.

Step 4 Image is sent to the Raspberry pi board

The image taken is then sent to the raspberry pi board for processing. The raspberry pi board will be mounted to the back of the segregator bin and will be powered with the help of batteries. This image will be stored on the board in.jpg format.

Step 5 Image is used for prediction

The raspberry pi board will also contain the saved machine learning model. The model will first be trained on a dataset and tested using images taken by the raspberry pi camera. After modifications are made to the model based on the results from the test, we can import the pre-trained model to the raspberry pi board. The

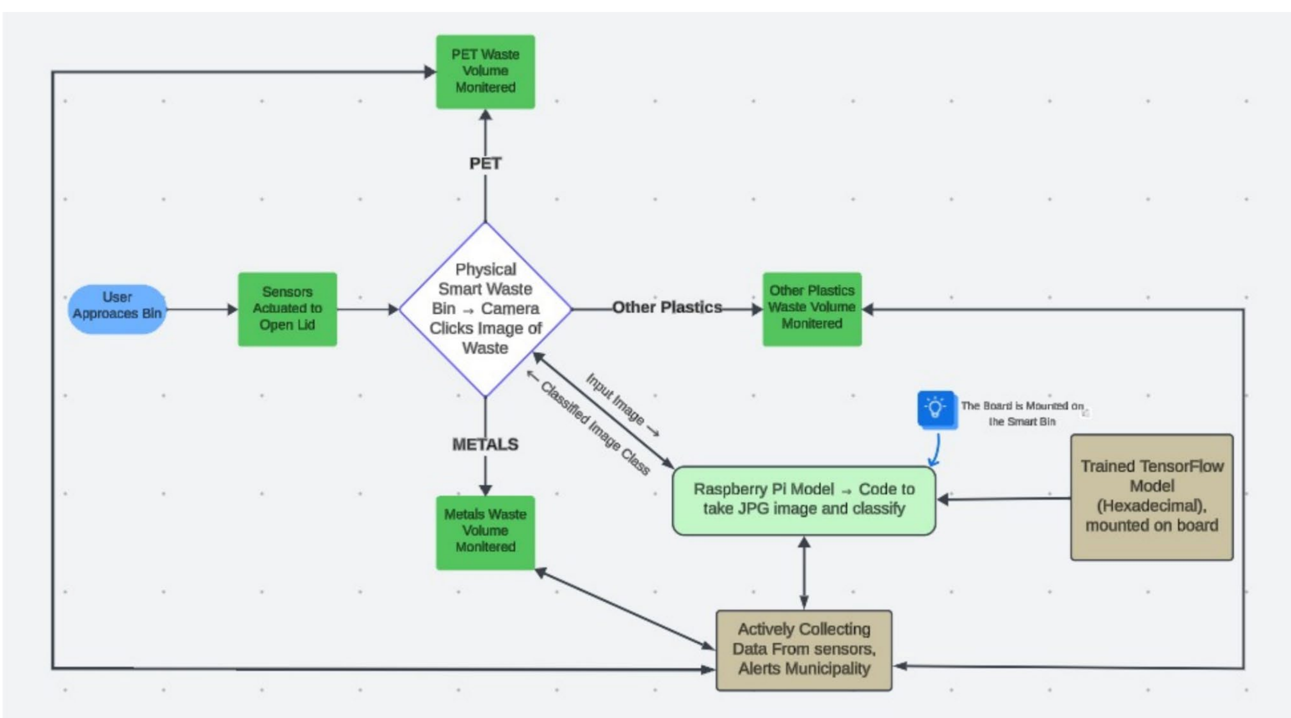


Fig. 2 Swimlane diagram of the proposed model

image is taken by the pre-trained model and a prediction is made by the model.

Step 6 Model predicts output

The machine learning model will then classify the image into one of the three classes possible. This is done with the help of convolutional neural networks which are able to detect features from the images and place the image in a category based on the presence or absence of these features.

Step 7 The segregator moves to the appropriate bin

On receiving an output, the segregator will be automatically driven to the appropriate bin for segregation of waste. The segregator will be using a DC motor to move along the path and will ultimately be directly above the correct bin where the waste is to be thrown.

Step 8 The segregator drops the waste

The segregator will then open to drop the waste into the bin. This is done with the help of DC motors attached to a belt. Once the waste is dropped into the bin, the motor will turn again and the segregator will close. After doing this, the segregator will then be programmed to return back to its original position.

Step 9 Waste levels of the bin are monitored

In an effort to prevent the overflowing of the bins, the waste levels of each of the three bins will be monitored at all times with the help of ultraviolet sensors. The output of these sensors will be sent to the Thingspeak cloud platform for monitoring.

Step 10 Monitoring of bin levels with Thingspeak

We use the Thingspeak cloud platform to monitor the level of waste on the bin. The bins will have a certain threshold for monitoring the level of waste and if any of the bins were to cross this threshold, an alarm would be sent on the cloud platform.

3.1 Algorithm of the proposed model

1. Initialization

   - Set initial waste levels to 0 for PET Waste Level, Other Plastics Waste Level, and Metals Waste Level.
   - Define thresholds for maximum waste levels.

2. Main Loop

   - Run the following steps continuously.

3. User Detection and Lid Opening

   - Check for user proximity to the bin using the proximity sensor.
   - If a user is detected:
   - Actuate mechanism to open the bin lid.

4. Wait for User to Dispose of Waste

   - Monitor the lid sensor to determine if the lid has been closed.
   - Once the lid closes, proceed to the next step.

5. Measure Waste Level

   - Use the ultrasonic sensor to measure the distance from the lid to the top level of waste.
   - Calculate the waste level based on the measured distance and the known dimensions of the bin.

6. Capture Waste Image

   - Activate the camera to take a picture of the waste item.

7. Classify Waste

   - Input the image into the CNN model to classify the waste as PET, Other Plastics, or Metals.

8. Update Waste Level

   - Based on the classification, update the corresponding waste level (PET Waste Level, Other Plastics Waste Level, or Metals Waste Level) with the new measurement from the ultrasonic sensor.

9. Check Bin Status

   - For each waste type (PET, Other Plastics, Metals):
   - If the current waste level exceeds the predefined threshold:
   - Trigger an alert to notify the municipality or maintenance crew.

10. Repeat Process

    - Return to step 3 to continue monitoring and classification.

3.2 Mathematical model of the proposed work (Xception Model)

The powerful convolutional neural network created with depth wise separable convolutions is Xception model. This advanced network is specifically designed to work on images with dimensions of 224×224×3. Inside Xception, intricate mathematical processes take place, as it utilizes a multi-layered approach of convolution and pooling. Ultimately, it successfully converts the input image into a series of top-level feature representations.

3.2.1 Dropout

At each update during training, dropout layers randomly set a portion (in this case, 0.2 or 20%) of the input units to 0, which helps prevent overfitting. Dropout can be expressed mathematically for a given layer output vector v is as shown in Eq. (1).

$$v' = v \odot r \tag{1}$$

where v' is the output after applying dropout, $\odot$ signifies multiplication of elements, and r is a vector of random variables selected with probability from a Bernoulli distribution $p = 0.8$ (since 20% are dropped, 80% are kept).

3.2.2 Flatten

The feature map acquired from the preceding layers is reshaped into a single vector by the Flatten layer, which can then be fed into fully connected layers. If the feature map has dimensions $a \times b \times c$, flattening results in a vector of dimension $n = abc$.

3.2.3 Batch normalization

Through the process of subtracting the batch mean and dividing by the batch standard deviation, batch normalization normalizes the output of an earlier activation layer. It also permits the learning of scale and shift parameters during training. The output y of the batch normalization layer, given an input of z, can be computed as shown in Eq. (2).

$$y = \gamma\left(\frac{z-\mu}{\sqrt{\sigma^2+\varepsilon}}\right)+\beta \tag{2}$$

where μ and σ^2 are the mean and variance of z over the batch, γ and β are learnable parameters of the layer, and ε is a small constant added for nurical stability.

3.2.4 Dense (fully connected) layers

Linear transformations are executed by dense layers, succeeded by non-linear activations. The mathematical model for a dense layer with m output nodes and n input nodes is as shown in Eq. (3).

$$a = \phi(Wx + b) \tag{3}$$

where x is the input vector, W is the weight matrix, b is the bias vector, ϕ is the activation function (ReLU for hidden layers as shown in Eq. (4) and sigmoid for the output layer is as shown in Eq. (5)), and a is the output vector.

$$\text{ReLU(Rectified Linear Unit)} : \phi(x) = \max(0, x) \tag{4}$$

$$\text{Sigmoid} : \phi(x) = \frac{1}{1+e^{-x}} \tag{5}$$

The model takes input images and passes them through the Xception base model to identify key features. It then uses dropout to avoid overfitting by randomly disabling neurons during training. The flattened data is then standardized through batch normalization, making training more stable and faster. The result is processed by a sequence of dense layers with specific activations. The network classifies the processed features using dense layers, with a final layer employing sigmoid activation for binary classification.

4 Implementation

Our research involves the classification and segregation of wastes into three categories- PET, metals and other recyclables. The classification of wastes is done with the help of a Machine Learning model with the help of a neural network design which is known as convolutional neural network. Once the waste is classified, segregation is performed using a Raspberry Pi board. Furthermore, we also have various monitoring systems in place which are done with the help of sensors connected to the raspberry pi board and which can feed information to it.

4.1 Dataset used

The choice of dataset will play a pivotal role in the training of the model. A dataset is a collection of data or information that can be treated as a single unit by a computer. This means that while a dataset may contain several pieces data, it can be used to train a model with the aim of finding predictable patterns within a class. A dataset is usually broken up into two parts – a training set and a testing set. A training dataset will be used by the model for training purposes. The model would be modified based on the data provided here. The testing dataset will be used by the model after training to ensure that model is able to classify images correctly. The images here will not be used for altering the model. The training data may also be split into a validation dataset which can be used to verify if the model is being adjusted in the correct direction.

