VISVESVARAYA TECHNOLOGICAL UNIVERSITY
JNANA SANGAMA,BELAGAVI - 590018

A Project Report on

WASTE MANAGEMENT IN URBAN LOCALITIES

Submitted in partial fulfilment of the requirements for the award of the degree of

Bachelor of Engineering

in

Electronics and Communication Engineering

for the **Academic Year: 2021-22**

Submitted by

Rony Joseph	**(1NT18EC132)**
Tummala Sreeteja	**(1NT18EC176)**
Varun Raveendra	**(1NT18EC194)**
Suhas K M	**(1NT18CS168)**

Under the Guidance of

Dr. Vishwanath V
Assistant Professor
Dept. of Electronics and Communication Engineering

NITTE EDUCATION TRUST
NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

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An Autonomous Institution Affiliated to VTU

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

BENGALURU- 560 064

Certificate

Certified that the project work titled "**Waste Management in Urban Localities**" is carried out by Rony Joseph (1NT18EC132), Tummala Sreeteja (1NT18EC176), Varun Raveendra (1NT18EC194) and Suhas K M (1NT18CS168), bonafide students of Nitte Meenakshi Institute of Technology in partial fulfilment for the award of Bachelor of Engineering in Electronics and Communication Engineering of Visvesvaraya Technological University, Belagavi during the academic year 2021-2022. The project report has been approved as it satisfies the academic requirement in respect of the project work prescribed as per the autonomous scheme of Nitte Meenakshi Institute of Technology for the said degree.

Signature of the Guide	Signature of the HoD	Signature of the Principal
Dr. Vishwanath V Assistant Professor Dept of ECE, NMIT	**Dr. Ramachandra A C** HoD Dept of ECE, NMIT	**Dr. H C Nagaraj** Principal NMIT

External Viva-Voce

Name of Examiners	Signature with Date
1.	

DECLARATION

We are hereby declaring that

(i) The project work is our original work

(ii) This Project work has not been submitted for the award of any degree or examination at any other university/College/Institute.

(iii) This Project Work does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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NAME	USN	Signature
RONY JOSEPH THECKEVEETIL	1NT18EC176	
VARUN RAVEENDRA	1NT18EC194	
TUMMALA SREETEJA	1NT18EC176	
SUHAS KM	1NT18CS168	

Date: 14/07/2022

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NAME	USN	Signature
RONY JOSEPH THECKEVEETIL	1NT18EC176	
VARUN RAVEENDRA	1NT18EC194	
TUMMALA SREETEJA	1NT18EC176	
SUHAS KM	1NT18CS168	

Date: 14/07/2022

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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. Our project aims at providing a solution for waste management, specifically in urban localities where the most amount of waste is generated.

In this project we try to design and implement an efficient ‘smart waste management system’ and in doing so we use various technologies like machine learning for classification of waste during collection, IoT for monitoring the bin, and to make the process of disposal of this waste collected systematic and structured, and cloud to store the various types of data collected. We have implemented certain key features of our model so far and have seen promising results.

Upon completion of the project, this model 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. With the implementation of emerging technologies in the project with improvements in these fields model can also be updated and made more efficient and reliable.

Chapter 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 been double 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.

Figure 1 :Projection of waste generation by major countries

A lot of non-biodegradable waste makes its way to the landfills and has adverse effects on the environment as these substances aren't decomposed by the nature leading to them affecting the land and marine life around them. 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.

The best way to tackle this problem is by making sure the waste is segregated properly at the root itself that is at the garbage bins and to recycle as much as we can which helps us reduce the waste generated, reduce our carbon footprint, and helps us with the overall well-being of our environment and it also helps in saving our exhaustible resources for the future generations. Our aim through this project is to provide a smart waste management solution for urban areas which produce most of the nation's waste.

Chapter 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 our project, 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 [1], 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 [2], 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 [3], 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 [4], 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 papthe er, A Deep Learning Model for Odour Classification Using Deep Neural Network [5], 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” [6], 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 [7], 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” [8], 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" [9]. 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 [10]. 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" [11]. 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" [12] 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"[13] 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" [14], 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 [15]. 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" [16]. 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 [17][18].

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 [19].

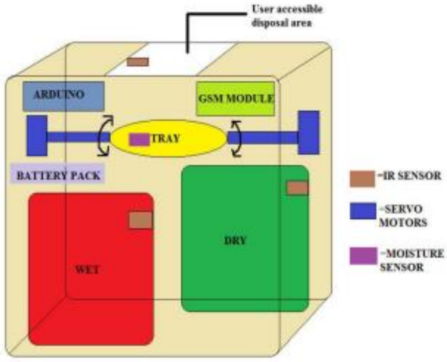
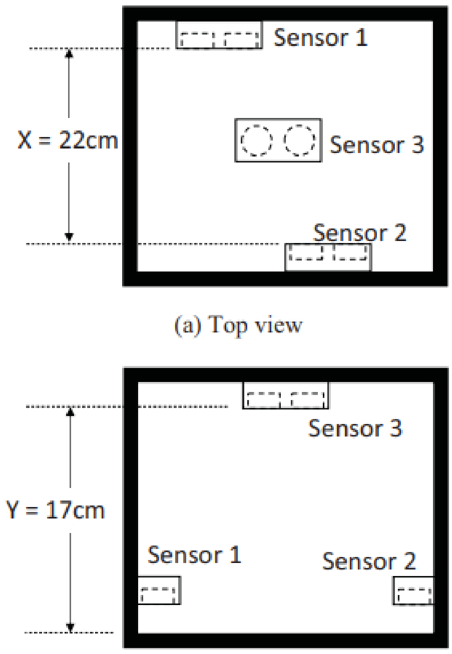


Figure 2: Waste segregation model [19]

One unique proposed system makes use of an array of sensors in determining the type of waste that was put, using the weight and size of waste, the system contains a large database that contains the weight and dimensions of different types of recyclable waste like paper, glass, plastic, and metal. The weight of the waste is determined by the output from the load cell, and the size and shape are determined by using an array of ultrasonic sensors that share their sensed value to the microcontroller, which gets mapped to a



(a) Top view

(b) Side view

Figure 3 :Array of sensors [20]

database determining the type of waste. This data is then used to categorize the waste into its category for recycling. The model works efficiently, but this methodology requires a large database to be effective which is not efficient as it requires a lot of memory for storing the data of different types of waste [20].

Though many systems include the use of sensors, one type of waste segregation system completely avoids the use of sensors for segregation. Instead, this method of the clustered assorted trash maintenance system has a conveyor belt on which the waste is thrown by a collecting plate, the waste goes through two different stages, the first stage incorporates the use of electromagnets and coil to generate a magnetic field which attracts all the metallic waste and dropped to a different container. The second stage is a method to separate dry waste from wet waste, by using an air blower and this dry waste is collected in a different container. The remaining waste that is still present on the conveyor belt is assumed to be wet waste and is discarded in a different container. This system theoretically sounds correct but there are some drawbacks when it comes to wastes like onion peels, milk packets, and tin cans (nonmagnetic metals) [21].

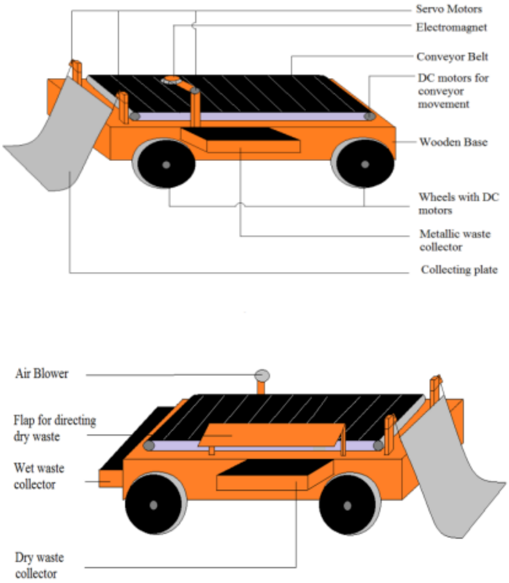


Figure 4: Conveyor belt mobile model [21]

Waste segregation systems have also been considered as a means of generating energy, in this method a GREEN BIN is used for segregation which incorporates the use of an inductive metal sensor and capacitive moisture sensor for segregating metal and wet waste respectively, in addition to this method uses the odour sensor(iAQ-100) to check the presence of biomedical wastes which is an important category to be segregated [18].

In simple terms, machine learning uses mathematical algorithms that receive and analyse input data to predict output values within an acceptable range. The choice of ML model used will have severe effects on the output obtained. Image classification is done using a class of models known as Convolutional Neural Network or CNN. Convolutional Neural Networks are a class of Deep Neural Networks, which use a technique called Convolution to obtain an output.

In “ImageNet: A large-scale hierarchical image database” [22], A new Database called ImageNet was developed. This Database was pivotal in the advancements of Image Classification Technology. Many famous Neural Networks like ResNet, AlexNet and MobileNet began with their efforts to classify ImageNet images.

ImageNet has been used as the benchmark for Image Classification Algorithms and has resulted in the creation of many award winning algorithms. One of these are D-CNNs or Deep Convolutional Neural Networks, which were presented on “Very deep convolutional neural network based image classification using small training sample size” [23]. This model uses a modified VGG-16 network for the ImageNet problems and adds a stronger regularizer to reduce the possibility of overfitting. It also uses Batch Normalization instead of Layer Normalizaion. The Authors were able to achieve an error rate of 8.45% error rate while also minimizing overfitting.

In “Garbage Waste Segregation Using Deep Learning Techniques, Institute of Physics” [24], four different models of the CNN, such as ResNet50, DenseNet169, VGG16, and AlexNet, trained on ImageNet, are used to extract features from images and feed them into a classifier to make predictions and distinguish a type of waste from its corresponding category. It was seen that of the four models used DenseNet169 provided significantly better results. However, with this increase in complexity comes an increase in computational requirements.

In “CNN Based Smart Bin for Waste Management” we look into various machine learning models to classify wastes and identify the Inception-V3 model while creating a CNN model from scratch. This model is then trained using a very small dataset. Raspberry Pi will then be used for segregation of the wastes. Inception v3 a particularly important Inception model as it focuses on maintaining the accuracy of previous models from the Inception family while reducing the computational complexity. This model achieved an accuracy of 78.1% on the ImageNet dataset. It is based on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy[25].

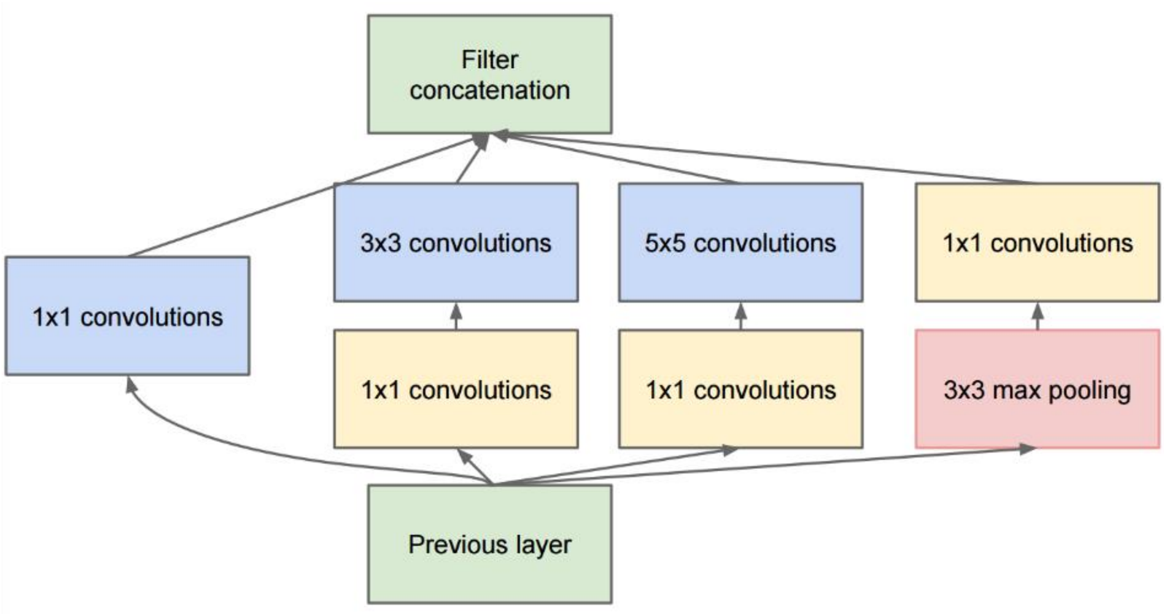


Figure 5: Inception V3 Architecture [25]

The Growth of Machine Learning and Image Classification as a field has led to the creation of Newer, Better, and Faster Models. An example of this is the “YOLO9000 model, which was introduced in the paper YOLO9000: Better, Faster, Stronger” [26]. YOLO9000 is a state-of-the-art, real-time object detection system that can be used to detect over 9000 objects using video footage. YOLOv2 uses techniques like Batch Normalization, Anchor Boxes and Direct Location Prediction to ensure better performance.

