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An Analytical Approach for Waste Segregation Using Machine Learning Techniques

Under the guidance of
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Abstract. Waste minimization is one of the most significant difficulties facing recycling systems in big cities in the United States. An estimated 62 million tons of rubbish is created in India each year. Plastic materials account for 5.6 million tons of the total garbage generated. Every year, around 60% of this waste is recycled. Furthermore, 11.9 million tons of solid trash are recycled from the 43 million tons of solid garbage that is produced. The segregation of garbage before composting or any other waste treatment operations is a severe challenge in the recycling business, despite the fact that the numbers appear to be in the positive direction. At the moment, garbage collected from households in India is not separated into several categories. It will take a significant amount of labor and effort to sort through this garbage. In addition, persons who work in this field are at risk of contracting a variety of illnesses as a result of the harmful compounds that are contained in the trash. As a result, the goal is to reduce the amount of human interaction while increasing the efficiency of the waste separation process. The suggested study aims to develop a Convolutional Neural Network-based image classifier that can distinguish between different types of waste materials and identify the object in question. Four distinct Convolutional networks models developed on Image Net are proposed in this study to extract characteristics from photos, which are then input into a classifier to generate predictions and distinguish between different types of garbage and the categories to which they belong. ResNet50, DenseNet169, VGG16, and Alex Net are the models that were used. ResNet50 exceeded all four models by a significant margin, whereas DenseNet169 outperformed them by a distance that really was closer to those of DenseNet169. Based on the experimental data, it was determined DenseNet169 excelled all four models by a significant margin.

Keywords: Waste segregation, deep learning, Convolutional Neural Network, Pre-trained models

1. Introduction

Recycling is an extremely significant phenomenon in maintaining a healthy and environmentally friendly environment. Due to increased public awareness among Indian citizens about the need of recycling products in order to reduce the use of environmental assets and rubbish disposal, the recycling business is thriving. People would be willing to utilize increasingly recycled products and to give back to the community by dumping of their waste in a manner that is environmentally friendly. Because of this, it is necessary to redirect more garbage to recycling companies, which can only be accomplished by proper waste segregation [1].

Every year, millions of tons of rubbish are generated around the world, with about one lakh tons of waste being produced every day in India. It is estimated that about 90% of this debris gets deposited into landfills or bodies of water. This has the potential to have a big negative influence on the environment. To maximize the number of recycled products and to decrease the risk of further waste contamination, it is necessary to sort the waste as quickly as feasible. Waste may be automatically sorted at both the local and regional levels with the use of clever garbage bins in this regard. It is currently necessary to perform human labor in order to recycle no biodegradable garbage.

Diverse recycling facilities for waste recycling, as well as the incorporation of a broad range of philters with tools, are required in order to remove complex elements of form from the current recycling process. Strengthening this extraction process would help to improve plant performance by reducing waste and waste sorting time while also minimizing waste generation. Aside from that, as opposed to manual classification, this would improve classification precision, which would be beneficial to both environmental and economic sustainability. The machine is fed a continuous stream of pictures in a manner similar to that which is used in garbage disposal facilities. The image makes a distinction between related things and categories each one independently in the process. It is necessary to divide photographs into six groups in order to employ the image recognition algorithm. Using this strategy, we can swiftly distinguish recyclable goods from non-recyclable objects using only a single photograph.

In addition to recycling, non-recyclable garbage is dealt with methods such as burying, burning and plasma combustion sometime after waste segregation has been completed, thereby eliminates materials that may degrade the quality of adjacent water bodies, soil, or air when burnt or buried. Hand-picking has become impossible as the volume of rubbish has expanded in tandem with population growth.