The size of the dataset has a very big impact on the accuracy of the model. The model should train on a dataset with a magnitude at least an order greater than the amount of trainable parameters. The amount of data required depends on the complexity of the problem and the complexity of the learning algorithm. The type of algorithm used will also affect the amount of data needed. Another common problem found in datasets used for classification is the imbalanced dataset. An imbalanced dataset is one which has an uneven number of data for each parameter. This could mean that a single class would have 50,000 images for training while another would contain only 1000 images. Training a model without fixing this problem will result in the model being completely biased.

There are many ways to fix this problem. The clearest and simplest of them is underdamping. Undersampling is the process of randomly deleting a few or many observations from the majority class in order to match the numbers with the minority class. Another method is known as oversampling. This is a process of generating synthetic data that attempts to randomly generate a sample of the attributes from observations in the minority class. There are several methods used to oversample a dataset for a typical classification problem. The most common technique is called SMOTE (Synthetic Minority Over-sampling Technique).

For our research, we needed a sufficiently large dataset of plastic and metal waste. The dataset must contain real-life images of plastics. As our camera was to be mounted on top of the segregator bin, our dataset was to contain images taken from above an object. The dataset would optimally be at a size of around 10,000 images. A sample of images from the dataset can be seen in Fig. 3.

While a google search generated dataset may provide many images, the quality of the images could be questioned. Many of the images will be taken of different angles and colors. The images provided may not be practical or even useful for a waste segregator model. Hence a practical but large dataset was required.

The dataset we used for this research Plastic waste database of Images – WaDaBa. In this dataset, 6 classes of various types of recyclable wastes were classified with a total of about 4000 images. The classes were PET, PE-HD, PVC, PE-LD, PP, PS and O. 40 photographs were taken of each object, each differing in the angle of the turnover small, and the degree to which the object is damaged with small, medium and large. For each type of destruction has been made 10 photographs. So, considering all variants for every object 40 photographs were taken, multiplying it by the number of objects, 4000 photographs were created in the database. The use of this dataset required the signing of an agreement form by the department head. The 6 classes of images were combined together to ultimately create a dataset of two classes, namely PET and other recyclables.

The distribution of these classes are shown in Fig. 4. The images were divided into a testing and validation dataset with the ratio 1:10. Besides these images we also managed to take images using the Raspberry Pi camera to reduce the unbalancing of the dataset. As the model we are creating required three classes, we needed to incorporate metal objects into the dataset. We did this with the help of the TrashNet and drinking waste classification dataset, from which we managed to obtain about 1000 images of metals. Similar to how the WaDaBa dataset is created, the images were taken from above on a dark background.

The images mainly composed of aluminum cans and foil along with other commonly used metals. This helped us achieve a total of 4980 images for the training dataset with 2200 of them being PET plastics, 1760 of other recyclables and 1020 metals.

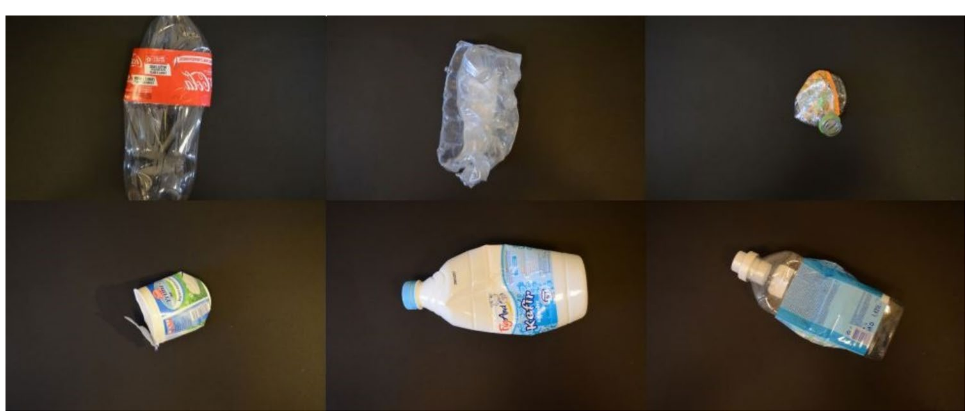


Fig. 3 Sample images

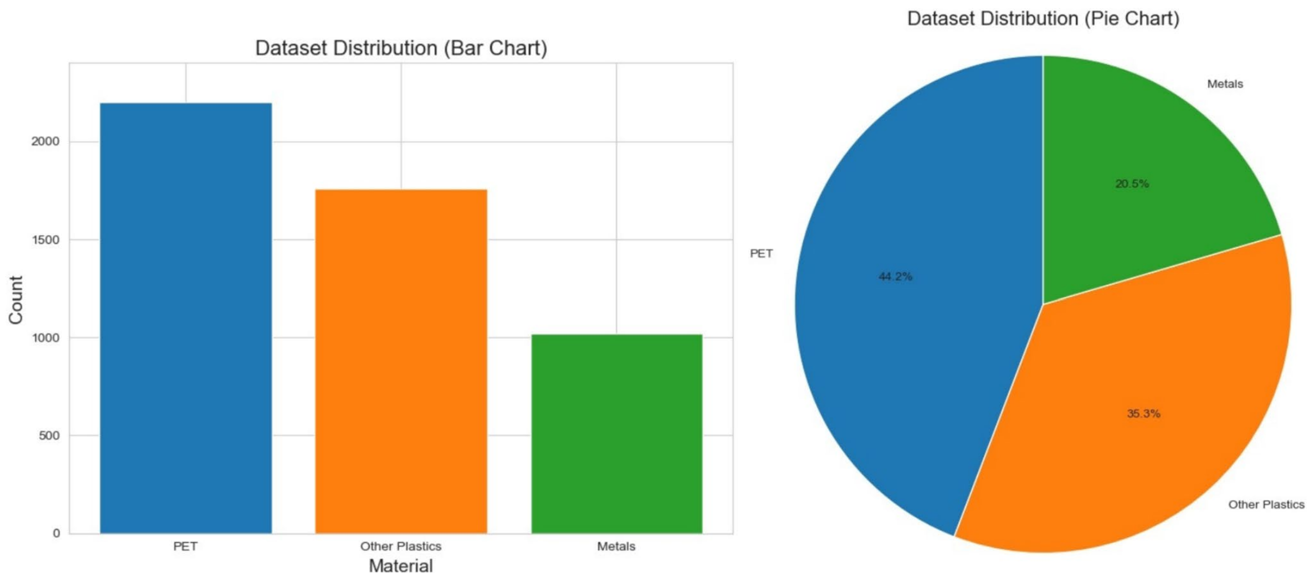


Fig. 4 Dataset distribution

Fig. 5 Sample test image

Testing the dataset involved using creating of a new dataset using the images from the segregator bin. We use a dataset of about 500 images. The model will be modified if the result of the testing dataset is not as expected. Figure 5 shows a sample test image.

4.2 Classification model

Machine Learning is a branch of Artificial intelligence or (AI) where a machine or a computer is capable of using past experiences as a learning tool in an effort to predict outcomes. The performance of a machine learning model is improved with the help of constant training. Machine learning algorithm is divided into two types – supervised and unsupervised. In supervised learning, we use a set of labelled data. The algorithm can measure its accuracy through the use of a loss function, adjusting until the error has been sufficiently minimized. Supervised learning itself can be divided into two classes – Classification and Regression.

Classification model working is as shown in Fig. 6 involves training a model with labeled data in an effort to classify images into fixed targets. This involves dividing the data into quantitative ranges each of which is labeled as a class.

The aim of classification is to determine which class an object belongs to. The data will be classified based on the dependent factors of the object. The supervised learning model will use be trained to identify and segregate the dependent variables from the independent variables while also trying to establish the relationship between the dependent variable and the class it can belong to.

For our research, we use a classification machine learning model which is able to classify images into categories. This machine learning model is known as Convolutional Neural Network Model or CNN model a convolutional neural network, is a machine learning neural network model designed for processing structured arrays of data. As images can be represented using these structured images, the model has found great success in the classification of images. Convolutional neural networks are used as the building blocks for many image classification models and even found success in natural language processing.

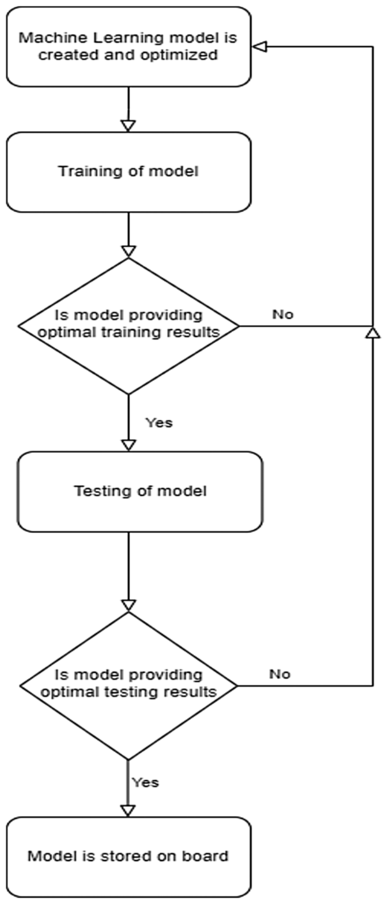


Fig. 6 Workflow of the model Created

Convolutional neural networks can activate features of an image, such as lines, gradients, circles, or even eyes and faces. These features will be used for the classification of images into categories. It is this property of CNN that makes it powerful for image classification. Unlike earlier computer vision algorithms, convolutional neural networks can operate directly on a raw image and do not need any preprocessing. One of the key features of convolutional layers is that neurons are organized into three dimensions, the spatial dimensionality of the input (height and width) and depth.