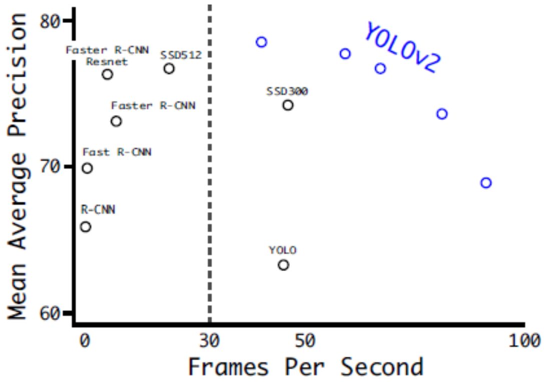


Figure 6: Precision of YOLOv2 with respect to frames per second [26]

A paper by Mapua University describes the automatic waste segregation system using an image recognition module that has a raspberry pi camera and the Inception V3 model being incorporated in the model which is shown to have an accuracy of 75% for the dataset of 2,500 images trained with TensorFlow. This model was able to determine the type of waste thrown and then categorize them as compostable and non-compostable waste. The paper also mentions that the model accuracy can be improved by expanding the training dataset [27].

The paper "Automatic Detection and Classification System of Domestic Waste via Multi-model Cascaded Convolutional Neural Network", mentions how the lack of sustainable waste classification technology has led to the development of newer technologies in this field of waste segregation, there exist several deep learning methodologies having various advantages in accuracy, speed and size. Waste has different shapes, sizes and overlays, therefore relying on one model with restricted feature extraction capabilities to remove type 1 error predictions is not efficient. Thus, a new methodology proposes the use of multiple deep learning algorithms eventually combining their advantages. Using three sub-deep learning networks DSSD, YOLOv4, and Faster-RCNN to obtain a highly accurate prediction, cascading our classification model with the detection model. This methodology focuses on three main elements, first, they have a detection and classification system which works with a CNN model to classify kitchen waste and non-kitchen waste. Second, this system has an MCCNN (Multi Cascaded Convolutional Neural Network) neural network that combines the advantages of different neural networks to improve detection and decrease the number of false positives. Third, this system utilizes the LSWID which is a large dataset for domestic waste classification, which improves the overall average accuracy by 10% [28].

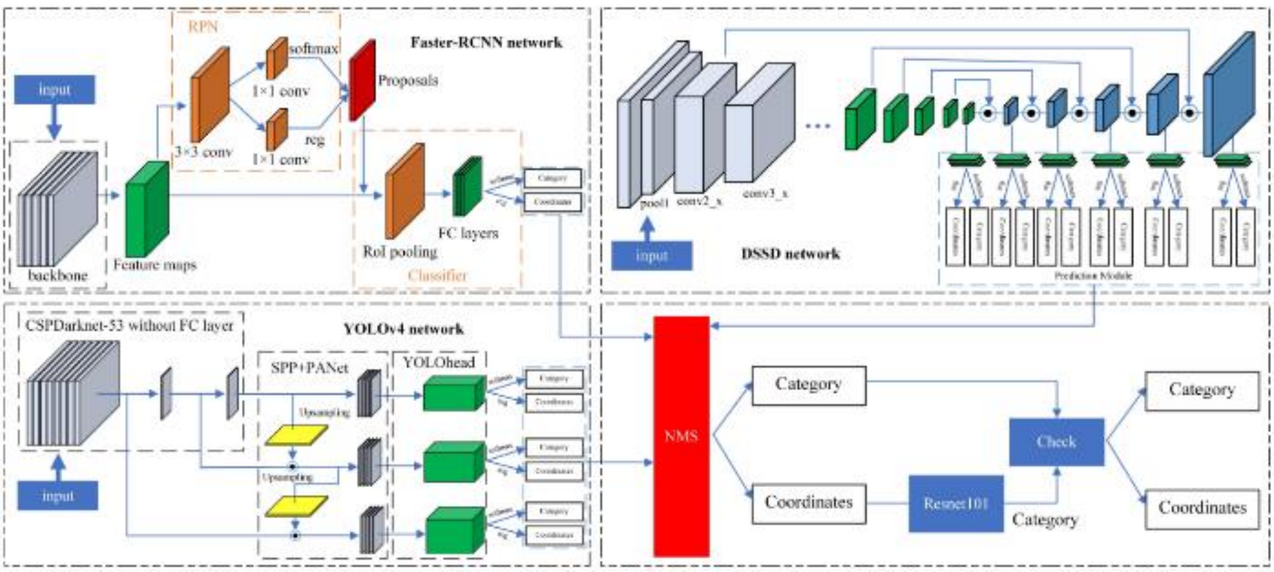


Figure 7: Faster RCNN [28]

In the paper CompostNet by the students of UC Santa Cruz, they have proposed a model that provides machine learning solutions to categorize waste produced after eating a meal. They utilize the dataset that was collected for TrashNet, which consisted of 2527 images of classes glass, plastic, cardboard, metal, paper, and trash. The dataset was appended with photos of food waste and landfill waste. This dataset was then used for their two versions of CompostNet, the first version utilized a pretrained MobileNet that was partly retrained to the new dataset. The second version of CompostNet was built with three convolutional layers and was run for 20 epochs, the model's final testing accuracy was 22.6%. The first version had an accuracy of 77.3% for the same number of epochs, this version of CompostNet was a better model than compared to CNN TrashNet. This model was then implemented on a mobile device using the TensorFlow Lite [29].

In the paper AI-based Waste Classifier with Thermo-Rapid composting, they incorporate a method of segregation utilizing the technology Computer machine Vision and deep learning. To improve classification, they use the Support Vector Machine (SVM). SVM plots its data in an n-dimensional space with its feature at a specific coordinate and its value. The image of the waste is captured using a Raspberry pi high-quality camera and then the image is processed and classified by a popular deep learning model YOLOv3 weights which were trained using accurately collected data. This is then classified as organic and non-organic. The organic waste then undergoes the Berkley Method of rapid composting [30].

In a paper by Hamad Bin Khalifa University which addresses the problem faced by an image-based classification of waste materials, they propose an approach called double fusion where multiple deep learning models are combined using fusion and score-level fusion. This paper explores the strengths of many early and late fusion techniques individually and jointly combined. This method proposes a three-step process- Feature extraction, Classification, and Fusion. Feature extraction is done by several deep models and SVMs-based classification. After classification, the capabilities of early and late fusion are fused which is the main strength of the process. This methodology is then compared with classical individual deep models and then concludes that the fusion of early and late fusion methods performs better than the best individual fusion methods [31].

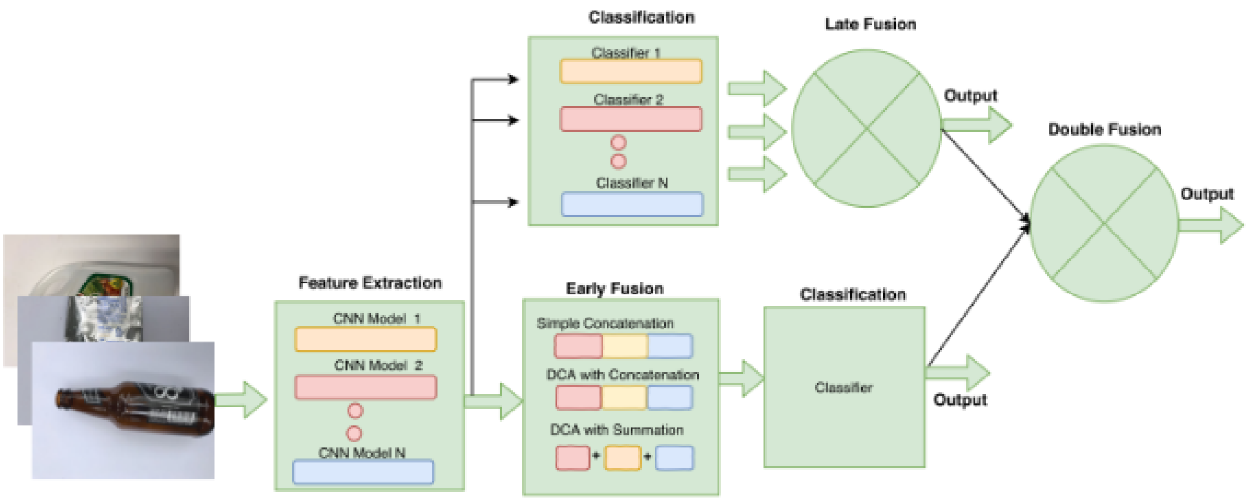


Figure 8: Multiple Fusion CNN

"An Internet of Things Based Smart Waste Management System Using LoRa and TensorFlow Deep Learning Model" is a paper that focuses on LoRa communication protocol and real-time object detection and classification. The object detection model is pre-trained with images and a frozen inference graph is utilized for object detection. The model uses SSDMobileNetv2 to perform waste classification locally, this reduces the dependency on the cloud and without internet connectivity. LoRa communication is employed to inform the authorities of the status of the bin and its location [32].

In a paper published by the Hebei University of Engineering and Hebei Weilifang Technology, taking into account of classification, identification of solid waste, a multi-object solid waste classification and detection method based out of transfer learning is introduced. The Faster RCNN model is built through ResNet50 +RPN, the transfer learning method is structured to handle the detection and classification of multi-target solid waste with high accuracy. This method effectively reduces the training time of the model at a higher rate of accuracy. The region proposal network makes the model reach a higher accuracy in the detection of different types of waste in an image. The results of this model also demonstrate that it can classify five types of waste in case of varying background, object obstruction, and other cases with good generalization capability [33].

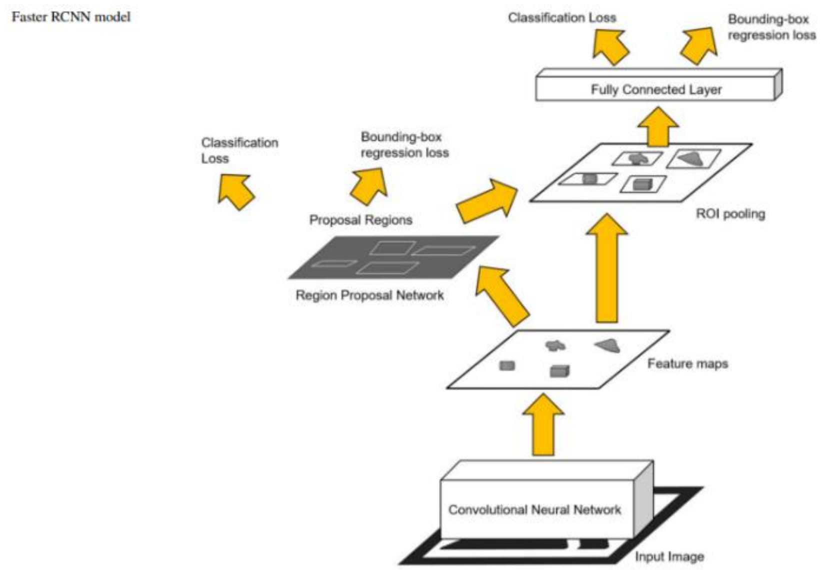


Figure 9: Faster RCNN + ResNet 50 [33]

In a paper published by Zhihu Yang and Dan Li, WasNet, a data augmentation combination was constructed for training the model. Then, a lightweight neural network was designed called WasNet. This neural network was designed referring to the previously present highly accurate neural networks. The dataset was continuously altered for a number of convolutional layers and the depth and the width of the network to get the optimal network architecture. WasNet was found to be more efficient than the currently popular lightweight neural network [34].