To address this issue, we can automate the entire process by developing a classification algorithm that used a convolutional neural network (CNN), which would reduce the amount of time required for waste separation while also increasing its efficiency. CNN stands for convolutional neural network, and it is a type of artificial neural network that is widely utilized in image analysis. CNN reduces the amount of pre-processing required for a given image dataset [3]. One of the most important factors in CNN's success has been its capacity to learn high-level abstractions from raw input visual data [5]. Some automatic garbage segregation approaches have already been developed [7, 12], even though they have primarily been focused on embedded applications with the less precise waste classification than is currently available.

VGG16, ResNet50, Alex Net and DenseNet169 are the four pre-trained CNN models that were used in this experiment. For the aim of computer vision research, these pre-trained models have been previously trained on the Image Net dataset, which contains about 22,000 object types [4]. The bespoke CNN architecture necessitates a big amount of data and demands a substantial period of time to train. Being educated upon that ImageNet dataset, pre-trained models are less susceptible to these problems because their weights have previously been tuned. Although the models are not capable of achieving 100 percent accuracy, they are designed to produce a high quality classifier while also minimizing errors to the greatest extent possible.

2. Related Work

It is proposed in this work to employ four separate CNN architectures learned on Image Net to extract characteristics from photos, which are then input into a classifier to generate predictions and classify a type of garbage from the category to which it belongs. The models that were employed were ResNet50, DenseNet169, VGG16, and Alex Net. The experimental results demonstrated that DenseNet169 beat all four models by a significant margin, and also that ResNet50 outscored DenseNet169 by a percentage that was comparable to that of DenseNet169.

It is the goal of the research presented in [2] to simplify this procedure by employing machine learning techniques in the detection of garbage in photos. In recent years, deep learning with CNNs and vector support machines have become two popular learning methods that have been implemented (SVMs). When employing a trash image with 256 to 256 colors, a distinct classifier is generated for each algorithm, which classifies garbage into three primary categories: plastic, paper, and metal, with each algorithm having its own classifier. The accuracy offered by both base classifiers was compared in order to determine which one was the most appropriate, and the one selected by the Raspberry Pi 3 was then implemented. The pi was in charge of a mechanical device that steered garbage away from its original position and into the appropriate waste collection container.

Specifically, the author employs only two neural networks in order to calculate classification speed and apply the most effective models on the Raspberry Pi. Results reveal that CNN scored 94.8 percent correctly, while SVM scored 83.8 percent correctly on the same test. SVM has proven to be exceptionally adaptable to a wide range of waste categories. George E Sakr-et-al. employed the CNN training NVIDIA DIGITS and the SVM training Matlab 2016a to train their CNNs and SVMs, respectively. A limitation of the training sets, according to the author's analysis, was the restricted amount of pictures available. The photos were downsized from their original resolution of 256×256 pixels to a resolution of 32×32 pixels after being compressed. It was as a result of this deterioration that over-fitting became a bigger problem. With regard to the Raspberry Pi 3, the overall execution time of the final model used in this study was extremely short (0.1s).

It took a team of people to develop the Auto Trash Project [3], which is an automated trash can sorting device that separates waste into compostable and recyclable components]. The group utilized Google's tensor flow tool to identify the object, then they developed their own layer on top of it. The can is divided into several sections, and the spinning top can be used to deposit an object in the appropriate portion based on how it was classified. Auto Trash will only categorize commodities into recycled materials or compostable categories; however, categorizing products into more than two major categories will be more beneficial to the recycling process in general.

Spot Garbage[4] is a smartphone-based device that helps people find garbage. There is a rubbish pile that it sees and uses the mobile entry location to pinpoint exactly where the waste is located. In order to classify picture garbage, convolutional neural networks are included in the framework. The GINI (Picture garbage) dataset was used to train this model, which achieved an absolute accuracy of 87 percent. Trash in the immediate vicinity of the user can be reported using this app by individuals. The authors used patches created from Bing Image Searches to train the algorithm, which they then used to test their findings. Using case studies, this study demonstrates how to reduce the amount of memory consumed while increasing the amount of space consumed on the computer. The estimating time taken with zero accuracy errors is also reduced in this study.