One of the biggest contributors to the growth of Convolutional neural networks and image classification is the creation of the ImageNet dataset. This dataset contains more than 14 million images, with a little more than 21 thousand groups or classes. More than a million of these images have bounding box annotations. Since 2010, this dataset has been used in the ImageNet Large Scale Visual Recognition Challenge or ILSVRC. This is an annual competition that was held between 2010 and 2017 for creating a machine learning model capable of classifying all the images in the dataset. Many important image classification models were created here, and this paved the way for modern Machine learning technologies. One of the earliest success stories of the ImageNet dataset came with the AlexNet model.

The AlexNet model is a simple convolutional neural network model which consisted of eight layers. As shown in Fig. 7, the first five were convolutional and max pooling layers followed by three fully connected layers. The first convolutional layers were a filter of size 11×11 with a stride of 4. This would mean that the convolutional filter (or feature vector) was capable of looking at 11×11 pixels of the image at a time and would move at a rate of 4 pixels on completion of scanning the previous 11×11 pixels. If the image taken is of color, it can be considered as a 3-dimensional array and the convolutional filter will be applied on each of the three arrays (each array will represent a primary color). The filtered output will then pass through a max-pooling layer. Here the size of the image will be reduced and compressed to reduce the memory required for processing the image. We follow with another convolutional layer of size 5×5 and a max pooling layer. This is continued with 3 convolutional layers of 3×3

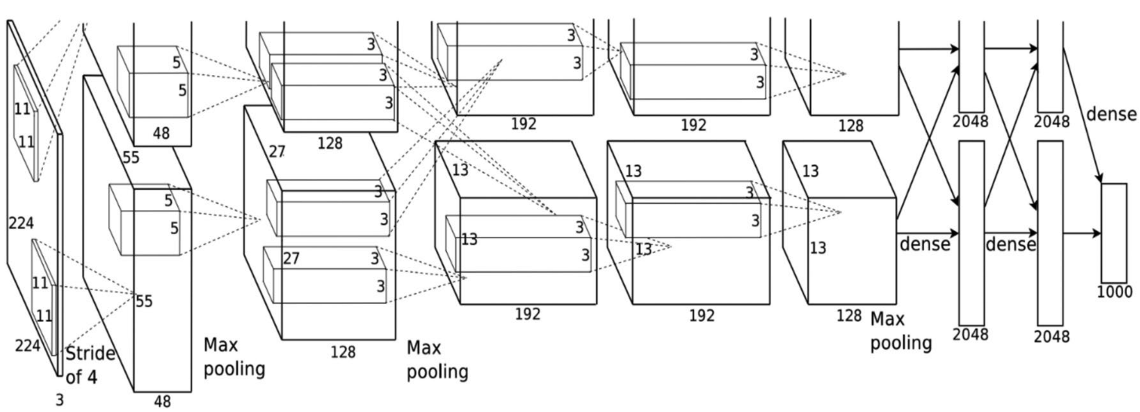


Fig. 7 Alexnet model

dimensions and a final max pooling layer. The output of this layer is given to a dropout layer. The Dropout layer randomly sets input units to 0 with a frequency of rate at each step during training time, which helps prevent overfitting. Inputs not set to 0 are scaled up by 1/ (1—rate) such that the sum over all inputs is unchanged. This data will then be fed to three fully connected layers with the final layer of size 1000. AlexNet uses a softmax activation function on the final layer. Softmax is a very popular multiclass classification activation function which is able to give the probability of an object belonging to a class.

The AlexNet model found great success on the ImageNet dataset and was able to classify images into 1000 different classes. It achieved a top-1 error rate of 39.7% and a top-5 error rate of 18.9% which was considerably better than the previous state-of-the-art models present at that time.

The next major breakthrough in ILSVRC came with the creation of a deep convolutional neural network known as "Inception". This model was especially important as it was said to be the first model to reach an error rate similar to that of the average human. It uses several functions to push performance, both in speed and accuracy. Inception model workflow is shown below in Fig. 8.

While deeper convolutional networks may provide better results, it could also result in overfitting of the model while drastically reducing the computational performance. Hence in order to improve classification accuracy while also reducing computational performance, the authors created an "Inception layer". The block representation of inception layer is shown in Fig. 9

The key idea of this layer is deploying multiple convolutions with multiple filters and pooling layers simultaneously in parallel within the same layer. The intention of this is to let the neural network learn the best weights when training the network and automatically select the more useful features. Additionally, it can also reduce the number of dimensions to provide a more computationally friendly model. This computational benefit could be utilized by the units and layers of the later stages. The side-effect of this is an increase in the computational cost for training this layer.

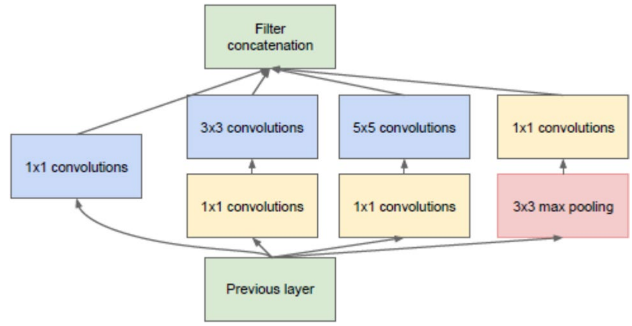


Fig. 9 Inception layer

Another feature that we looked into was the skip-layer which was first introduced by the Resnet model. While it may seem reasonable to assume that a convolutional neural network with more layers could produce a more accurate output, this was not the reality. One of the biggest problems seen with a deeper convolutional model is the possibility of overfitting. Overfitting is the phenomenon where a model trains on a dataset up to a point where the model function is too closely aligned to the dataset and is unable to provide accurate results for images that are not a part of the dataset.

Skip connections are connections used in deep neural networks which feed the output of a particular layer directly to later layers in the network that are otherwise not directly adjacent to that output layer. With the help of a skip connection, we may be able to provide an alternative path for the gradient (with backpropagation). It is experimentally validated that these additional paths are often beneficial for the model convergence.

Another brilliant image classification model is the Xception architecture model (also known as the Inception v4 model). The Xception is a convolutional neural network that has 71 layers depth. Xception is the next version of the inception Architecture which replaces the known Inception modules with Depthwise Separable Convolutions.

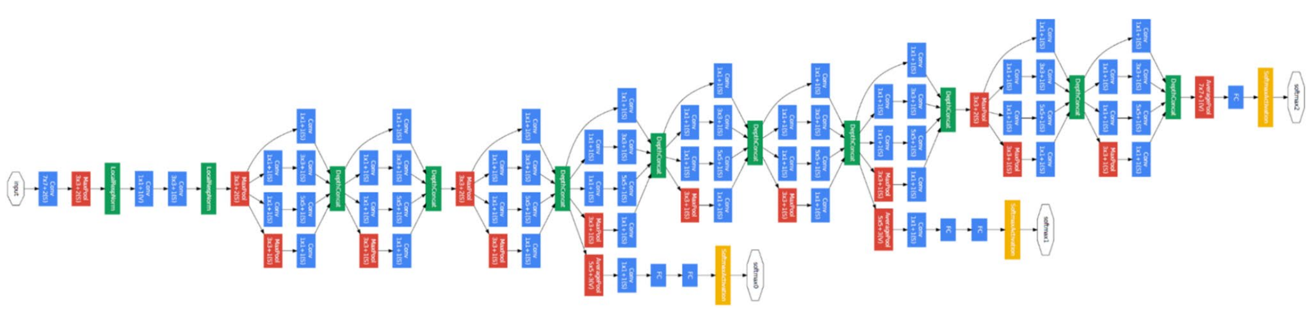


Fig. 8 Inception model

The Xception model is known as an improvement of the previously mentioned Inception architecture model. While the Inception model consists of deep convolutional layers and wider convolutional layers that work together, Xception model contains two levels, where one of them has only one layer. This layer divides the output into 3 segments and forwards it to the next set of filters. The first level has a single convolutional level of 1×1 filter, while the next has three convolutional levels of a 3×3 filter.

One of the defining features of the Xception model is the use of a Depthwise Separable Convolution (Fig. 10). Depthwise Separable convolution is a convolutional method used that considers each channel as a separate entity and performs convolution on each of these channels separately. Hence this will consist of two stages, firstly filtering where the Input image is split into three arrays. Each array will then be filtered with the convolutional kernel. The kernel used could be the same for all three channels. The output of each o the three channels is then stacked to get the output. Once stacking is completed, we can move on to the next stage which involves combining the three arrays.

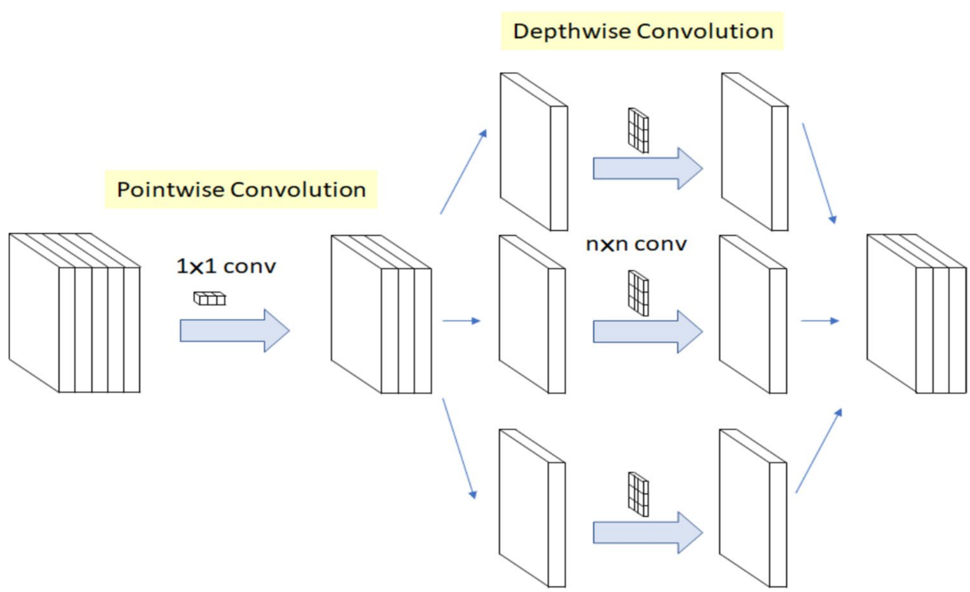
The key advantages of depthwise separable convolution are:

- They use a lesser number of parameters to modify a convolutional model and hence can reduce the possibility of overfitting
- They are significantly cheaper in computation while also maintaining accuracy

Xception architecture uses a modified Depthwise Convolution which performs a piecewise Convolution before the Depthwise Convolution. The modified Depthwise separable convolution performs 1×1 convolution first then channel-wise spatial convolution. As shown in Fig. 11, the Xception model is 71 layers deep.

