

# IMPLEMENTATION OF SMARTBIN USING CONVOLUTIONAL NEURAL NETWORKS

Sachin Hulyalkar<sup>1</sup>, Rajas Deshpande<sup>2</sup>, Karan Makode<sup>3</sup>, Siddhant Kajale<sup>4</sup>

<sup>1,2,3,4</sup> Student, Dept. of Computer Engineering, Sinhgad College of Engineering, Pune, India

\*\*\*

**Abstract** - A huge amount of solid waste is generated in the urban areas. The waste consists of diverse waste materials that requires different ways of treatment. Hence, this mixed waste cannot be treated all at once in a safe manner. Segregation of waste is an important aspect in waste management. It has been attracting researchers from all fields as valuable material can be lost beyond recovery if proper segregation and recycling techniques are not used. Till now, human intervention was needed to manually segregate these waste materials. The proposed system has been designed for effective automatic segregation of waste at the source itself, thereby reducing the physical efforts. The system is based on concepts of Machine Learning, Image processing and Internet of Things (IoT). The objective of this project is to capture images of a single waste material and effectively identify and segregate it into four classes viz. Metal, glass, paper and plastic. The model used for this project is Convolutional Neural Network (CNN), a Machine Learning algorithm. This system will ensure effective automated waste management and will speed up the process of segregation without any human intervention.

**Key Words:** Machine Learning, Convolutional Neural Networks, Image Processing, Internet of Things.

## 1. INTRODUCTION

Segregation and then recycling of waste materials is necessary for a sustainable society. The current segregation and recycling processes requires facilities to sort garbage by hand and use a series of large filters to separate out more defined objects. The motivation is to find an automatic method for sorting trash. This has the potential to make processing plants more efficient and help reduce waste, as it is not always the case that the employees sort everything with 100% accuracy. This will not only have positive environmental effects but also beneficial economic effects.

Most contemporary waste management methods viz. landfill and incineration are becoming increasingly expensive and energy inefficient. The financial costs of managing the long-term environmental impacts of waste disposal are at many times not remotely feasible. The purely environmental costs such as negative effects on habitat, wildlife and biodiversity are also recognized. In other words, waste disposal is not sustainable and will have negative implications for future generations.

These landfilled and incinerated waste materials contain plethora of solid waste materials which may or may not be

useful. However, it becomes necessary to segregate the useful materials from the trivial waste materials so that they can be recycled and reused.

## 2. LITERATURE SURVEY

In the last few decades, researchers and scientists have been working on accurately classifying the images into their respective classes. Traditionally, due to lack to computational power and limited image datasets, image classification was very difficult. But today, due to ever increasing processing power of the GPUs and the availability of large datasets, it has become feasible to employ computer vision techniques efficiently.

The segregation of waste includes two basic steps – identification and separation. The traditional waste segregation techniques include weight based segregation, Trommel separators which depends on the particle size, Eddy current separators which is used for segregation of metals, X-Ray technology can be used to distinguish different waste material based on their densities.

Identification of the waste is an important step before separation and it can be done efficiently with the help of different machine learning and image processing algorithms. Convolutional neural network (CNNs) are most preferred for classification of images. The CNNs allow us to extract unique traits from the image and then classify it into predetermined classes. Due to introduction of the GPUs, the computational power of the computers has increased significantly and hence large image datasets can be processed in a very short amount of time and thus CNNs have gained popularity in the last few decades.

1. According to a recent study by George E. Sakr, Maria Mokbel, Ahmad Darwich et. Al. Convolutional neural networks have had a great impact on pattern recognition. Before the introduction of CNNs, features were manually picked and designed and then followed by a classifier. The CNN have provided an extra advantage which allows it to automatically learn the features from the training data. The architecture of CNN makes it especially potent for image recognition. The study suggests that large labelled data sets have become available for training and validation. Moreover, CNN learning algorithms have been implemented on the massively parallel graphics processing units (GPUs) which accelerate learning and inference and thus it becomes favourable for image recognition [2].