When it comes to waste, [5] examines the categorization of waste into six categories that include metal, paper, cardboard, and so on. A manual collection of roughly 400 photographs per group was completed using a list and a pen and paper. The input photos were classified into a number of different groups using the Classification Mechanism Promoting Transforming Functions (SIFT) and CNN classifier, which were the frameworks utilized to classify them. This scenario involved the usage of an eleven-layer CNN architecture in order to create a network that was somewhat comparable to the Alex Net architecture. Experiments have demonstrated that the SVM is more effective when compared to the CNN. Seventy percent of the total data was utilized for training the mechanism, with the remaining thirty percent being used for testing the mechanism. When using a training error of 30 percent, it was possible to reach an accuracy of 63 percent. In order to detect maximum precision, such categories were removed from the analysis because there were no optimal hyper parameters available. This demonstrates that the CNN was not fully validated.

The author of paper [6] discusses the Gray Level Co-Event Matrix (GLCM) technique for garbage detection and classification, which he developed himself. In order to optimize the waste assembly operation, advanced contact mechanization and global location control (GLCM) have been combined. A number of GLAM parameters, including scrolling and quantification, have been examined in order to determine the optimal parameter values in trash photographs. The suggested approach makes use of a range of networking technologies, including geographic information systems (GIS), radio frequency identification (RFID), and general packet radio systems, in order to address current issues and to make solid waste management and performance easier (GPRS). To extract functionality, the GLCM is employed, which is subsequently fed into the multi-layer panel (MLP) and the closest K for waste separation (KNN). The findings supported the notion that the KNN classification method was employed.

Yash Desai and colleagues [7] suggested a method for classifying garbage into degradable and non-degradable categories that makes use of CNN. A flap can be used to separate garbage into different classifications once it has been sorted. Following that, the automated order is of great assistance during the period spent on sanitation. Waste that has been ordered can also be sorted and managed by the companies in a coordinated fashion.

Pushkar Sathe and colleagues [12] offer a micro controller-based autonomous waste rubbish sorting system that makes use of proprietary neural networks. This concept divides garbage into four categories, which are paper, glass, plastic, and metallic waste. Four dust bins are connected to a servo motor, which controls their movement. The system recognizes the type of trash and opens the dust bin that corresponds to that waste type. The disadvantage of this approach is that if any non-recyclable garbage is found, it will be classified into one of the four current categories.

The Convolutional Neural Network (CNN), the Alex Net, and the Bag of Features are three of the methods introduced by Zabir-et-al. [13] (BoF). This study utilized the MCIndoor20000 dataset, which contains photographs of Marshfield Clinic's entrance doors, signage, and stairwells, among other things. BoF generates precision that is approximately identical to that of CNN, proving that machine learning is nearly as good as deep learning in terms of accuracy and precision. According to the findings of the studies, Alex Net exceeds CNN and BoF when it comes to accuracy and precision.

In a study published online, Hoque et al. [14] built a CNN-based method to identify trash and release your trashcan when waste is to be placed in the trash bin, and they shared their findings. Using this strategy, it becomes easier to segregate waste at the most fundamental level. In total, four types of waste have been separated and sorted: glass, paper, plastic, and metal debris.

To tackle the efficiently and successfully collecting waste in rivers that do not flow, Osiany and colleagues [15] conceived and constructed an Automatic Waste Collector (AGATOR), a rotor robotic model, which they called the AGATOR. The complete load can weigh up to 5 kg when it reaches the rubbish can. When collecting rubbish, the robot moves at an average speed of 0.26 metres per second.

The developers of a smartphone application that detects the presence of a pile of rubbish in a photograph completed another project, G.Mittal and colleagues [16]. The photographs were gathered by Bing Image search, and the authors used the Alex Net model to calculate their accuracy, which was 87.69 percent.