Understanding the features and problems of the popular image classification model was crucial in our effort to create an image classification model. We came across numerous problems while building our model and looked into the solutions posed by the various architectures for solutions. The results of our model were compared with that of the existing architectures.

Fig. 10 Depth-wise convolution



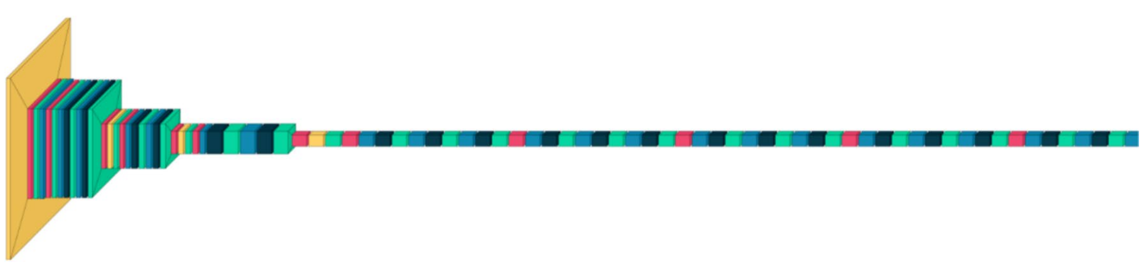


Fig. 11 Xception classification model

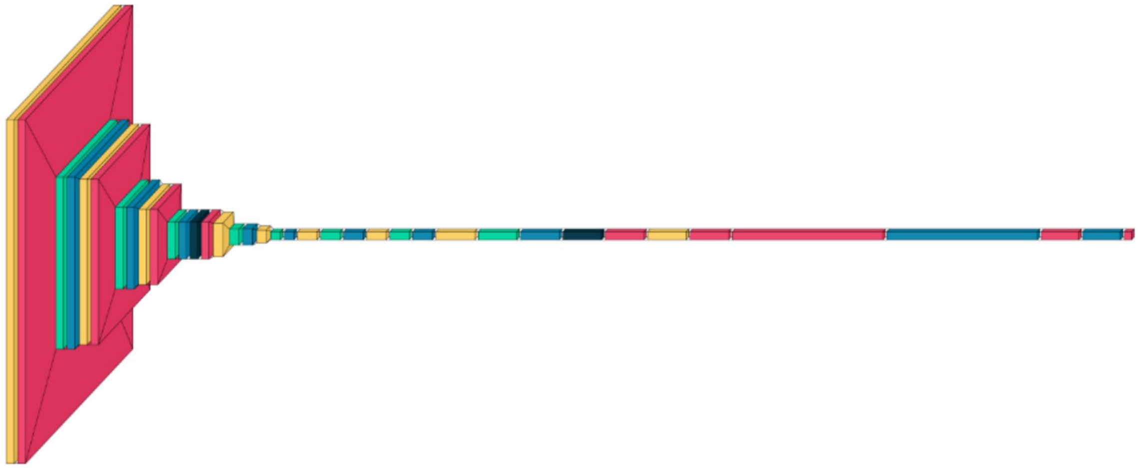


Fig. 12 38-layer classical convolutional neural network

As shown in Fig. 12, the model created for this research is a 38-layer classical convolutional neural network. It consists of 8 convolutional layers which contain different-sized filters. The first convolutional layer is of size 11 × 11 and converts the input layer into dimensions 214 × 214x32. This layer will provide 11,648 parameters. The activation function used here is a ReLu activation function. The rectified linear activation function or ReLU activation function is a piecewise linear function that can output the input directly if it is positive, or else will output zero. It is usually seen as the default activation function for many types of neural networks as it is easier to train and often achieves better performance.

This layer is followed by a batch normalization layer. Normalization is a preprocessing technique that is used to standardize data. It is the process of transforming the data to have a mean of zero and a standard deviation of one. Not normalizing the data before training could result in a drastically harder to train network and may also decrease its learning speed. Batch Normalization is the normalization technique done between the layers of a Neural Network instead of in the raw data. It serves to speed up training and use higher learning rates, making learning easier. It can accelerate training, with cases of halving the epochs or better, and provides some regularization (a technique of tuning a function by adding an additional penalty term in the error function), reducing generalization error. We then perform a max pooling to reduce the dimensions of the image to 107 × 107x32.

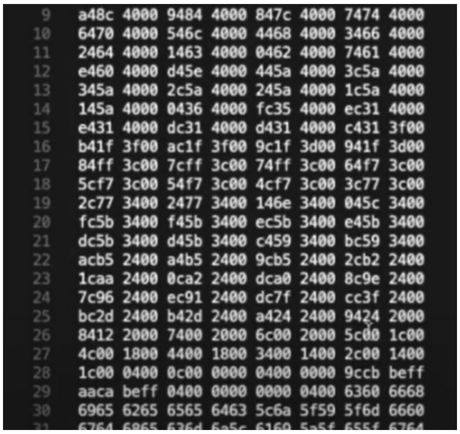
We follow this with a dropout layer. The dropout layer will have a score of 0.5. This would mean that 0.5 or 50% of the neurons in the layer will be randomly dropped during a run. The dropout layer performs a key role in reducing the possibility of overfitting.

We have similar convolutional and max-pooling layers of size 5 × 5, 3 × 3 and 1 × 1 feature vectors. This provides a total number of 20,401,955 parameters with 20,397,155 of them being trainable. Each of these layers will use a kernel regularize of L2 regularization. The regularization is the process of adding penalties on layer parameters or layer activity such as the error function during the process of optimization. These penalties are summed into the loss function that the network optimizes. A kernel regularizer has the regularizer applied to the layers kernels. L2 regularization, also known as ridge regression, performs kernel regularization by adding a squared magnitude of penalty coefficient. It deals with multicollinearity (independent variables are highly correlated) problems by constricting the coefficient and by keeping all the variables. It is computationally efficient for analytical data.

The final layers are flattened and fully connected with 8000 neurons. All these layers will finally converge to create a layer with 3 neurons using a softmax activation function.

4.3 Localizing the Classification model

The classification model being the central aspect of the model must be onboarded to the Raspberry pi processor, which will localize the classification of the waste that is disposed. In order to implement this we must make use of techniques that will optimize and format the classification program that will be suitable for running on the Raspberry pi processor. The classification model program is converted to TensorFlow lite file. A TensorFlow Lite file is a file that contains an optimized format of the saved machine learning model. A converter known as the TensorFlow Lite is used to convert the saved model from.pb/.h5 to the.TFLite format. This file is filled with hexadecimal values that only a TFLite Interpreter can use. The TFLite Interpreter is installed on the Raspberry Pi processor. Once an image is captured from



a48c 4000 9484 4000 847c 4000 7474 4000
6470 4000 546c 4000 4468 4000 3466 4000
2464 4000 1463 4000 0462 4000 7461 4000
e460 4000 d45e 4000 445a 4000 3c5a 4000
345a 4000 2c5a 4000 245a 4000 1c5a 4000
145a 4000 0436 4000 fc35 4000 ec31 4000
e431 4000 dc31 4000 d431 4000 c431 3f00
b41f 3f00 ac1f 3f00 9c1f 3d00 941f 3d00
84ff 3c00 7cff 3c00 74ff 3c00 64f7 3c00
5cf7 3c00 54f7 3c00 4cf7 3c00 3c77 3c00
2c77 3400 2477 3400 146e 3400 045c 3400
fc5b 3400 f45b 3400 ec5b 3400 e45b 3400
dc5b 3400 d45b 3400 c459 3400 bc59 3400
acb5 2400 a4b5 2400 9cb5 2400 2cb2 2400
1caa 2400 0ca2 2400 dca0 2400 8c9e 2400
7c96 2400 ec91 2400 dc7f 2400 cc3f 2400
bc2d 2400 b42d 2400 a424 2400 9424 2000
8412 2000 7400 2000 6c00 2000 5c00 1c00
4c00 1800 4400 1800 3400 1400 2c00 1400
1c00 0400 0c00 0000 0400 0000 9ccb beff
aaca beff 0400 0000 0000 0400 6360 6668
6965 6265 6565 6463 5c6a 5f59 5f6d 6660

Fig. 13 Preview of flite file

Raspberry Pi using the Pi camera this image is pre-processed and sent to the TFLite interpreter. The TFLite interpreter then runs the inference using the TFLite file and generates the output that results in the type of waste classified, in this research it will be either PET, Metal or Other Plastics. This output is then fed back to the Raspberry Pi for the process to continue. The image showing the conversion of the classification model to TensorFlow Lite and the inferencing of images for output is shown in the Figs. 13 and 14.

4.4 IoT model

In the IoT model as shown in Fig. 15, we have 2 key functions: Person detection for automated bin opening and monitoring the level of waste inside the bins. We use ultrasonic sensors in both cases as they have a range of 2–400 cm.