The paper “Waste Classification using Convolutional Neural Network on Edge Devices” proposes a brilliant classification system that is created using a deep pre-trained Xception CNN model classifying wastes into 4 categories. The dataset created by Thung and Mindy Yang which is the TrashNet dataset is used to train the model. The Xception model is used as the base model for transfer learning. The Xception model uses a depth-wise convolutional model with residual connections. On training the model for about 15 epochs it led to an accuracy of about 92%[35].

Chapter 3

Drawbacks in Existing Systems

In the present situation, Waste segregation is an extremely important but difficult task. The world produces 2.01 billion tonnes of solid waste annually with 33% of that not managed in an environmentally safe manner.

The mechanisms that exist for a smart bin now are based on various sensors, for example, in the case of one the papers we've reviewed, they have used ultrasonic sensors which aren't very viable and consume more power and takes more time making it less efficient in high traffic scenarios like malls.

Most of the existing models segregate dry waste into recyclables but our model's aim is to segregate wet waste, for example, a banana peel and a dry waste item like a steel can. The dry waste is then segregated into different types of recyclables and different operations can be done on them individually like compression of paper which saves us space, etc. Our model can also be trained to deal with biohazardous waste given the current situation of covid-19.

While other models use sophisticated sensors our aim is to integrate the sensors we use with machine learning making it more efficient as there will be more data points that we can filter through. At the same time, we need to make sure the feature extraction we do is as relevant as possible to the problem statement to make sure that our model provides high accuracy and takes less time to process the segregation of garbage.

Our model can be executed at a more budget-friendly price making it possible for us to make a network of these smart bins, unlike other models where the price of the single unit itself is quite high comparatively. Forming a network of these bins helps us carry out the cleaning of the bins and disposing of waste more efficiently which other models fail to do so.

Chapter 4

Impact on Society

The idea of the project resulted from our thought process to help our society fix waste management issues in urban localities. The speed at which waste was being generated was much faster than the speed at which the govt and the municipality were moving. We realized very quickly that there was a significant gap between the disposal and clearing of the waste. The main aim of our project was to help fix these issues in an automated manner that doesn't involve any human interference.

According to reports of the Quantity & Characteristics of Indian Municipal Waste a study that was conducted, stated that the per capita waste generation on average is varying between 0.2KG to 0.6KG in cities with populations ranging from 1.0 lakh to 50.0 lakh. Also every year the net solid waste that is collected in the cities is increasing at a very commanding speed of 5% per year. Helping the municipality not only with segregation but with monitoring will help the environment push towards a more sustainable lifestyle which is turning out to be a necessity for us more than a choice.

The speed at which our model is able to classify will be saving a lot of fundamental resources that are going to waste or could be used elsewhere in other areas to make our nation a more sustainable place to live in.

The normal cleaning-up process which our government is currently making use of takes weeks together from the initial point where the waste is being disposed of at home into different bins based on the type of waste that is being disposed of (i.e. Organic and Plastics), the waste inside the bins are then collected by garbagemen who come in vehicles or vans which are usually very dirty and contaminated because of the waste they travel around with. Then eventually the municipality disposes of the waste into large pits which have been dug up in land paving a pathway for them to generate more landfills. From then on waste is being further segregated by ragpickers who handpick most of the waste of these land filles and are found in abundance in our Country due simply because we generate so much waste. All this hustle and bustle is simply nullified at its early stage because we are solving the issue of segregation at its root cause.

A study by economic times in 2021, stated that the government had allocated up to 40,700 crores for waste management in over 2 lakh localities under the Swachh Bharat Mission. We are sure that we can help reduce such staggering numbers that are being invested into waste management in our country. Our prototype not only saves the government a lot of financial resources but it has the capacity to generate revenue by selling PET plastics, metal, and other waste directly to private organizations, companies, and industries that are in need of this waste in order to manufacture by recycling. Our model's approach to waste classification will save time labor and money for everyone involved in the nation not only the government.

Chapter 5

Project Objectives

Our main objective is to build a framework for smart waste management where machine learning, IoT, and Cloud are seamlessly integrated with one another. The machine learning model is used in the classification of the type of waste being discarded. The IoT model's main use case is for monitoring the bin and the waste inside of it. Cloud platforms are used to store the data collected and our waste classification model.

The following are the main objectives of the project:

1. Creating a Convolutional Neural Network Model for Classification of waste into three classes, PET plastics, metals and other recyclables.

2. Integrating sensors for Monitoring the waste collected.

3. Designing an efficient model of "Smart Bin" for seamless integration of the Classification and the Monitoring system.

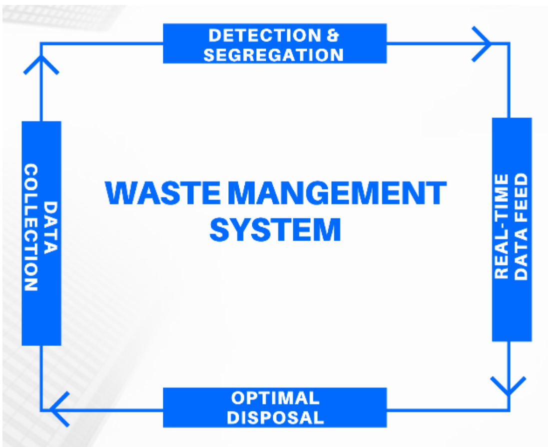


Figure 10: Waste Management System Development Flow

4.1 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, colour 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. Our aim is 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. We aim on integrating the functions of these models for the creation of our own convolutional neural network model. One model which we will draw features from is the Xception model.

The main aim is to create a convolutional neural network model. This model will make use of convoluted layers to classify the images into the three categories given. The accuracy of the model is expected to reach upwards of 90% and the model must be able to classify the images in real-time.

4.2 Integrating sensors for Monitoring the waste collected.

In order to monitor and actuate the Smart bin, the model will be equipped with sensors which interfaces to the Raspberry Pi 3 A+ board.

We aim to create a model which first detects the arrival of a user in order to actuate the bin to allow the user to dispose waste.

The user approaches the Smart bin, sensors equipped must sense and actuate to open the lid of the bin, then as the bin closes when the user presses a switch and the process continues. A camera mounted on top, must be used to capture the image of the waste thrown for classification.

The Smart bin fills up over time and has to be recycled, in order to ensure easy monitoring, we need to implement a monitoring system for the bins to sense the level of waste in each bin, followed by a notifying system that helps authorities to be alerted to clear the bin once it fills up.

Thus, once classification of waste is completed and segregated sensors must be used to monitor the level of the bin. This sensor data is logged on to a cloud platform and used for notifying authorities once the bin is full.

4.3 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.

Chapter 6

System Methodology in Block Diagram

Figure 11: Block Diagram Explaining Project Methodology

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 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 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.

Chapter 7

Implementation of the Project

Our project 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 a 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.

7.1 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 number 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 that has an uneven number of data for each parameter. This could mean that a single class would have 50000 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 under-sampling. Under sampling would mean deleting some data or images from the larger class in order for that class to reach the size of the smaller class.Under-sampling results in a smaller dataset as compared to the original one given. Similar to this another method we can use is known as oversampling. Here we generate artificial data or images which are added to the smaller class until the size of the smaller class.

For our project, 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 10000 images.

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 colours. 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 project 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. Each type of destruction has 10 photographs from different angles. So, taking into consideration all the variants for every object, it tallies up to 40 photographs, multiplying this by the total 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.

Figure 12: Sample Images

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 imbalancing 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 where 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.

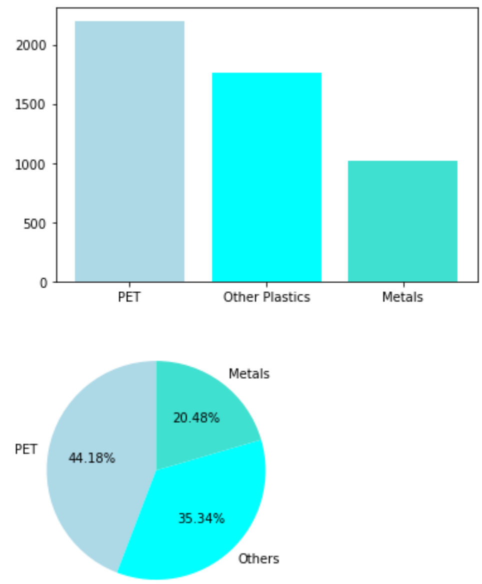


Figure 13: Graphical representation of the Dataset

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 14: Sample Test Image

7.2 Classification Model

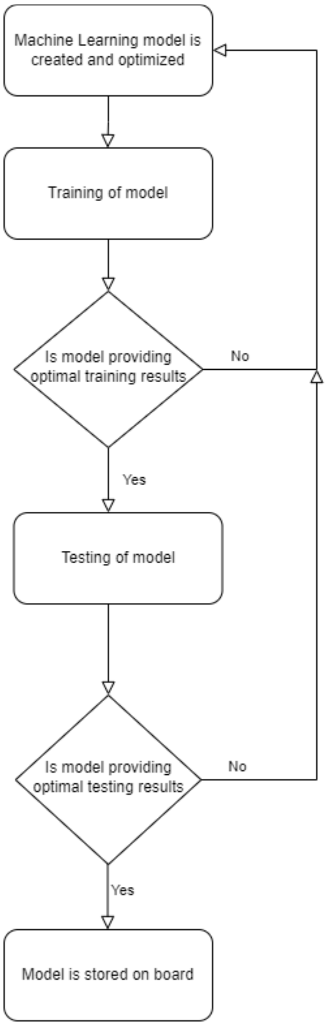


Figure 15: Workflow of creation of Classification Model

The subject of Machine Learning is a branch of 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.

Technically the machine learning algorithm is subdivided into two types – supervised and unsupervised. In supervised learning, we make use of a set of labeled 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 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 project, 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.

Convolutional neural networks are used to highlight features of images. These are usually grooves, lines, or circle's and the way these features are positioned. The presence or absence of these features can be used by the model to predict if it belongs to a particular class. It is this property of CNN that makes it powerful for image classification. One of the key features of convolutional layers is that neurons are organized three-dimensionally which are height 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 around 14 million images, which were organized into a little more than 21 thousand 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 was an annual machine learning model exhibition.

The AlexNet model is a simple convolutional neural network model which consisted of eight layers. The first five were convolutional and max pooling layers followed by three fully connected layers. The first convolutional layers were a filter of size 11x11 with a stride of 4. This would mean that the convolutional filter (or feature vector) was capable of looking at 11x11 pixels of the image at a time and would move at a rate of 4 pixels on completion of scanning the previous 11x11 pixels. If the image taken is of colour, 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 colour). 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 5x5 and a max pooling layer. This is continued with 3 convolutional layers of 3x3 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.

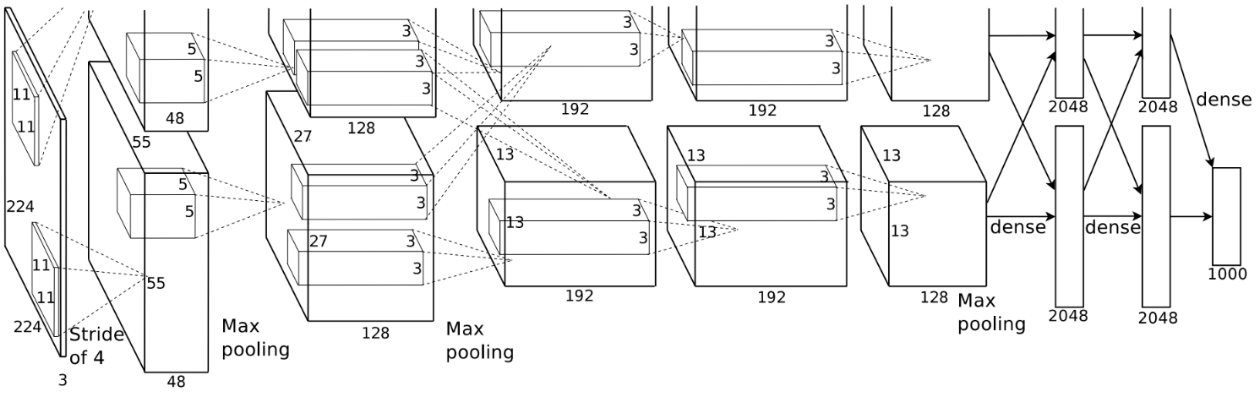


Figure 16: AlexNet Model

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.