Sachin Hulyalkar and colleagues [17] presented a method that automatically separates garbage at the point of generation, minimizing the need for physical effort. In order to construct the application, a confluence of machine learning approaches, picture recognition technologies, and the Internet of Things were used (IoT). By utilizing image recognition software, the purpose of this project is to photograph a single waste item and to identify and categorize it properly into four groups; they are: metals, glasses, papers, and plastics.

Pavithra [19] has designed a smart garbage system that seeks to use infrared sensors and gas sensors, with the gas sensors detecting the presence of dangerous gases in the waste and the infrared sensors detecting the amount of waste in the system's trash bin. RFID tags are installed in a municipal corporation office and connected to a PC. If the garbage bin is completely full, the information is forwarded to the corporate office, which will empty the bin. Unmanned aerial vehicles (UAVs) are used to detect solid garbage, according to a method developed by Anjali and colleagues [20]. The motion of a UAV is used to identify solid waste (UAV). Drones are being used to detect waste by utilizing image processing algorithms that identify waste contaminated regions and provide information to the proper authorities, according to the company. They have interfaced with Arduino, which captures photos, as well as GPS and GSM modules, which are used for communication and location tracking, respectively. The scope of this research is confined to the detection of large quantities of waste, with segregation falling outside the scope of the investigation.

According to Chandaluru Priyanka and Sri Ramya [2], Machine Learning techniques including such SVM, KNN, and Decision Tree were used and compared to CNN in their research. The CNN algorithm outperforms the Machine Learning methods that were previously mentioned. When compared to the datasets of other researchers, theirs is far superior. Studies over the years used less than 1000 photographs to train the model, however they currently use more over 3000 photographs to train the model, according to the findings.

3. Dataset and Data Collection

The images used throughout the proposed work were acquired from a dataset created by Gary Thung and Mindy Yang while doing research on garbage segregation [6]. Initially, there are 2527 photos in this dataset. Because the dataset is so limited, we supplemented it with additional photos obtained from Google Images. As seen in Table 1, some of the photographs acquired from Google Images will be used later in this project and will be inappropriate to just that particular class. They were contributing to a model that is less accurate. As a result, these incorrectly categorized photos have been removed. The dataset is divided into six categories: cardboard, glass, metal, paper, plastic, and rubbish, with a total of 4,163 photos in each category.

Table 1. Details of Dataset

Class	**Number of images In Existing Dataset**	**Number of images of Modified Dataset**
Cardboard	403	651
Glass	501	769
Metal	410	819
Paper	594	909
Plastic	482	878
Trash	137	137
Total images	2527	4163

4. Methodology

It is a technique used to extract characteristics from a dataset that is used in classification. This is performed by categorizing information into different clusters based on the characteristics of the knowledge. A unique model that predictions and classifications is produced by additional training it on previously collected data. A fundamental component of the proposed system is comprised of three main modules: pre-processing, contrast enhancement, and classification techniques. It is the process of multiplying the number of photographs by scaling, magnifying, turning and other means in order to make new photographs. It is hoped that by using this technique, the model will be more accurate in its capture of 'components' and will also be able to accurately predict images with greater accuracy. During the feature extraction process, the system attempts to characterize the unlabeled information as precisely as possible.

1. Architecture of proposed system

Figure 1 depicts pre-trained models that are capable of working with a particular dataset. Following the processing and data augmentation, the pre-trained algorithms pre - trained Convolutional neural database are employed for something like the extraction and categorization of features from the image data.