The person detection system utilizes ultrasonic sensors to detect when a user approaches the bin to discard a waste item. The sensors detect the presence of the person and actuate the DC motors connected.

to the lid of the bin, opening the bin for the user to drop the waste and closes after a switch is ON, a sensor can also be used as a switch (IR sensor, motion sensor, sound sensor, etc.). As shown in Fig. 16, the ultrasonic sensors are placed in the front of the bin just below the lid opening.

For the sole purpose of monitoring the waste bin, we have placed ultrasonic sensors inside the bins as shown in Fig. 17. The waste monitoring system utilizes ultrasonic sensors to gauge the distance between the sensor and the waste in the bin. Monitoring of the bin has been made possible by another free service we use, that is the ThingSpeak cloud platform. The ultrasonic sensors are coupled to the service

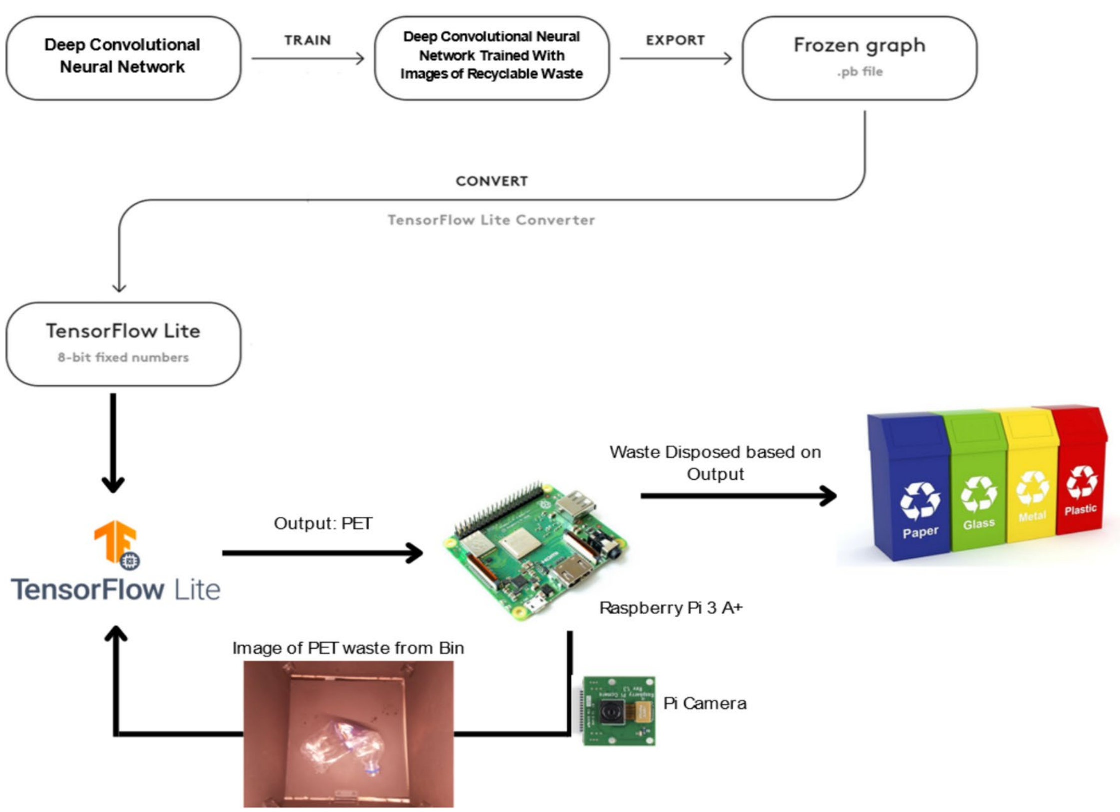
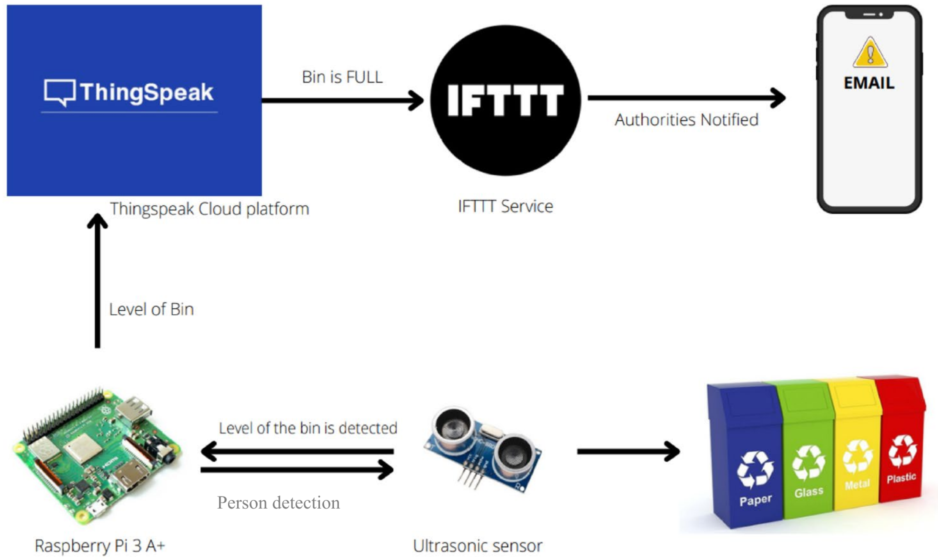


Fig. 14 Localized model

Fig. 15 IOT model



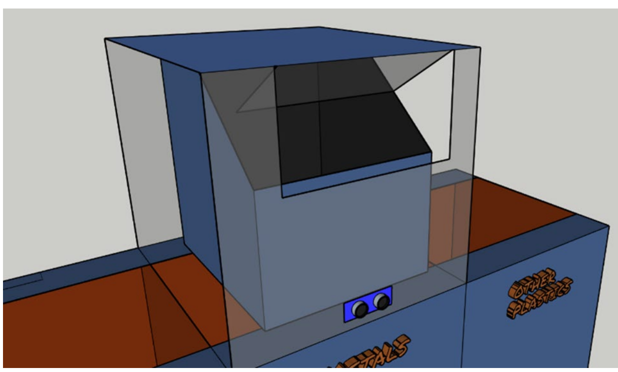


Fig. 16 Ultrasonic sensor for person detection

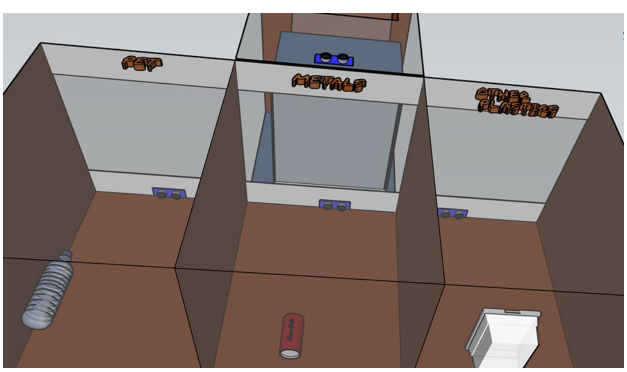


Fig. 17 Ultrasonic sensor for waste level detection

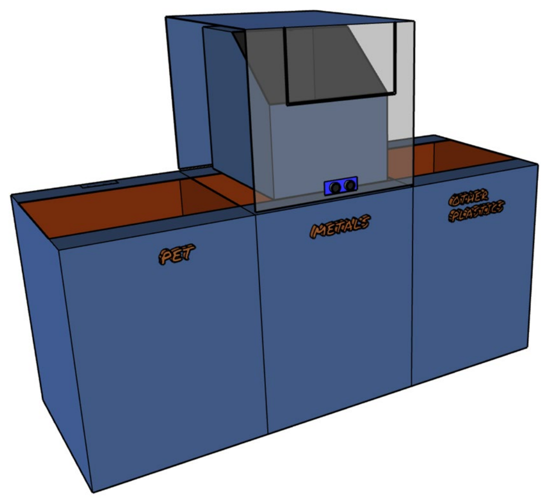


Fig. 18 3D rendered image of the model

provided by ThingSpeak. This data helps us measure how filled the dustbin is and a threshold value is set, which when crossed sends out an alert to an interconnected IFTTT service that sends an alert (email) to the right personnel so they can come and empty the bin and dispose of the waste before it overflows and becomes inconvenient to use (Figs. 18, 19 and 20).

We have placed QR code scanners on the bins to understand the state of the waste collected in the bin. On scanning the code, a link will appear on the mobile screen which will have to be clicked on to navigate to our monitoring page, this page will be holding the data that has been collected from the ultrasonic sensors inside the bin.

Fig. 19 Actual camera image of the model

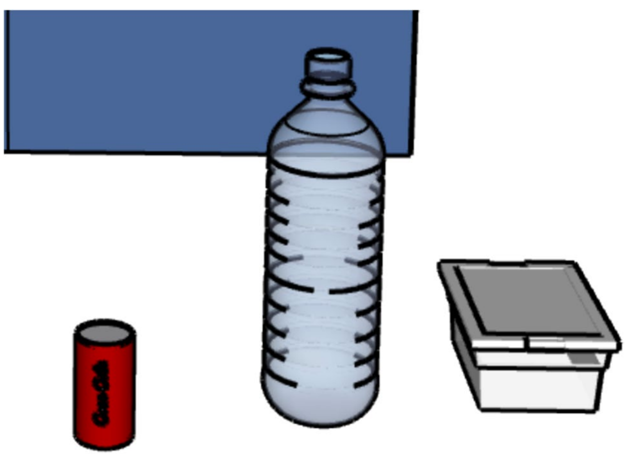


Fig. 20 3D rendered Images of waste Metal, PET and Other plastic

The data collected by ThingSpeak can be used in the time series format, where we can see from the image above/below that we understand the situation of waste collected in the bin at different intervals of time. The intervals of time at which data can be collected will have an order and set which is followed which in turn will help us perform data analytics to find insights into questions that can't be answered otherwise like what type of waste is thrown at what time exactly? Which waste is disposed of more often and why?