- Gary Thung and Mindy Yang of Stanford University presented a report that suggests that CNNs can be effectively used for classification of trash materials. The report also states that by tuning the hyperparameters appropriately, the accuracy of the CNNs can be increased significantly. Moreover, the dataset also plays a crucial role for determining the accuracy of the model. Thus, the accuracy can be increased substantially by adding new images to the existing datasets [1].
- An "AutoRecycle" project by Huafeng Shi, Saurabh Bondarde and Vishakh B V of Columbia University built a prototype which allowed the waste material to get segregated into the respective compartment of the dustbin after identification. The prototype used a flap mechanism to redirect the waste into the respective compartment. A camera is used to capture the image and once the identification data is received, high torque stepper motors are used to rotate the flaps to a desired angle so that the waste material falls in the appropriate compartment of the dustbin [5].

### 3. MOTIVATION

Waste management has become the need of the hour and it becomes a necessity to separate the waste materials at the point of origin. Segregation of waste at the point of source is extremely important because then it becomes very easy to treat those waste materials independently for further reusing and recycling. The amount of waste generated is nowhere close to the amount of waste recycled or treated.

Biodegradable (wet waste) and non-biodegradable (solid waste) is currently being separated using manual methods (putting solid and wet waste into separate bins). Using these methods, the wet waste can be effectively used for creating manures, fertilizers, bio-gas, etc. But this is not the case for dry waste. Dry waste may contain useful waste materials like metal, glass, paper, etc. which can be efficiently recycled and reused. A traditional method of dry waste segregation includes incineration i.e. burning of the waste. Manual separation of solid waste is a very tedious task and inefficient. Hence, segregation of dry waste at the point of source is very crucial to avoid further use of complex segregation techniques at the waste disposal sites.

#### Motivation for using CNN -

There are various machine learning algorithms besides CNNs for classifying images like Artificial neural networks (ANNs), SVMs, RNNs. It is observed that CNN outperforms most of the ML algorithms when it comes to image classification provided there are large number of images present in the dataset.

### 4. METHODOLOGY

The project is divided primarily into 3 modules: -

- The classifier module.

- The Raspberry Pi module.
- The website module.

#### 4.1 Classifier module

For predicting the category to which the incoming waste material belongs to, the Machine Learning algorithm of Convolutional Neural Networks (CNN) is used. The model classifies the incoming image into one of the four classes – metal, plastic, paper or glass. Around 400-500 images of each class were used [1]. The images mostly contain household waste items like plastic bottles, soda cans, plastic cups, paper bags, glass bottles, etc. The dataset collected by Gary Thung and Mindy Yang was also referenced for this project [1]. We are periodically updating the dataset with more images so that the system will be able to accurately classify a wide variety of waste materials into their respective categories. As CNN is a type of deep learning algorithm, the data gathered was not large enough to obtain a workable accuracy of the model. We were able to solve this problem by using image augmentation techniques. During the training phase, we used the following techniques for image augmentation – rotation, width shift, height shift, rescaling, normalization, shear transformation, zoom transformation and horizontal flipping [4]. We used these transformations randomly so that our model would never be able to see the exact same picture twice. This helped us generalize our model better.



Fig-1: Actual Image





The algorithm works in a two-phase cycle, the forward pass and back propagation. During the forward pass, the image is passed to each of the above layer and the output is calculated. The expected output is compared to the actual output and the error is calculated. After the error is calculated, the algorithm then adjusts the weights i.e. the spatial values of each of the filters and the biases upto the first input layer. This adjustment of the weights or the spatial values of the Filters is the backpropagation phase. This backpropagation phase is used in conjunction with optimization techniques such as gradient descent to lower the error as much as possible.

The CNN used in this project was implemented in Google's TensorFlow using Keras, which provides a high level of abstraction over TensorFlow. All the images in the dataset were resized to 150x150 before feeding as input to the network. The network was constructed in the following manner –

- Layer 0 – Input Image of size 150x150x3.
- Layer 1 – Convolution with 32 filters of size 3x3 with stride 2
- Layer 2 – Max Pooling with size 2x2 filter, stride 2
- Layer 3 - Convolution with 32 filters of size 3x3 with stride 2
- Layer 4 - Max Pooling with size 2x2 filter, stride 2
- Layer 5 - Convolution with 64 filters of size 3x3 with stride 2
- Layer 6 - Max Pooling with size 2x2 filter, stride 2
- Layer 7 – Fully connected layer with 64 neurons
- Layer 8 – Fully connected layer with 5 neurons
- Result – Softmax scores, 4 classes