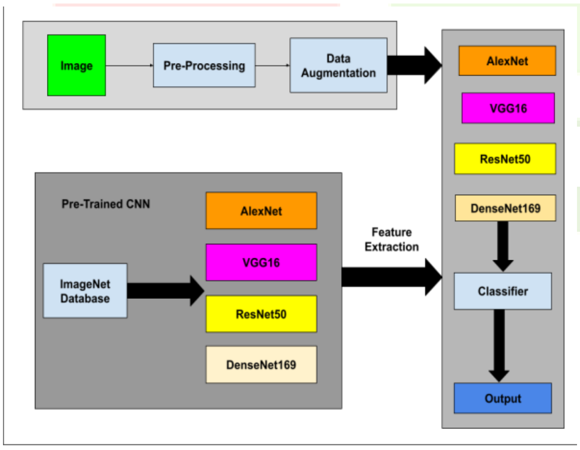

Figure 1. Methodology of proposed work

2. Pre-processing and data augmentation

Pre-trained models are unable to handle the dataset because it is too tiny. Over-fitting is something to be concerned about. As a result, various preparations must be made before to the training model. The addition of photographs from the Google images service more than doubles the amount of the dataset. In addition, various augmentation techniques, such as Randomized Re-sized Crop and Random Horizontal Flip, are employed to enhance the image.

3. Convolutional Neural Network

The Convolutional Neural Network (CNN) is a type of neural network that is widely utilized in image processing. It is distinguished by its hidden layers, which are referred to as convolutional layers. Each convolutional layer is comprised of a collection of filters. These filters look for patterns or characteristics in the photos that can be detected. The following are the layers of the most basic CNN:

1.3.1 *Convolutional layer:* The Convolutional Neural Network (CNN) is a type of neural network that is widely utilized in image processing. It is distinguished by its hidden layers, which are referred to as convolutional layers. Each convolutional layer is comprised of a collection of filters. These filters look for patterns or characteristics in the photos that can be detected. The following are the layers of the most basic CNN:

1.3.2 *Pooling layer:* In this layer, a window with a normal size of 2×2 is placed so over feature map, and the value with the highest optimum amount is identified in the window, with all other values being ignored. It has the effect of decreasing the picture scale.

1.3.3 *Fully connected layer:* During the course of this sheet, the actual image detection and classification takes place. The shrunk pictures are taken and merged into a single vector for further processing. This vector is compared to the vectors derived from the trained images, and the image is classed as a result of the comparison. The CNN architectures that were used in this investigation are listed below.

Alex Net. It has eight layers in total, with the first five stages being convolutional neural networks and the last three tiers being fully connected layers, for a total of eight layers. After each convolutional layer, there is a max-pooling layer to prevent overflow. The activation function of the Rectified Linear Unit (ReLU) is utilized. When it comes to adding nonlinearity, ReLU is recommended over Tanh. It speeds up the process by 8 times without affecting the precision of the measurement. It only accepts photos with a resolution of 256×256 pixels. If the photos are of a different size than 256×256, they are first transformed to 256×256 before being utilized [9].

VGG16. Despite the fact that Res Net will be introduced later, VGG networks are intended to increase the depth of current CNN designs. With a step of size one, the convolution layer makes use of 3×3 filters, which reduces the amount of variables in the structures. VGG networks are substantially more difficult to train when comparing to Alex Net networks. Waste separation is accomplished by the use of a 16-layered VGG network [11].

ResNet50. For the purpose of knowledge transfer, the Residual Network (ResNet) architecture is considered to be a useful starting point. The ResNet50 architecture can be broken down into five steps. In each level, there is a convolutional block as well as an identification block present. Each convolutional block contains three convolutional layers, each of which is a convolutional layer. It is introduced in order to make the training of deeper networks more convenient. In comparison to VGG architecture, it is seven times more detailed while being less complex [8].

DenseNet169. In addition to being unusual in that each layer is related to virtually every other layer in a feed-forward fashion, the Dense Net structure is also very scalable. Each surface will continue to receive picture attributes from all of the layers that came before it. As a consequence, even after multiple levels of processing, the traits remain intact.