5 Results and discussion

Once the device counters a person approaching the bin, a trigger is sent to the raspberry pi board which then initiates the movement of the servo motors to run in the clockwise direction. The dimensions of the movement of the servo motors have been coded into the raspberry pi model, hence the lid will open to an extent that will help the user dispose of the waste into the bin and closes after a time period of 3–4 s which is sufficient enough to put the waste object into the bin for further classification purpose.

The following pics depict the exact way the classification model performs.

The above image is the rendered image and the actual image of the built model of the prototype 2, the images below show the working of the model for all 3 types of waste thrown in the bin.

5.1 When "PET" waste is thrown in the bin

See Fig. 21.

5.2 When "Metal" waste is thrown in the bin

See Fig. 22.

5.3 When "Other Plastic" waste is thrown in the bin

See Figs. 23, 24 and 25.

5.4 Classification model accuracy

The accuracy of classification model is depicted in Figs. 24 and 25. It has got an accuracy of about 92% through CNN classification model which was designed based on the Xception model over 20 epochs which when compared to powerful object classification models is equally efficient and reliable. While few of the existing models exude high accuracies, they are computationally expensive while the other algorithms which are computationally inexpensive do not have a reliable accuracy. Hence it is important to find the right balance between these two factors which we believe we have achieved through our custom CNN classification model. The Comparative analysis of three models: AlexNet,(A), InceptionNet (B) and MobileNet(C) is as shown in Figs. 26, 27 and 28.

5.5 Cloud integration of model

It has been successfully integrated the sensors with ThingSpeak cloud platform. The ultrasonic sensor data is used to monitor the level of waste in the respective bins. This data is sent to ThingSpeak platform and using the tools provided by

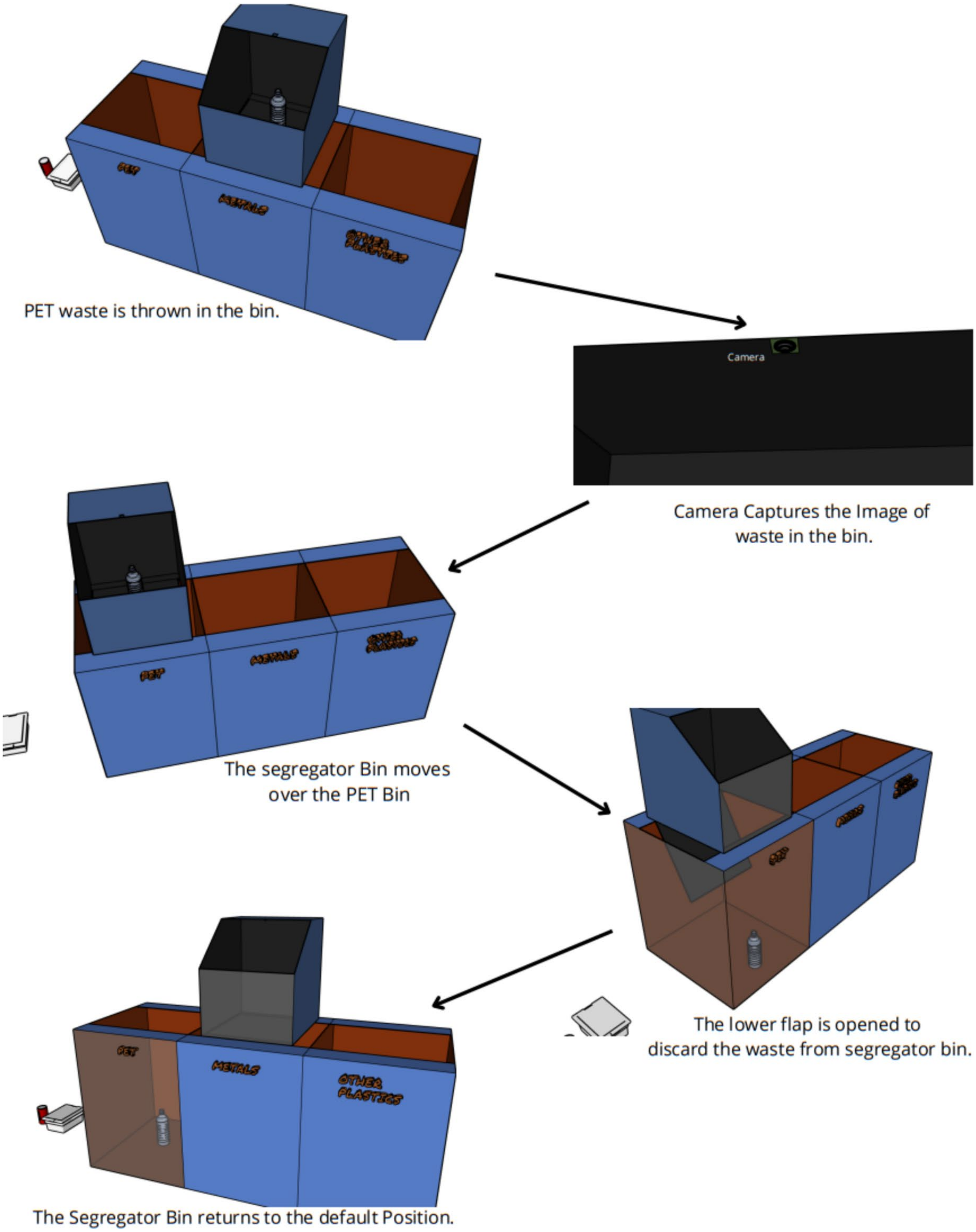


Fig. 21 Working flow for PET

the platform we were able to visualize this data for a better understanding of the data. Below you can see the data for different classes of waste. A line graph is used to visualize data. The x-axis represents the time of the day at which the data point was collected, and the y-axis represents the level of waste in the bin.

Let us look at an example from the table below. It can be seen that in 'PET'waste data a lot of data points are collected

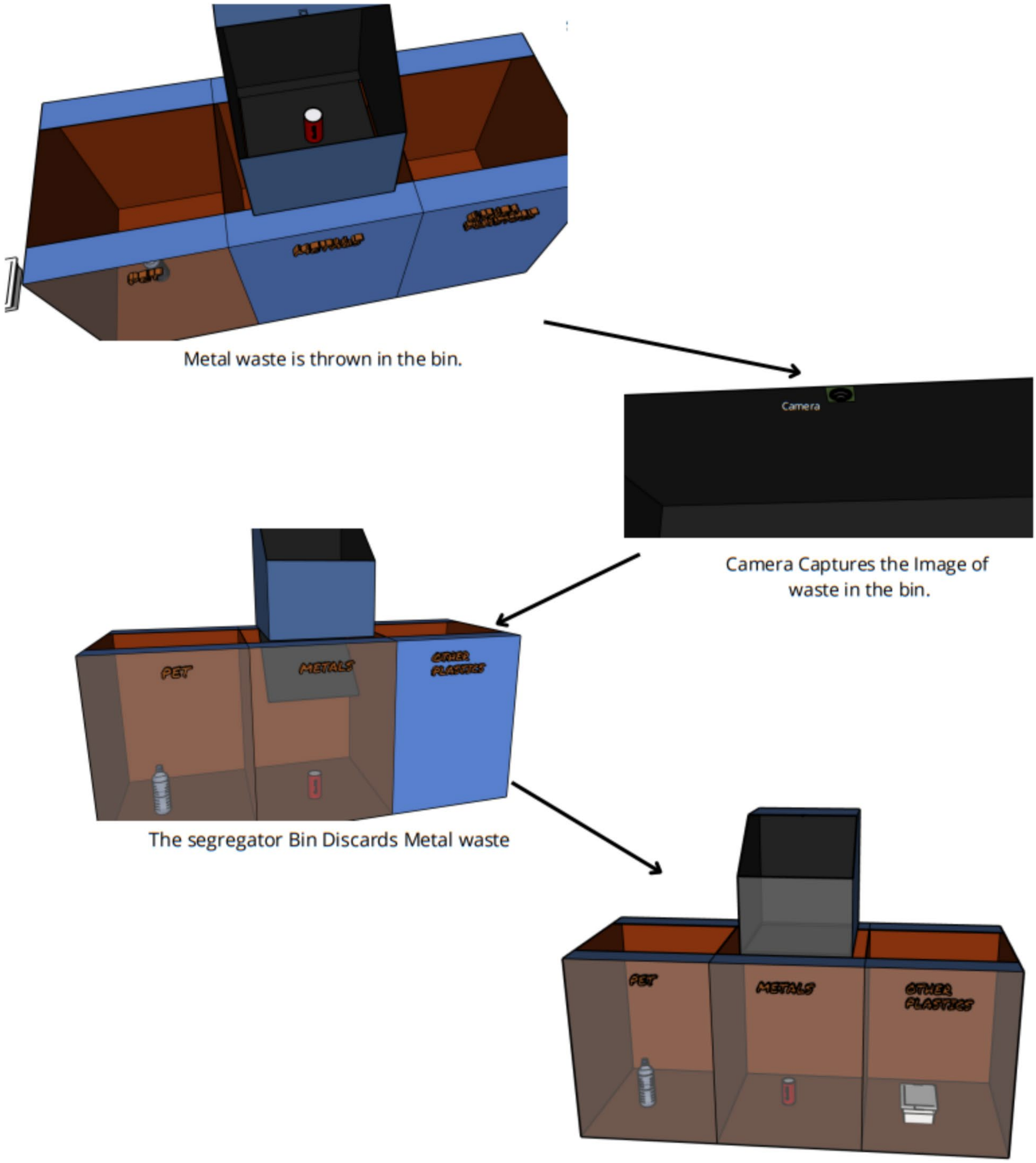


Fig. 22 Working flow for metal

as it is the most commonly disposed waste. Similarly you can see that data collected for 'Metals' and 'Other Recyclables'.