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 key idea of this layer is deploying multiple convolutions along with multiple filters as well as pooling layers that co-exists simultaneously in parallel within the same layer. The intention of this is to let the neural network learn on its own the ideal weights while in the process of training the network and eventually automating the selection process of he 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.

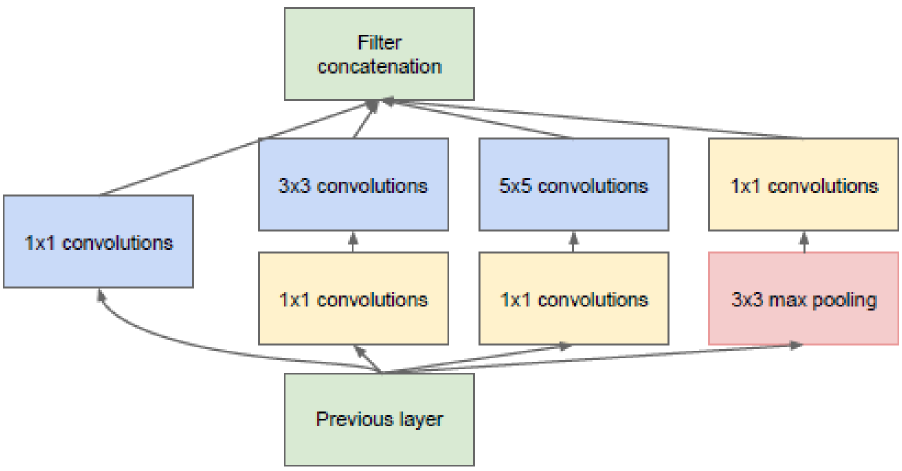


Figure 17: Inception Layer

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.

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, the 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 1x1 filter, while the next has three convolutional levels of a 3x3 filter.

One of the defining features of the Xception model is the use of a Depthwise Seperable Convolution. Depthwise Seperable 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 seperable 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

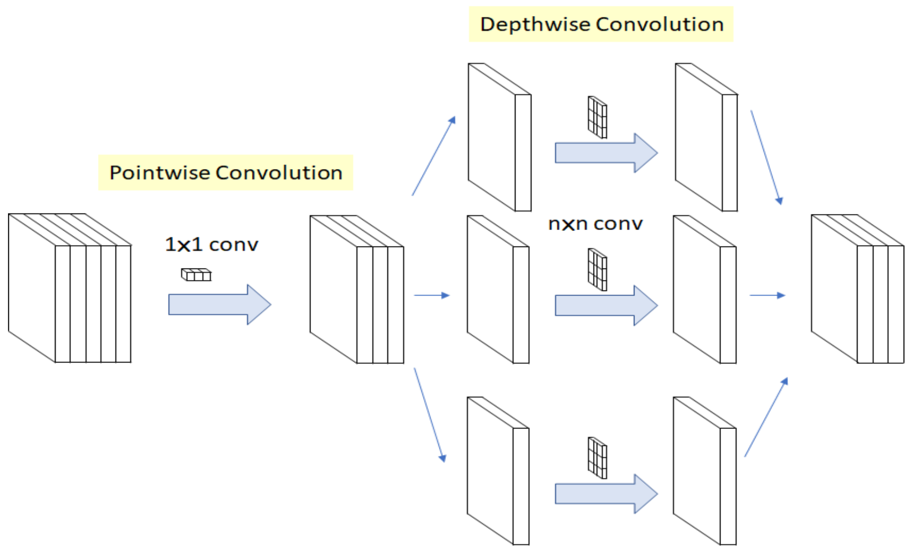


Figure 18: Depth wise Separable Convolution

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**.**

Figure 19: Xception Classification Model

Understanding the features and problems of 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.

The model created for this project 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 11x11 and converts the input layer into dimensions 214x214x32. This layer will provide 11648 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 107x107x32.

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 5x5, 3x3 and 1x1 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 regularizer of L2 regularization. Regularizers 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

Figure 20: CNN Classification Model

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.

7.3 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 Converter 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.

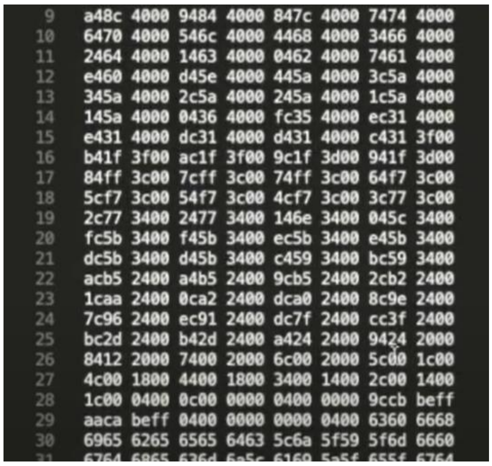


Figure 21:11 Preview of the .tflite file

Once an image is captured from 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 project 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 figure below.

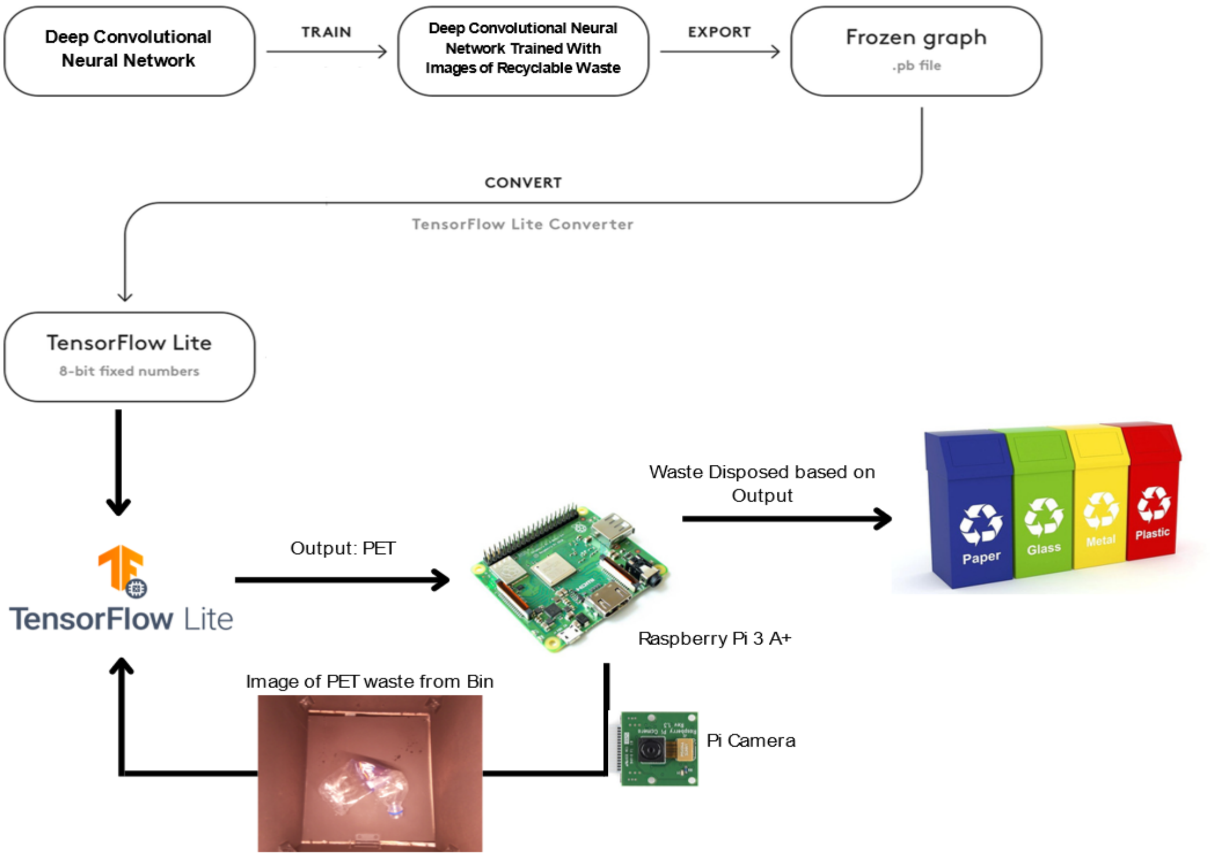


Figure 22: Localized Classification Model

7.4 IoT Model

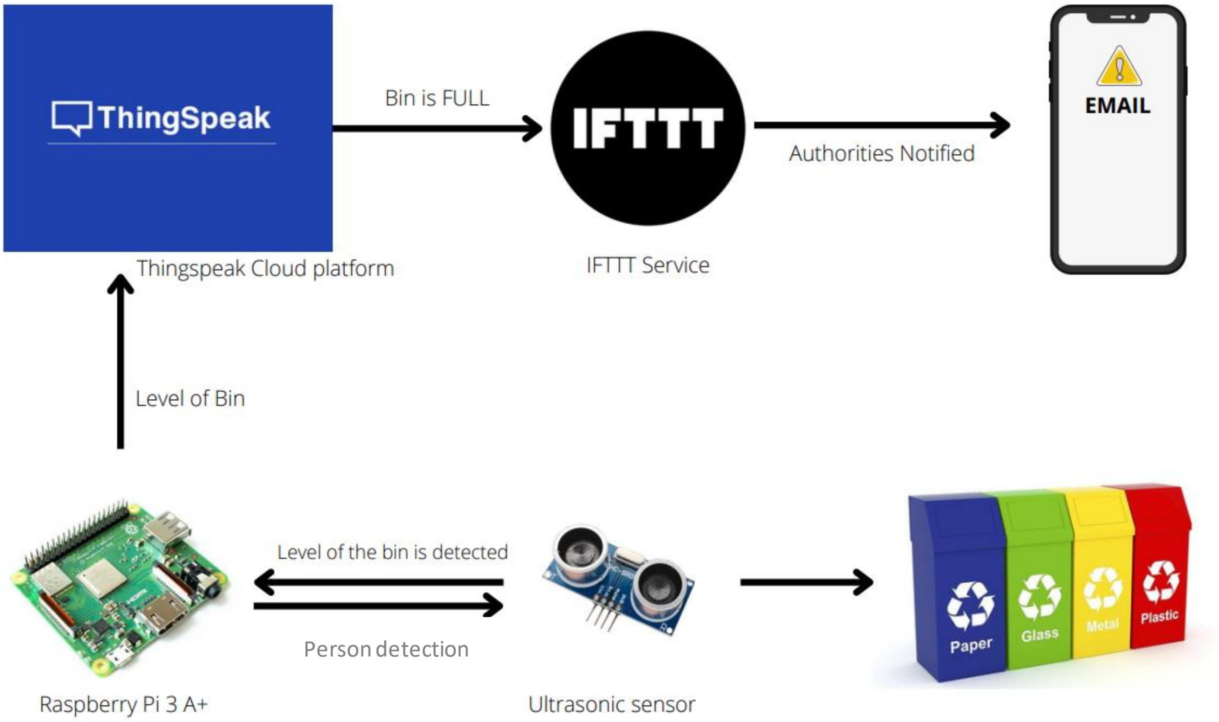


Figure 23: IOT Model

In the IoT model, 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 the figure, the ultrasonic sensors are placed in the front of the bin just below the lid opening.

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 clock-wise 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 seconds which is sufficient enough to put the waste object into the bin for further classification purpose.