Table 2. Initial test set accuracy

Model	Recall (%)	Precision (%)	Accuracy (%)
AlexNet	79.8	82.7	83.7
VGG16	85.1	88.2	86.9
ResNet50	84.2	89.6	89.7
DesneNet169	92.1	92.1	92.6

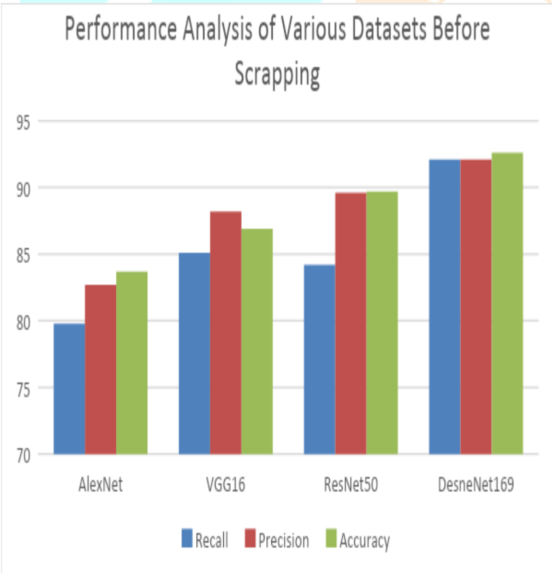

Figure 2. Performance Analysis of Various Datasets using CNN before Scrapping

After adding images and eliminating misclassified images from the dataset, the models performed admirably, as seen in Table 3. The results are reported in Table 3.

Table 3. Accuracy after Scraping

Model	Recall (%)	Precision (%)	Accuracy (%)
Alex Net	84.4	88.8	89.3
VGG16	86.6	90.1	91.7
ResNet50	88.2	90.6	93.4
DesneNet169	92.5	94.5	94.9

In the Dense Net design, the use of functions helps to reduce the number of variables [10, 11, 12].

4. Results and Discussion

After the models has been constructed, the following stage is to monitor the effectiveness of the newly constructed model using a variety of assessment measures.

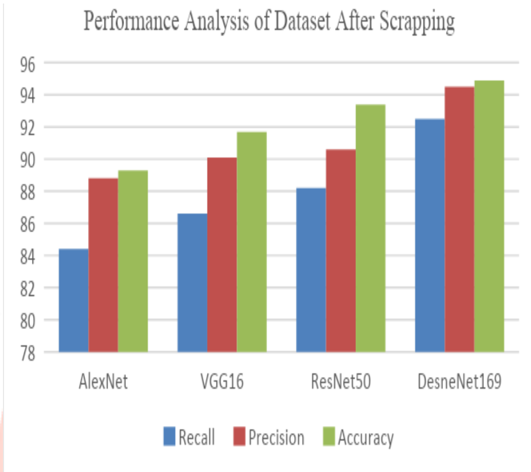

Figure 2. Performance Analysis of Various Datasets using CNN after Scrapping

In spite of the fact that efficiency has not changed considerably in DenseNet169, it has increased by approximately 6 percentage points in Alex Net, 5 percentage points in VGG16, and 4 percentage points in ResNet50, respectively. Therefore, internet scraping as well as the elimination of misclassified photographs proved to be successful in the building of models with poor precision when compared to other methods.

5. Conclusion

Using machine learning, the goal of this study is to categorize waste products into different groups. In order to reach this goal, we used pre-trained architecture as well as six different trash classification categories to help us along. In order to eliminate misclassified photographs from websites, web scraping is performed, and that has proven to be useful in the creation of low accuracy models. When contrasted to the other variants, DenseNet169 outperformed the rest of the competition. The output of ResNet50 is also much more comparable to that of DenseNet169 than the output of DenseNet169. The subcategory of 'glass' is the one who is misclassified or misunderstood the most commonly of the six categories examined here. We must provide extra and clear 'glass' images in order to increase the model's overall clarity.

References

[1] Miranda, Ruben, Blanco and Angeles. 2010. "Environmental awareness and paper recycling". *Cellulose Chemistry and Technology*.Vol. **44**. pp. 431-449.