This sensor data is also used in sending alerts to the respective personnel. The alert system we have put in place is mainly used to notify when the bin level exceeds a set threshold. IFTTT service is used to send alerts through mail. Below you can see how the sensor data is used to send alerts in the form of mail.

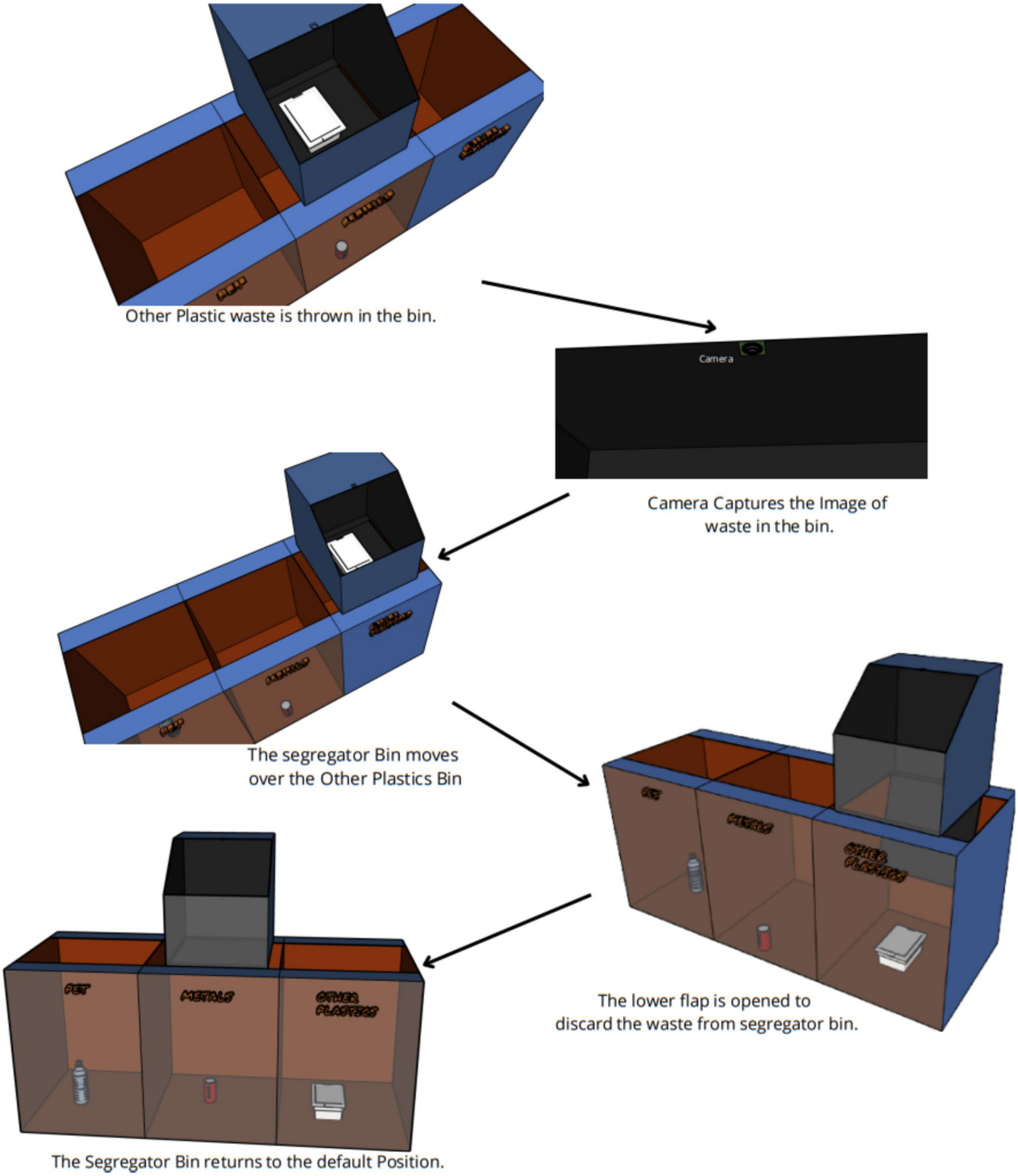


Fig. 23 Working flow for other plastics

6 Conclusion

The prototype developed has great promise in the real-world application of waste management in urban localities. The proposed model is able to accurately predict the class of the waste around 95% of the time. With the help of this model, the human intervention is excluded in waste management, Thus, reducing unnecessary effort and preventing

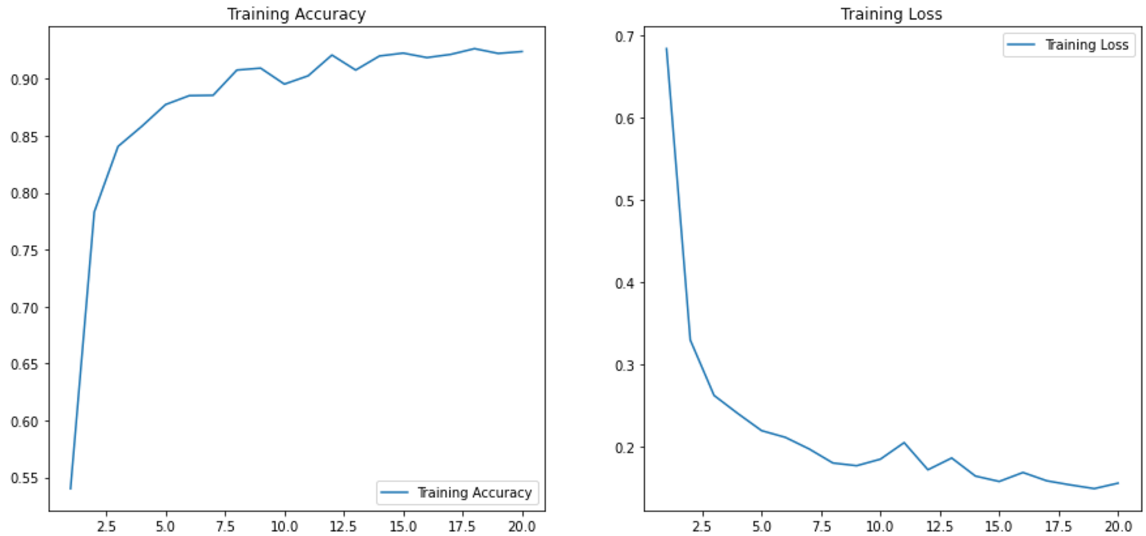


Fig. 24 Training Accuracy + Loss obtained

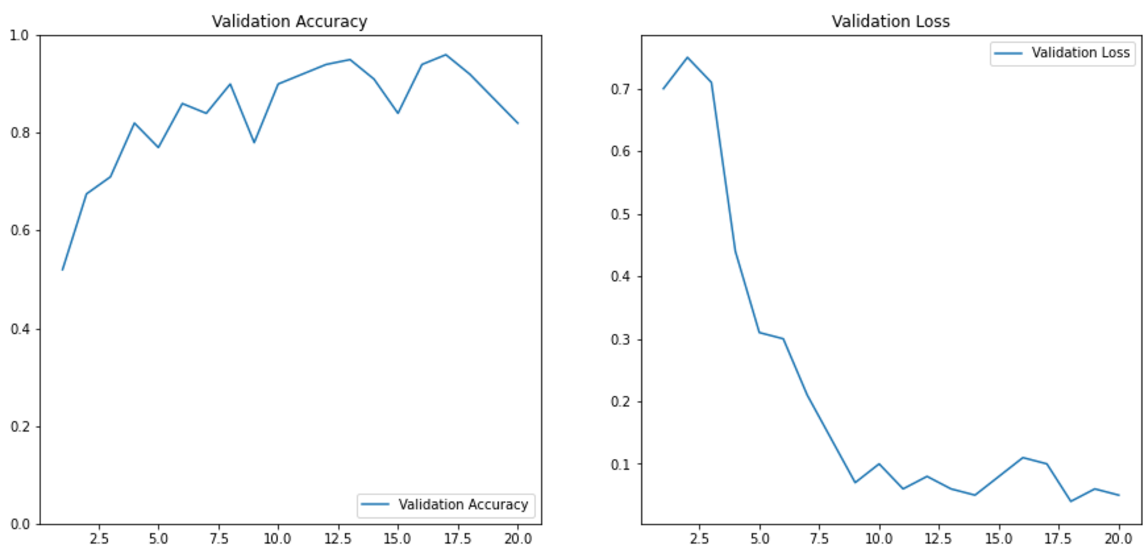
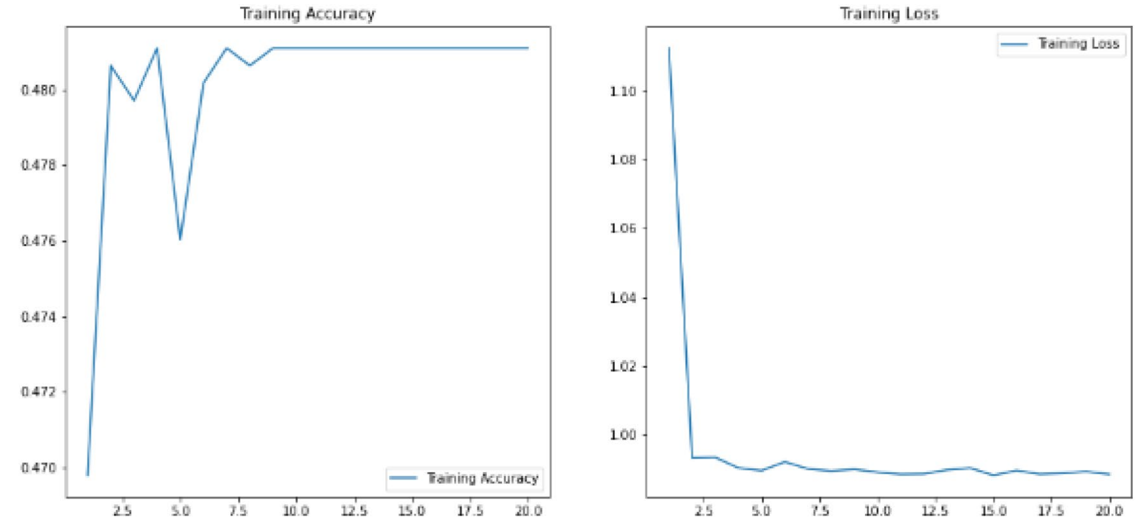


Fig. 25 Validation Accuracy + Loss obtained

harm which comes in the way of this activity. By setting up this system in schools, colleges, and parks, It is possible to reduce improper handling of waste and help to keep the area clean.