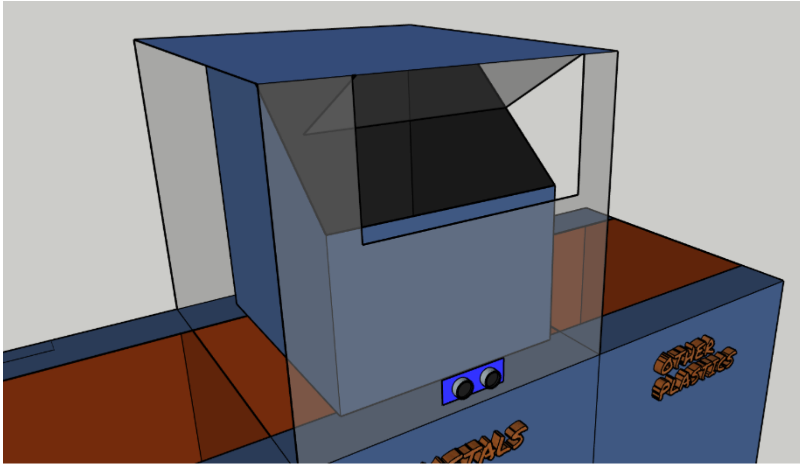


Figure 24:Ultrasonic sensor for Person Detection

For the sole purpose of monitoring the waste bin, we have placed ultrasonic sensors inside the bins. 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 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.

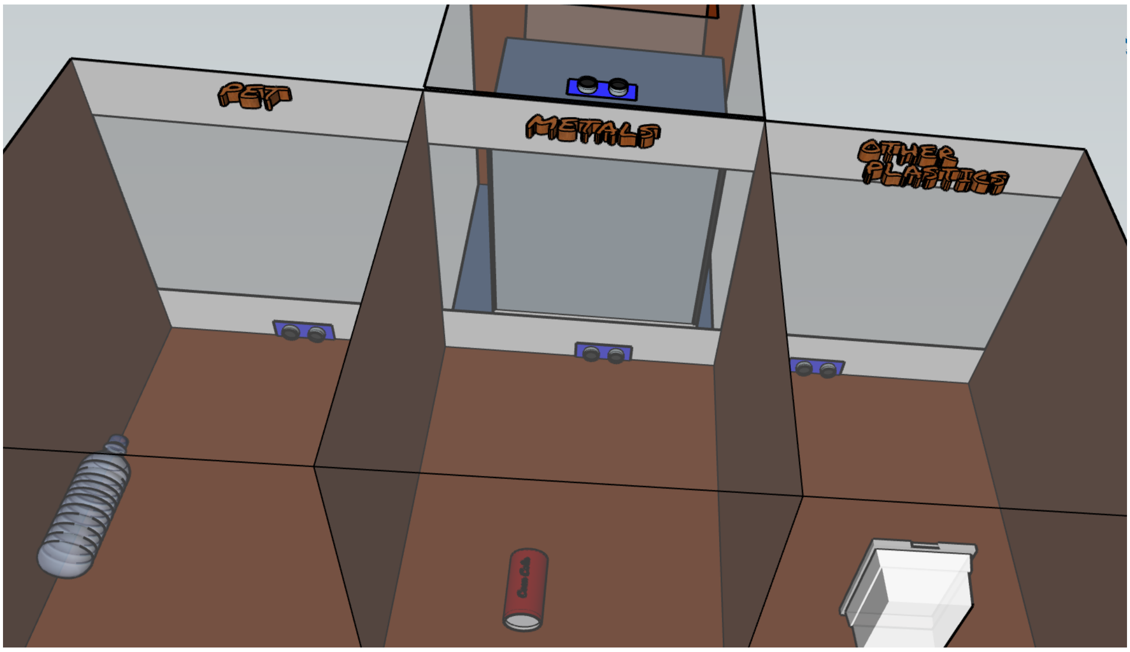


Figure 25:12 Ultrasonic Sensors inside the bin for Level Detection

We have placed QR code scanners on the bins in order 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.

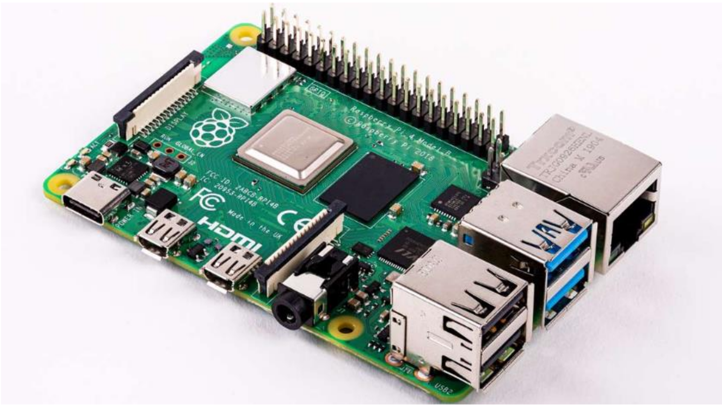
The data collected by ThingSpeak can be used in the time series format, where we can see from the image above/below that we understand the situation of waste collected in the bin at different intervals of time. The intervals of time at which data can be collected will have an order and set which is followed 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?

Chapter 8

Hardware and Software Requirements

8.1 Hardware Requirements

1. **Raspberry Pi:**



The Raspberry Pi is a cost-effective micro-processor, and charge board that plugs into a PC screen or TV. They have been used as a standard console in IoT applications. This little gadget of the size 85.6mm × 56.5mm empowers devices. All things considered, they can also be used to investigate, monitor and register, as well as to figure out how to program in technologies like Scratch and Python.

It is capable of handling all processing power a PC can, from an easy tasks like opening a web page and playing high-quality video, to making bookkeeping sheets and word/phrase-handling.

Furthermore, Raspberry Pi is capable of connecting with the rest of the world and has been widely used in a cluster of computer-produced projects, from music machines as well as parent locators to weather conditions stations and tweeting perching spaces with infra-red cameras. We need to see the Raspberry Pi being utilized by kids all around the world to figure out how to program and comprehend how PCs work.

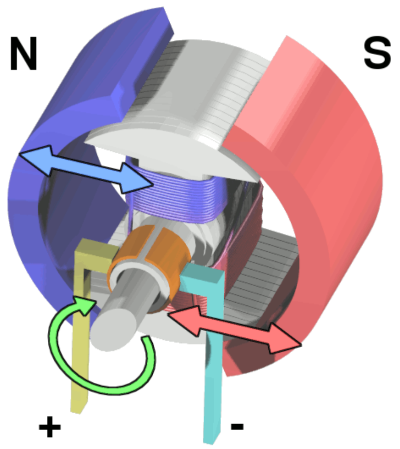
Some of the main features of Raspberry Pi are; that the processor used is a Broadcom BCM2837B0, Cortex-A53. It has storage space or in other words memory of 512MB LPDDR2 SDRAM. The connectivity of the device is configured to 2.4 GHz and 5 GHz.

2. Ultrasonic Sensor:

- An ultrasonic sensor is a device that actions the distance to an electronic device using ultrasonic sound waves. An ultrasonic sensor is one that makes use of a transducer to send and receive ultrasonic heartbeats that transfer back data that informs us about the proximity of an object. It makes use of a transducer device which is used to send and receive ultrasonic pulses that hold some kind of information about another device's proximity from the sensor itself. The sensor decides the distance to an objective by estimating time slips between the sending and getting of the ultrasonic heartbeat.
- Some highlight features of the ultrasonic sensors are; the supple voltage that could be fed to the device is 5V (DC). It has a modulation frequency of 40Hz, with a constant output of 0 – 5V(Output is high when obstacle detected in range).

3. DC Motors:

A DC Motor is a revolving actuator or direct actuator that takes into account exact control of precise or straight position, speed and acceleration. It comprises of an appropriate engine coupled to a sensor for position criticism.



Working of a brushed electric motor with a two-pole rotors also known as armature and also a permanent magnet stator can be seen in the illustration above. "N (for North)" and "S (for South)" assign the polarities to the inside axes of the magnets; the outside have on the other hand have opposite polarities. The + and - signs indicate as to where the DC current is being applied to the commutator faces which in return supplies current to the armature coils.

8.2 Software Requirements

1. Machine Learning Libraries

The creation and optimization of the machine learning model involved the use of many libraries which are available and used by python language. Some of the key libraries were numpy, visualkeras tensorflow, matplotlib, and PIL

Numpy- numpy or numerical python is a python library used for supporting multi-dimensional arrays and matrices. It is the fundamental package used for arithmetic computations in Python. Numpy can be used for multi-dimensional array creation by binding the arrays within square brackets. This is particularly important in the case of image classification as the images are represented in multi-dimensional arrays.

```
(22564,)
[[[255 255 255 ... 255 255 255]
  [255 255 255 ... 255 255 255]
  [255 255 255 ... 255 255 255]
  ...
  [ 41  37 231 ... 238  86  81]
  [244 102  90 ...  10 214  19]
  [ 23 214  56 ... 152 134 239]]

 [[241 242 247 ... 249 243 244]
  [249 243 244 ... 242 248 243]
  [242 248 242 ... 243 242 248]
  ...
  [  6  29 203 ... 255  46  77]
  [230  84  94 ... 251 245 246]
  [251 245 246 ...  15  33 199]]

 [[224 224 224 ... 255 255 251]
  [255 255 251 ... 255 255 255]
```

Figure 26: NumPy representation of image

Visualkeras- The representation of models visually could be a great help in understanding the complexity and issues related to that model. Visualkeras is a Python library that can help visualize neural network architectures. It supports layered style architecture generation which is great for

Convolutional Neural Networks, and a graph style architecture, which works great for most models including plain feed-forward networks.

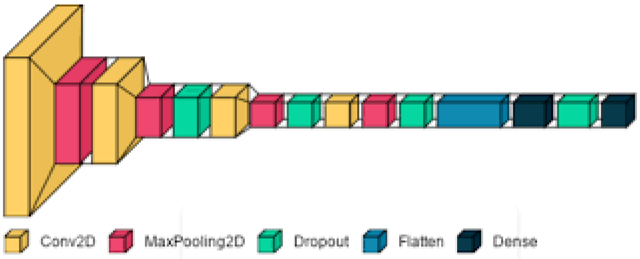


Figure27: Visualkeras model

Matplotlib- Another important visualizer library. This library is used for a visual representation of labeled data. It provides features such as line, scatters, scatter, histogram.

Keras- The first option for deep learning frameworks that you can choose is Keras. This is a neural network interface that was written to work with the Python coding language. This one is a great option if you would like to create some deep neural networks and you want to experiment with it quickly. It also works on top of other options like Theano, TensorFlow, and CNTK.

Keras is great because it focuses more on being user friendly for beginners, extensible, and modular as well. However, it is not able to handle any of the low-level computations that you may want to do. It will do this through another library that is known as Backend.

2. <u>Thonny Python:</u>

Thonny is a free Python Integrated Development Environment (IDE) that was exceptionally planned in view of the fledgling Pythonista. In particular, it has an implicit debugger that can help when you run into terrible bugs, and it offers the capacity to do step aerobics articulation assessment, among other truly magnificent highlights.

However, Thonny is planned for novices, it has a few helpful highlights that likewise make it a decent IDE for undeniable Python improvement. A portion of its elements is punctuation mistakes featuring, debugger, code fulfillment, step-through articulation assessment, and so on.

3. Tensor Flow and TFLite:

TensorFlow is a free and open-source programming library for AI and man-made consciousness. It tends to be utilized across a scope of undertakings yet has a specific spotlight on preparing and derivation of profound brain organizations, it can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.

TensorFlow Lite provides a set of tools that enables on-device machine learning by allowing developers to run their trained models on mobile, embedded, and IoT devices and computers. It supports platforms such as embedded Linux, Android, iOS, and MCU.

4. ThingSpeak:

ThingSpeak is an IoT analytics platform service that allows you to aggregate, visualize, and analyse live data streams in the cloud. You can send data to ThingSpeak from your devices, create instant visualization of live data, and send alerts.

For our case we will be using ThingSpeak to log our data on two elements, the type of waste and the level of each bin. After the results are received from the ML model the waste is categorized and collected in the particular bin, the data on the type of waste is sent to ThingSpeak also updating the level of the bin.

The data collected on the cloud is then used to visualize and trigger an operation. The trigger is used to send the current level of the bin which is "full or needs to be inspected" to the board, this is sent to authorities through email using an IFTTT Service.

ThingSpeak has recently launched a feature in which emails can be sent without any external service, beta phase.