The loss has been computed using binary cross-entropy and the optimizer used is RMSprop. The CNN was trained for around 3 – 3.5 hours on a GTX 1050 Ti. The train/validation split was 350-400/50-100 per class and 50 epochs were used. As augmented samples are used for input, even if they increased the dataset size, they were highly correlated. This could have resulted in overfitting of the data. The problem of overfitting was solved by modulating the entropic capacity of the network – the amount of information stored in the model. A model that can store a lot of information has the potential to be more accurate but it also ends up storing irrelevant features. In our case, we used a very small CNN with few layers and few filters per layer alongside data augmentation and dropout of 0.5. Dropout also helps reduce overfitting, by preventing a layer from seeing twice the exact same pattern. Thus, the model which stores less information ends up storing just the most significant features found in the data and are likely to be more relevant and generalize better.

### 4.3 Raspberry Pi Module

The Raspberry Pi is attached to the Smart Bin model and is the brains behind the working of the Smart Bin. The following are the tasks which are executed by this module: -

1. Capture the image only when the waste falls into the bin.
2. Send the image to the classifier.
3. Control the servo motors to redirect the waste in such a way that it falls into its respective bin.

This module captures the image only when the waste falls into the bin and sends it to the classifier module. A PIR sensor is used which detects if the waste has been kept in the Smart Bin or not. The PIR Sensor is controlled using GPIO pins. As the Raspberry Pi is not computationally powerful enough to perform the operation of predicting the type of the image, the classifier has been offloaded to another, more powerful machine. The Raspberry Pi and the classifier communicate with each other via Dropbox. Using the GPIO Pins of the Raspberry Pi, this module controls the servo motors, which in turn tilt the flaps according to the incoming waste [5]. A database has been maintained which keeps a track of all waste which has been segregated by the bin. The entries in the database are also updated by this module.

The Segregation Mechanism works in the following manner:

The Smart Bin has a main flap which turns in two directions. The main flap is used for placing the waste object. There are two sub flaps present. The waste from the main flap falls on any one of the two sub flaps according to the result [5]. Based on the result, the two sub flaps further turn in two directions, providing a way to redirect the incoming waste into one of the four compartments.

### 4.4 Website Module

The website module consists of code in HTML, CSS, PHP and JavaScript. The main job of the website module is to provide the information and at a glance look at the overall waste processed by the bin. In the analytics part, this module reads the data updated by the Raspberry Pi module and also provides a graphical monthly statistical report about the percentage of waste segregated by each bin, which enables the user to gain an insight about how much quantity of waste of each type has been processed by a particular bin. A smart tip is also displayed which enables the bin manager to take corrective measures if certain amount of harmful waste (say plastic) is becoming out of control in a certain area.

The website for analysis of the smartbins is live on <http://smartsegregator.heliohost.org/mywebsite.php>

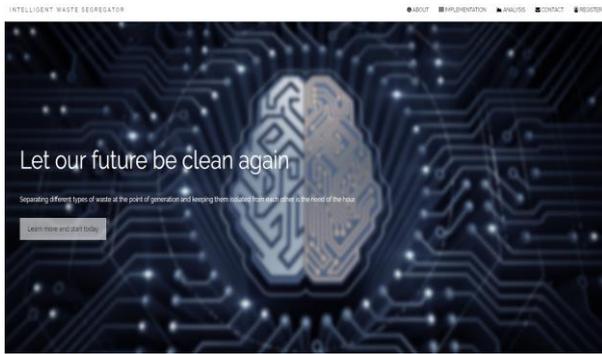


Fig-6: Website Home page

### 5. RESULTS

Initially by using totally different models of CNN, we couldn't achieve an accuracy which was large enough to accurately segregate most of the waste materials. By using the aforementioned hyperparameters for the CNN, we were able to achieve around 85-90% accuracy on training data and 80 - 86% accuracy on validation data.