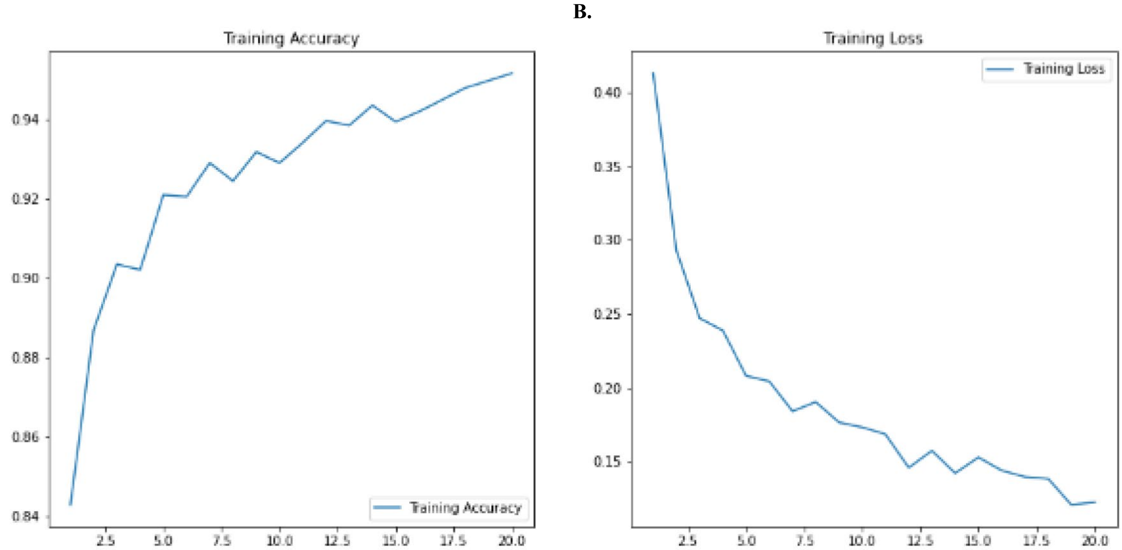
While the machine learning model shows promising results it has great scope for improvement. It is possible to fine tune this model by adding convolutional layers and improving the max pooling constraints, leading to a more accurate model and ultimately a more accurate waste segregation system. However, this improvement comes with greater computation cost and complexity. This model can also face the problem of overfitting. Considering this, It has been chosen a relatively simple convolutional model which is able to predict the object with sufficiently accurate results for our use-case. With advancements in visual computing algorithms, we could use a newer Convolutional model which can fit our requirements and segregate waste into a greater number of classes.

It was found that our model can provide timely monitoring of waste levels and is able to use ThingSpeak for visualization of this data. This can help authorities in identifying bins which are at capacity and taking appropriate action. It



A.

B.



C.

Fig. 26 Comparative analysis of three models: *AlexNet* (**A**), InceptionNet (**B**) and MobileNet(**C**)

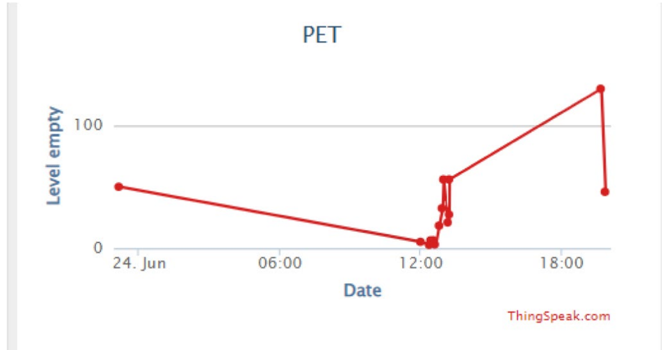
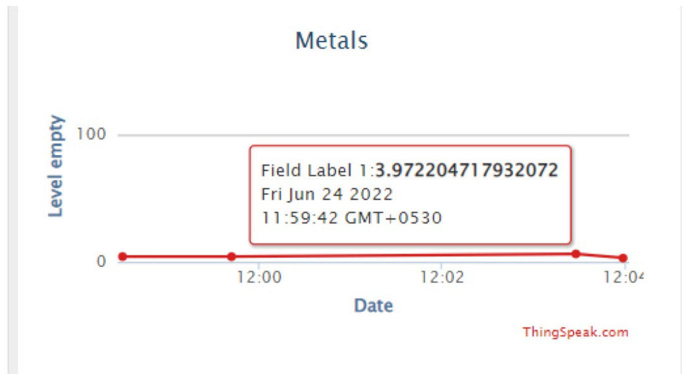
<table>
<tr><th>Type of Waste</th><th>As displayed on ThingSpeak platform</th></tr>
<tr><td>PET</td><td>
</td></tr>
<tr><td>Metals</td><td>
</td></tr>
<tr><td>Other Recyclables</td><td>
</td></tr>
</table>

Fig. 27 ThingSpeak graph of level of the bin at different intervals

removes the need for manual monitoring of levels as we are able to notify the appropriate authority when it breaches a threshold.

The Prototype which is built can provide good results and can be produced on a large scale. The sensor layout the working of the motors and classification of waste gave us an optimal result. The integration of our classification model locally on the microprocessor enables us to decrease latency which would lead to faster classification on the microcontroller. This methodology of integrating

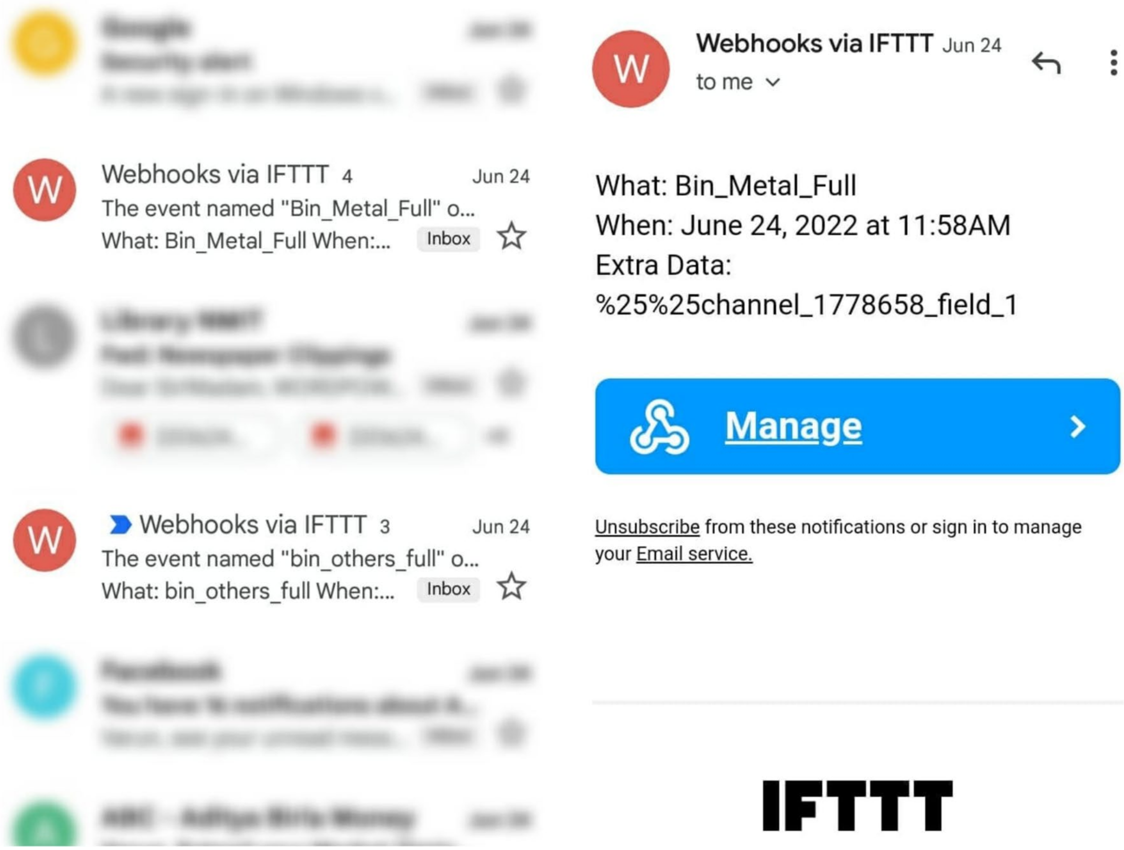


Fig. 28 Email alerts *received*

IoT architecture and the ML model paves way for more accurate segregation of waste in urban localities.

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Declarations

Conflicts of interest The authors declare that they have no conflicts of interest.

Informed consent Informed consent was obtained from all individual participants included in the study.

Human and animal rights This article does not contain research involving human and/or Animals participants performed by any of the authors.

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