5. IFTT:

If This Then That (IFTTT) is a confidential business organization that runs benefits that permit a client to program a reaction to occasions on the planet. IFTTT has associations with various specialist organizations that supply occasion warnings to IFTTT and execute orders that carry out the reactions. What the organization gives is a product stage that interfaces applications, gadgets, and administrations from various engineers to set off at least one mechanization including those applications, gadgets, and administrations.

Chapter 9

Experimental Results and Analysis

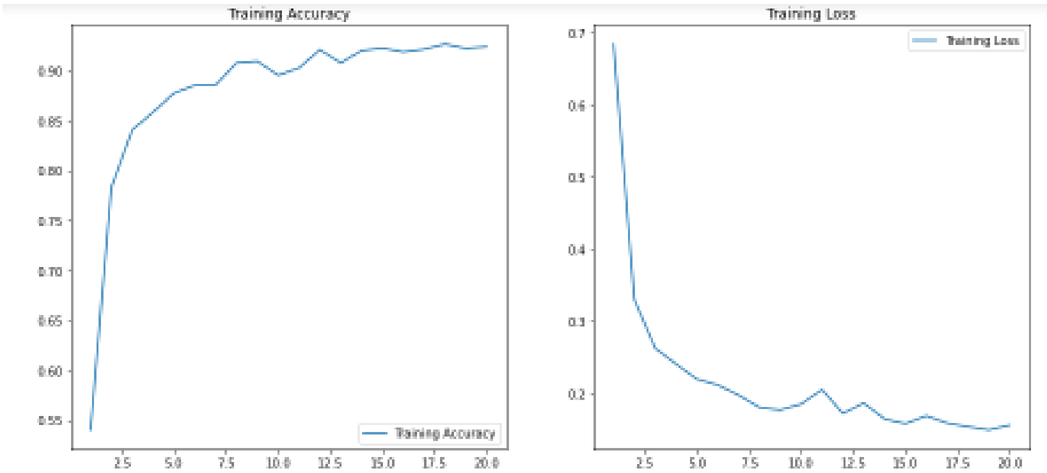


Figure 27: Training Accuracy + Loss obtained

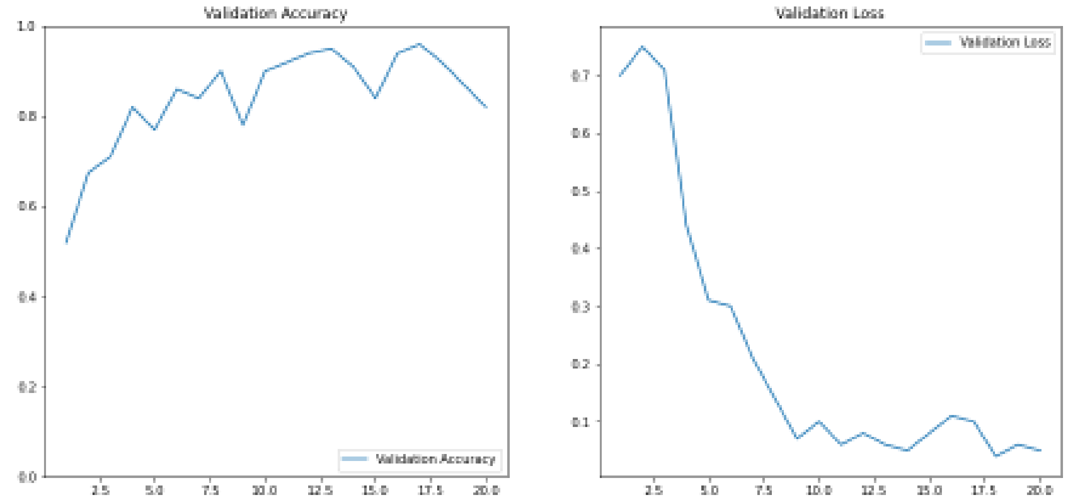


Figure 28: Validation Accuracy + Loss obtained

9.1 Classification Model Accuracy

We have obtained an accuracy of about 92% through our 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.

9.2 Cloud Integration in our Model

We were able to successfully integrate our 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 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. We can see that in 'PET' waste data a lot of data points are collected as it is the most commonly disposed waste. Similarly you can see that data collected for 'Metals' and 'Other Recyclables'.

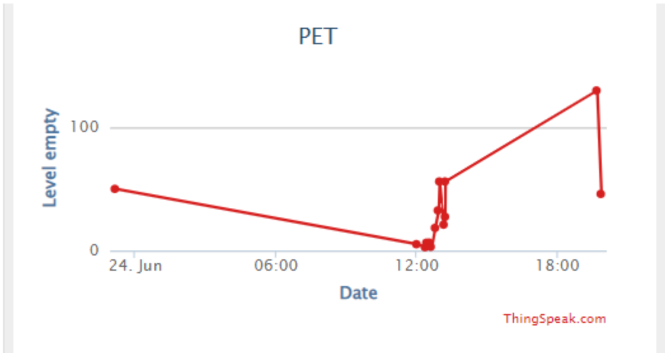
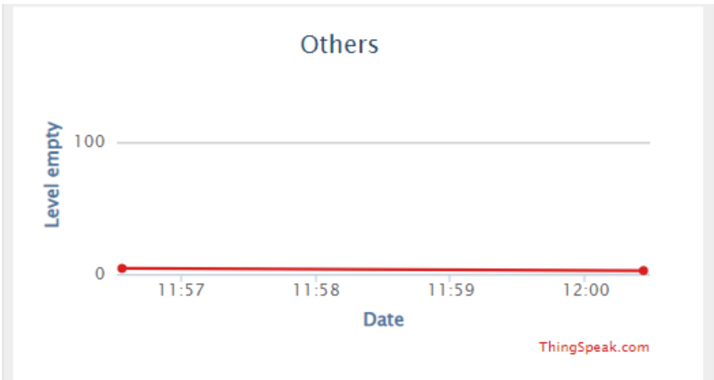
Type of Waste	As displayed on ThingSpeak platform
PET	
Metals	
Other Recyclables	

Figure 29: Thingspeak Graphical data for PET, METAL, Other Plastics

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.

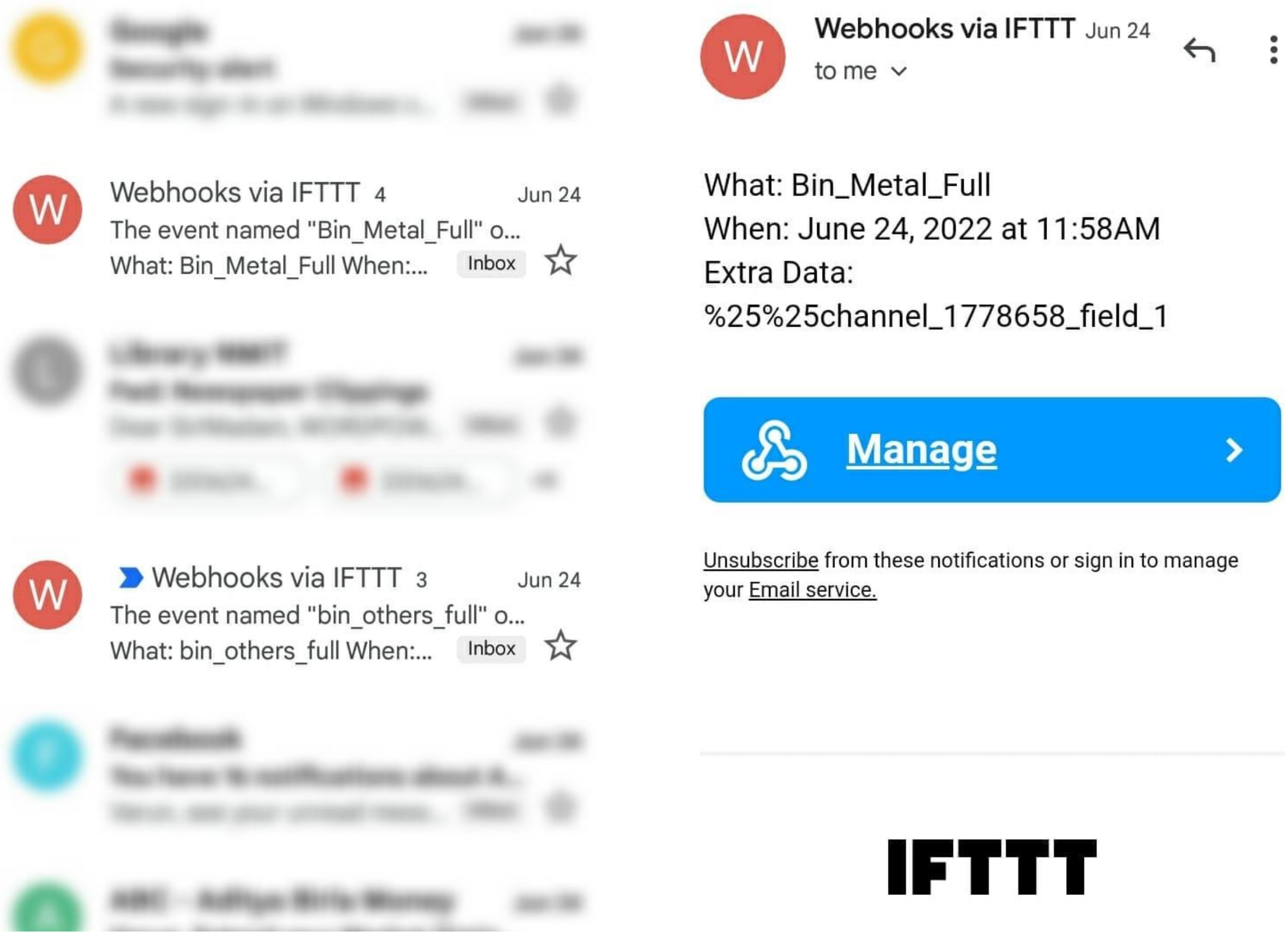


Figure 30: Example of the Email Alert System.

9.3 Development of our Prototype

Figure 31: Prototype 2

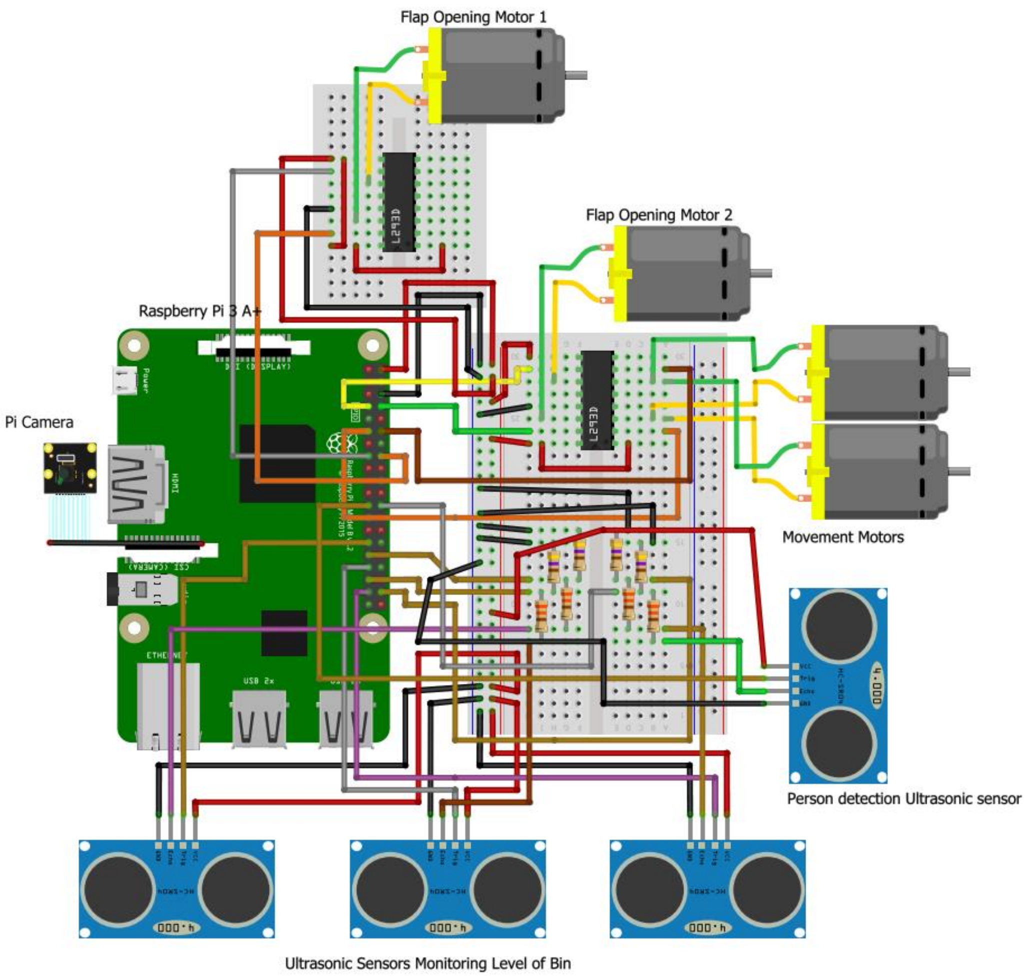


Figure 32: Circuit Diagram of Prototype 2

This is the prototype we built for testing the reliability of integrating sensors into the smart bin through which we have got results meeting our expectations. This prototype 2 is a physical model that incorporates on-board classification of the waste that is thrown in the bin. The model consists of all the hardware and software components mentioned above. The segregator which can be identified as an integral piece of the bin. Which can be identified on top the bin in Figure 18 has the camera module in it. This camera module captures and send the imaged to the Tensorflow Lite file. The Raspberry Pi has a Tensor Flow Lite file which is a compressed and microcontroller compatible version of our CNN model that runs whenever an image is captured, the image is classified as one of the three categories PET, Metal or Others. Once the identification is done the segregator's motors are actuated, it moves to the correct position and drops the waste in the assigned bin. All of this is achieved with Raspberry Pi as the control unit controlling the various components through the sophisticated connections. The circuit diagram in Figure 19 shows the connections made in the prototype.