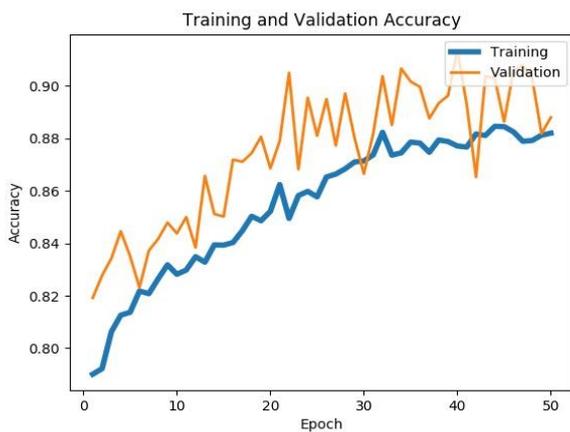


Fig-7: Training and Validation Accuracy

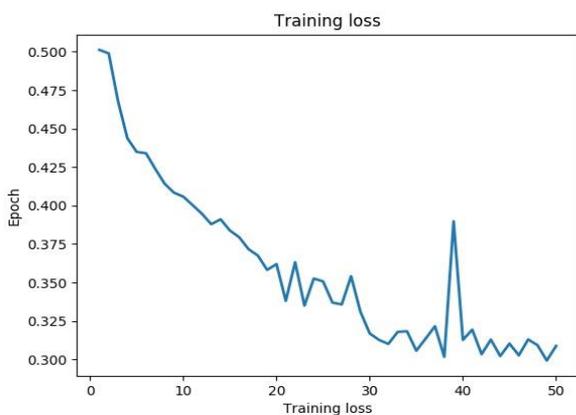


Fig-8: Training Loss

Following are the confusion matrices for each of the classes: -

		Predicted:	
		NO	Yes
Actual:	NO	TN = 4	FP = 1
	Yes	FN = 1	TP = 4
		5	5

Fig-9: Confusion Matrix for Metal

		Predicted:	
		NO	Yes
Actual:	NO	TN = 4	FP = 0
	Yes	FN = 0	TP = 6
		4	6

Fig-10: Confusion matrix for Plastic

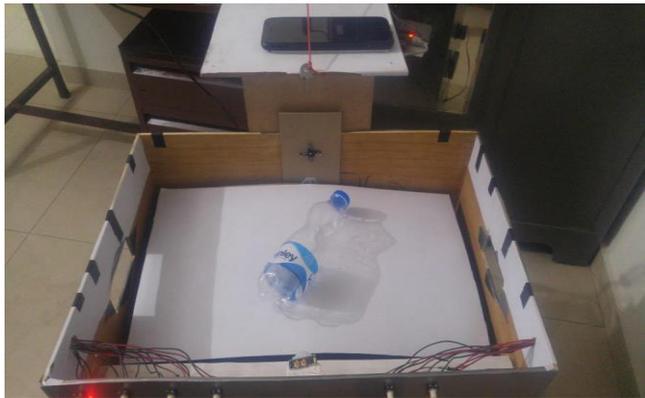
		Predicted:	
		NO	Yes
Actual:	NO	TN = 1	FP = 3
	Yes	FN = 4	TP = 2
		5	5

Fig-11: Confusion matrix for Paper

		Predicted:	
		NO	Yes
Actual:	NO	TN = 1	FP = 3
	Yes	FN = 4	TP = 2
		5	5

Fig-12: Confusion matrix for Glass

The Smart Bin was also able to accurately redirect the waste according to the result of the classifier into their respective compartments by using the servo motor mechanism. We ended up adding a mechanism to virtually convert one Smart Bin into four Smart Bins. The idea was to place multiple models of the Smart Bin at various locations to get information about the waste materials segregated at those locations. To simulate the working, by just pushing a button, the Smart Bin is converted to another location – the change is that instead of updating the entries of location 1 in the database, the Smart Bin now updates the entries of the Location denoted by the button in the database.



**Fig-13:** Object Placed on the main flap

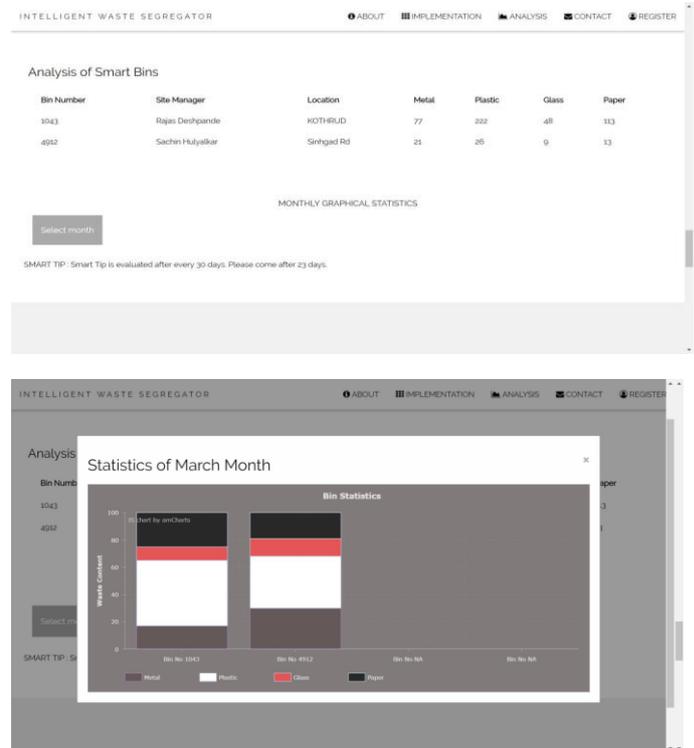


**Fig-14:** Flaps turn according to the result



**Fig-15:** Object segregated

The results are also displayed on the website. The website provides an at a glance view of the percentages of the waste material segregated by the Smart Bin at each of the Locations according to the month.



**Fig-16:** Analysis of SmartBin

## 5. CONCLUSION AND FUTURE WORK

The system is able to efficiently identify and classify the waste products into metal, plastic, glass and paper with an accuracy of around 84%. By adding more images to the dataset, the system will be able to classify a wider range of materials accurately. The input image dataset can be changed to a more application specific execution of this system. For instance, this system can be used in fast food chain restaurants like McDonalds and Subway where it would be able to classify the waste materials like soda cans, tissue papers, plastic cups, wrappers, etc.

Further advancements can be made in the system to increase its accuracy and effectiveness. Multiple robotic arms can be used to segregate the waste materials into the respective bins to speed up the segregation process, instead of using servo motors to redirect the waste who segregate only one object at a time into the bins. The concepts of image segmentation can be used to separate multiple waste materials in the same image. Occlusion Detection can be done in order to find the hidden objects. Furthermore, sensors can be used in the trash cans in order to keep a check on the waste levels.

## ACKNOWLEDGEMENT

We are grateful to our guide Prof. S. R. Hiray for her unwavering support and clear guidance. We are also grateful to our review committee for giving some valuable suggestions.

## REFERENCES

[1] Gary Thung and Mindy Yang, "Classification of Trash for Recyclability Status," CS 229, Stanford University, 2016.

Available: <https://github.com/garythung/trashnet>

[2] George E Sakr, Maria Mokbel, Ahmad Darwich, Mia Nasr Khneisser and Ali Hadi, "Comparing Deep Learning And Support Vector Machines for Autonomous Waste Sorting" in Multidisciplinary Conference on Engineering Technology (IMCET), IEEE International, November 2 - 4, 2016.

[3] Fei-Fei Li, Justin Johnson and Serena Yung, "CS 231N Course Slides and Notes", Stanford University. [Online]

Available: <http://cs231n.stanford.edu/>

[4] Francois Chollet, "Building powerful image classification models using very little data", [Online]

Available: <https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html>

[5] Huafeng Shi, Saurabh Bondarde and Vishakh B V, "AutoRecycle", Columbia University, 2016. [Online]

Available:<http://icsl.ee.columbia.edu/iot-class/2016fall/group8/#results>

[6] Amrutha Chandramohan, Joyal Mendonca, Nikhil Ravi Shankar, Nikhil U Baheti, Nitin Kumar Krishnan and Suma M S, "Automated Waste Segregator", IEEE 2014

[7] Matej Ulicny, Jens Lundstrom, and Stefan Byttner "Robustness of Deep Convolutional Neural Networks for Image Recognition", Intelligent Systems Department, Halmstad University, Box 823, S301 18 Halmstad, Sweden, Springer 2016.

[8] Ian Goodfellow, Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016.

[9] S. Sudha, M. Vidhyalakshmi, K. Pavithra, K. Sangeetha and V. Swaathi "An automatic classification method for environment: Friendly waste segregation using deep learning" in Technological Innovations in ICT for Agriculture and Rural Development (TIAR), 2016 IEEE, July 15- 16 2016.