9.4 Working of the Smart Bin

The working of the smart bin is described with the help of flowing images below:

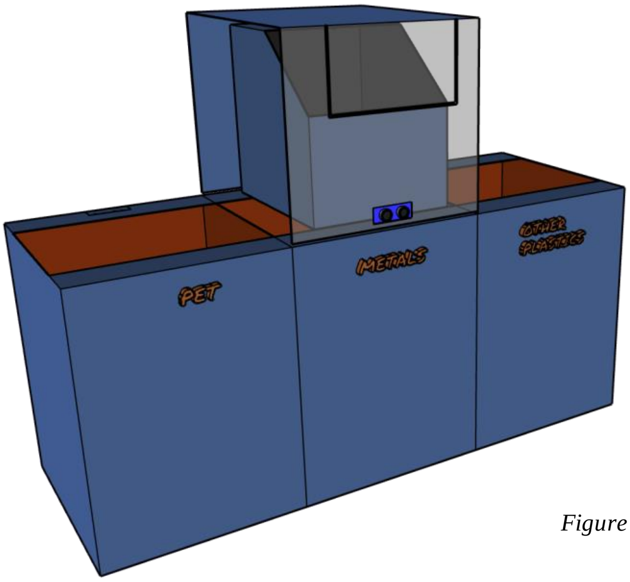


Figure 33: 3D rendered image of Prototype

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

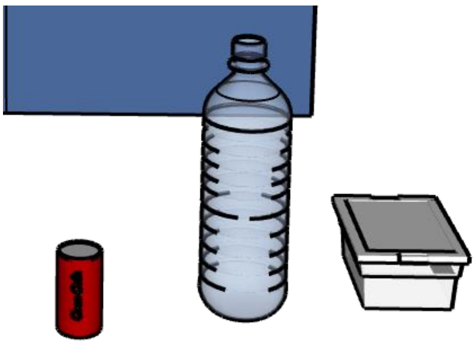


Figure 34: 3D rendered image of 3 types of waste Metal, PET, Other Plastic

<u>When “PET” waste is thrown in the bin:</u>

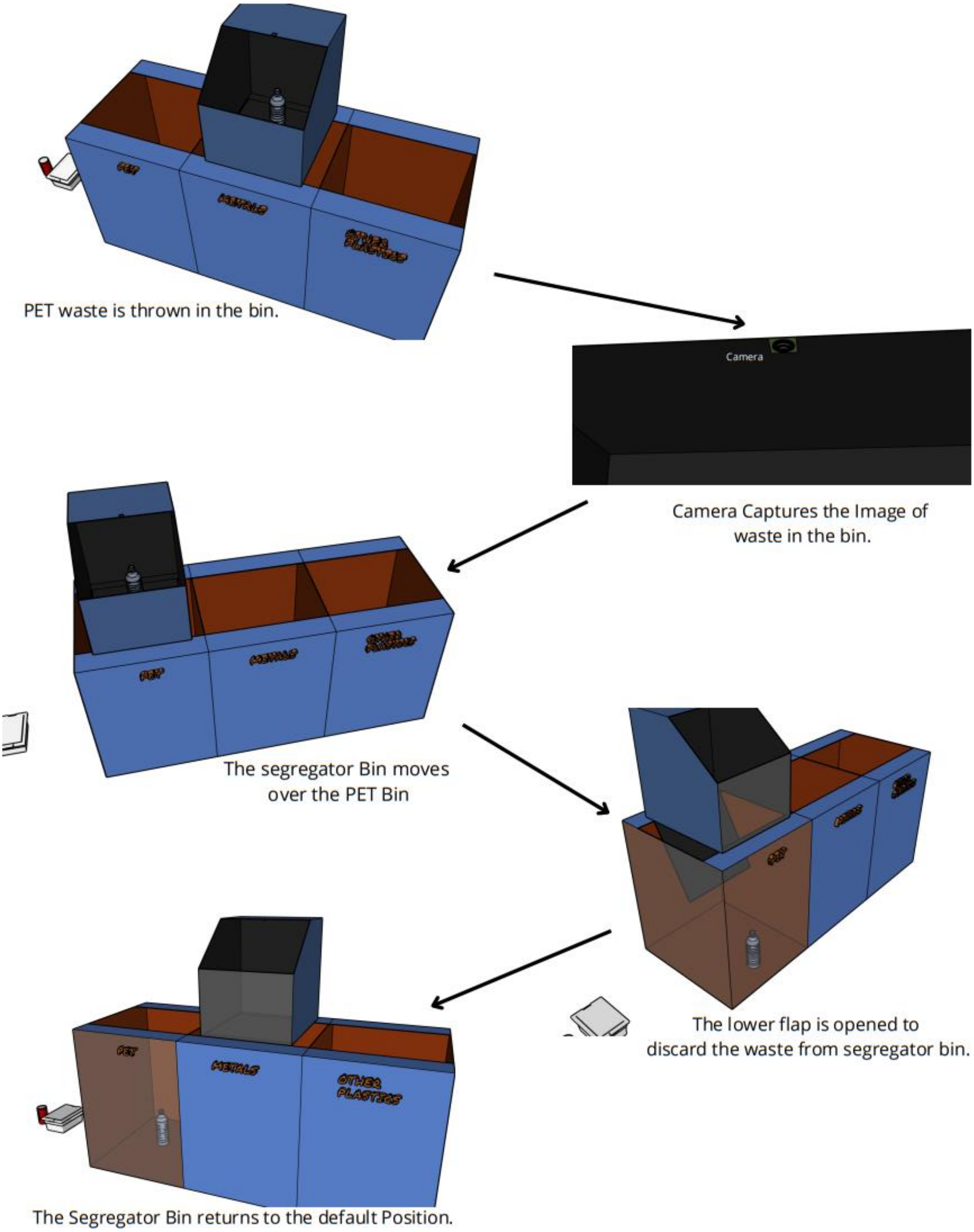


Figure 3513: Working flow for PET waste

When “Metal” waste is thrown in the bin:

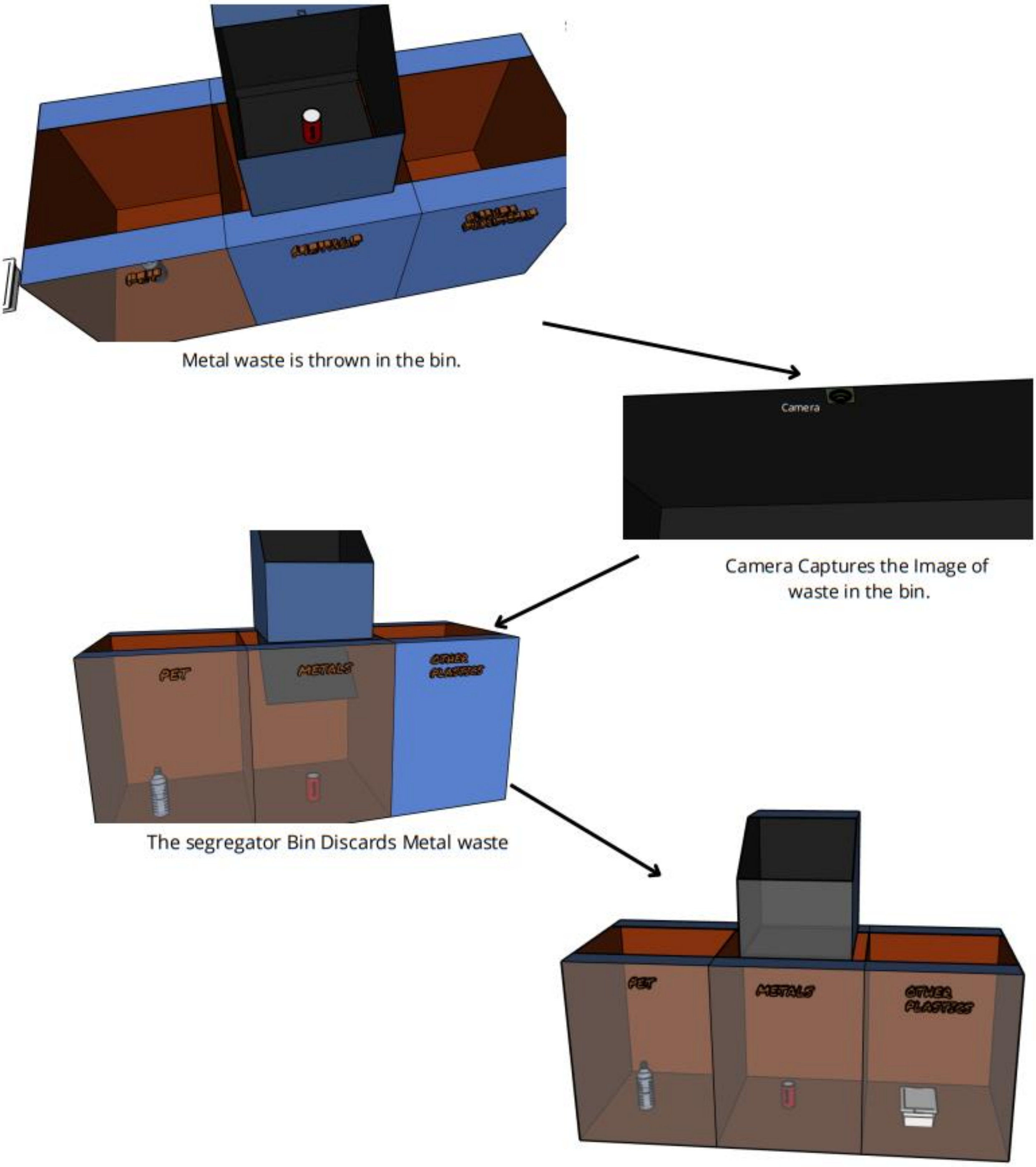


Figure 3614: Working flow for Metal waste

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

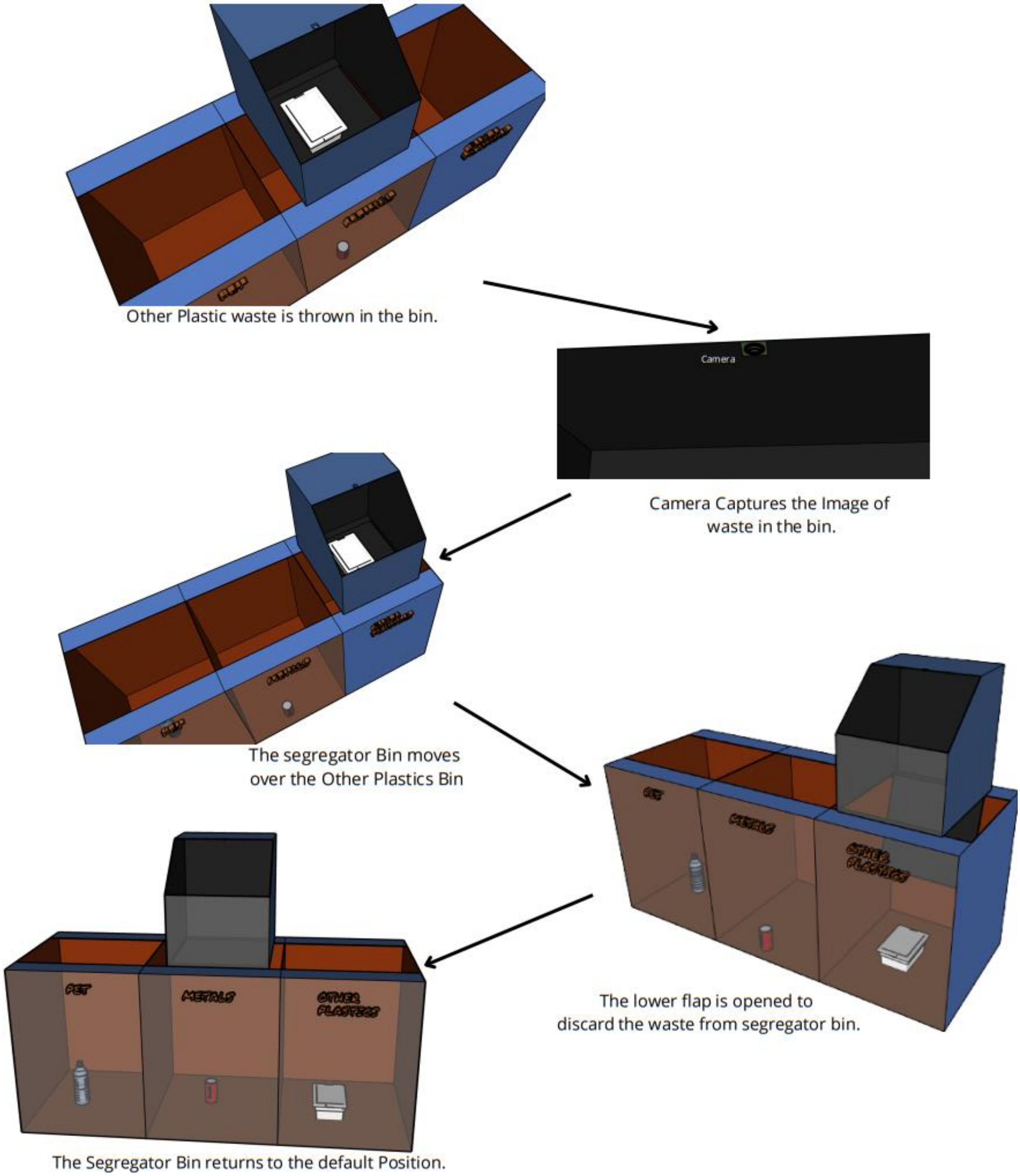


Figure 3615: Working flow for Other plastic waste

Chapter 10

Conclusions

This project Waste Management in Urban localities, provides a solution addressing the current problem of waste management- Segregation. This project follows the principle of Segregation at the source, this method is more efficient and thus faster recycling.

By analyzing the results obtained from the work done so far, it can be inferred that seamless integration of the classification model and the monitoring system is an efficient way in managing urban domestic waste. While we can improve upon our classification model by adding more convolutional layers and dense layers, we can also do this by obtaining a high-level processor for compiling the code, by running more epochs for specific time period. Different approaches with our dataset and data-processing methods can be taken into consideration for improving the classification model.

The timely monitoring of the level of the bin and simulation on ThingSpeak was successful and proves to be a reliable method for data collection and visualization. It is also suitable for notifying the local authorities and monitoring, the framework of Thingspeak and IFTTT service is a suitable for our monitoring system.

The Prototype we built provided 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 IoT architecture and the ML model paves way for more accurate segregation of waste in urban localities.

Chapter 11

Future Scope

11.1 Cloud Model

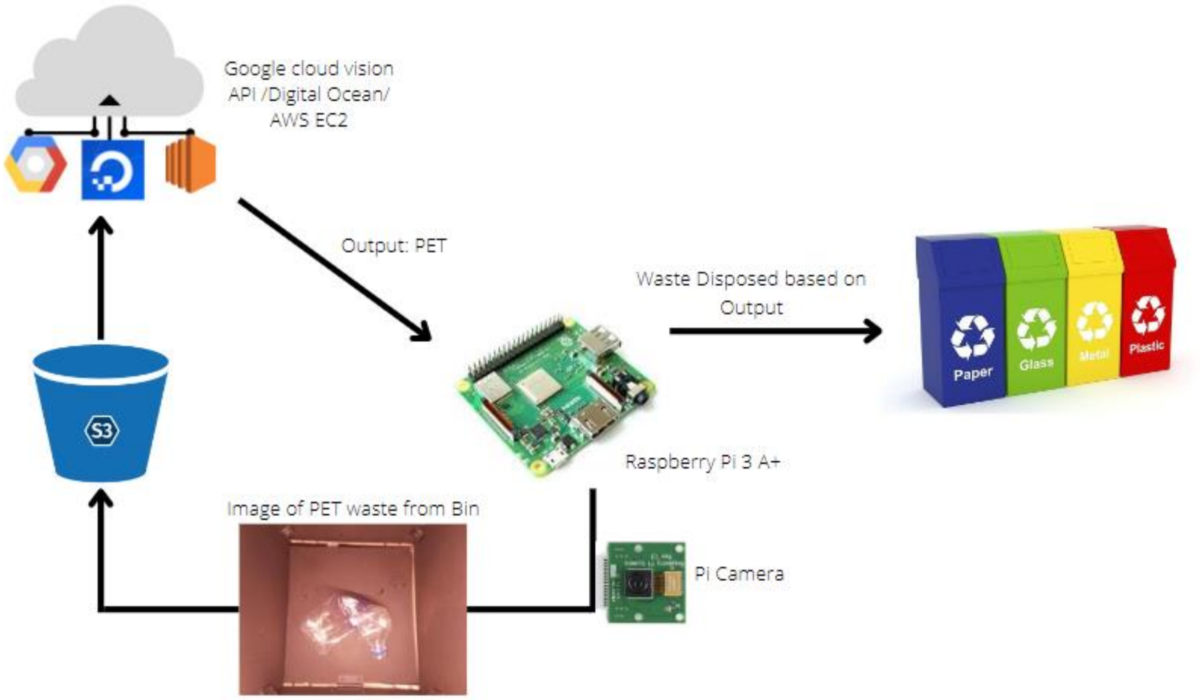


Figure 36: Cloud Model

Another version of this implementation can be done by hosting a cloud platform to run our machine learning model. The Raspberry pi is connected to the cloud via the internet. Once the image is captured from the Pi camera, this data is sent to the cloud which gives an output once the ML model determines the type of waste. This data is then used for segregation.

11.2 Multi-Waste segregator

A major drawback of our model is its ability to only classify one object at a time. If many objects are thrown into the segregator bin at once, they will need to be separated and segregated one at a time. Hence additional implementations need to be in place to ensure that only one object is placed in the segregator bin. Furthermore, having a bin capable of segregating multiple objects at a time provides a larger array of use cases.

One method of segregating multiple wastes at a time is by using image recognition/detection models. These models do not look at the image as a whole but rather identify objects in the image and label them using bounding boxes. The boxes will encompass the object and will be labeled with the predicted output. R-CNN is a popular image detection algorithm.

One major difficulty in the use of the image classification model is the creation of a bounding box training dataset. This requires us to label and bound each object in the image. The images need to be bounded appropriately and should avoid overlapping. Another problem with using the models deals with computational speed and complexity. The models are often very slow in image detection and may not be practical in real-time applications.

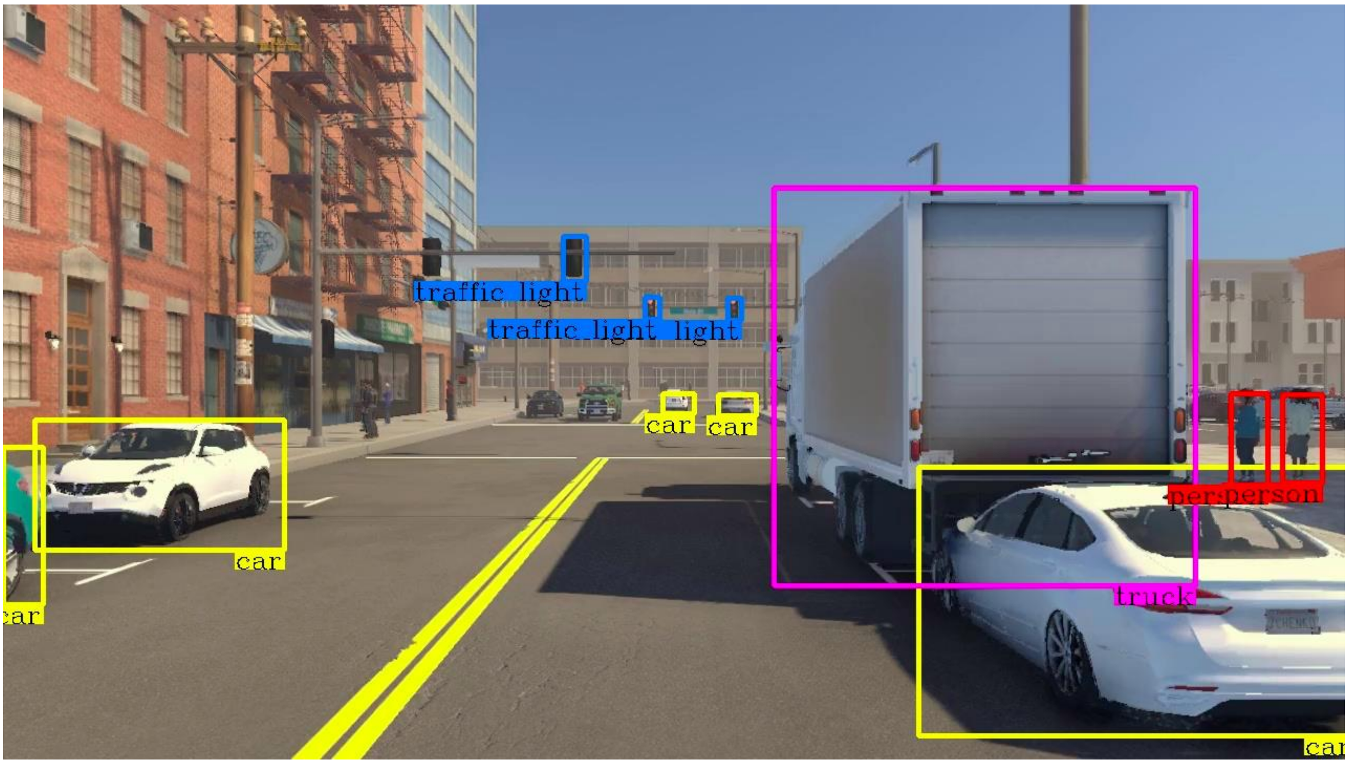


Figure 37:Bounding box image

11.3 Cheaper processor

The processor used for the current project model (Raspberry Pi 3A+) is seen as a more expensive option in terms of processing boards. We can reduce this cost by using the Raspberry pi zero, which can provide the required level of features while also reducing the cost to 700 Rs. The board is also half the size of the A+ series and could fit into the waste segregator easily. However, due to the limited amount of features provided by the board, it does not serve as a scalable option.

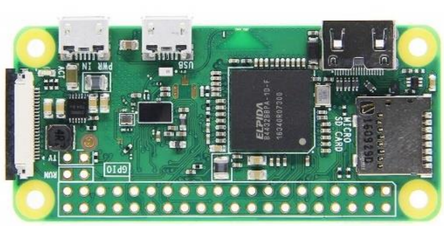


Figure 3816:Raspberry Pi Zero

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