[2] Chandaluru Priyanka, Sri Ramya P. 2020. Image Based Classification of Waste Material Using Convolution Neural Network, *International Journal of Advanced Science and Technology* Vol. **29**, 5, pp. 2967 - 2975

[3] Albawi S, Mohammed T A and Al-Zawi S. 2017. "Understanding of a convolutional neural network,", *International Conference on Engineering and Technology (ICET), Antalya*, pp. 1-6

[4] Deng J, Dong W, Socher R, L.-J. Li, Li K, and Fei-Fei L. 2009. "ImageNet: A Large-Scale Hierarchical Image Database", *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 248-255.

[5] Bakator M, Radosav D. 2018. "Deep Learning and Medical Diagnosis: A Review of Literature", *Multimodal Technologies and Interaction*.Vol. **2**, 47, pp. 1-12.

[6] Thung, Gary and Ming Xiang Yang. 2016. "Classification of Trash for Recyclability Status.", *Corpus* Id-27517432.

[7] Yesha Desai, Asmita Dalvi, Pruthviraj Jadhav, Abhilasha Baphna.2018. "Waste Segregation Using Machine Learning", *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, ISSN : 2321-9653, Vol. **6**, pp. 537-541.

[8] He K, Zhang X, Ren S and Sun J, 2016. "Deep Residual Learning for Image Recognition", *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, pp. 770-778.

[9] Alex Krizhevsky,Ilya Sutskever and Geoffrey E Hinton, 2010. "ImageNet Classification with Deep Convolutional Neural Networks", *ImageNet Large Scale Visual Recognition Challenge*.

[10] Gao Huang, Zhuang Liu, Laurens van der Maaten and Kilian Q Weinberger. 2017. "Densely Connected Convolutional Networks", *IEEE Conference on Computer Vision and Pattern Recognition*. pp. 4700-4708.

[11] Karen Simonyan and Andrew Zisserman. 2015."Very Deep Convolutional Networks for Large- Scale Image Recognition", *International Conference on Learning Representations (ICLR)*. pp. 1-14.

[12] Pushkar Sathe, Omkar Tawade, Tanmay Kale, Syed Samar Abbas and Diksha Thakur. 2019. "Waste Segregation using Convolutional Neural Network", *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, Vol. **7**, pp. 932-937.

[13] Zabir M, Fazira N, Ibrahim, Zaidah, Sabri and Nurbaity. 2018. "Evaluation of Pre-Trained Convolutional Neural Network Models for Object Recognition". *International Journal of Engineering and Technology (UAE)*.Vol. **7**. pp. 95-98.

[14] Shanjenbam Brojendro Singh, Abu Salah Muslaha Uddin Laskar, Biltu Roy, Aminul Hoque Choudhury, Zahidul Islam, Jakir Hussain Mollah, Shadeed Masood Hoque, Mohsin Ali and Pranav Kalita. 2016. "Design of Municipal Dry Waste Segregating Machine Using Conveyor", *International Journal of Innovative Research in Science, Engineering and Technology* (*IJIRSET*), Vol. **5**, pp. 7156-7162.

[15] Nurlansa, Osiany, Dewi Anisa Istiqomah and Mahendra Astu Sanggha Pawitra. 2014. "AGATOR (Automatic Garbage Collector) as Automatic Garbage Collector Robot Model". *International Journal of Future Computer and Communication*, Vol. **3**, pp. 367-371.

[16] Mittal Gaurav, Kaushal B Yagnik, Mohit Garg and Narayanan C Krishnan. 2016. "SpotGarbage: smartphone app to detect garbage using deep learning". *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing*. pp. 940-945.

[17] Hulyalkar Sachin, Rajas Deshpande, Karan Makode and Siddhant Kajale. 2018. "Implementation of Smartbin using Convolutional Neural Networks". *International Research Journal of Engineering and Technology (IRJET)* ,Vol. **5**, pp. 3352-3358.

[18] Adedeji, Olugboja, and Zenghui Wang. 2019. "Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network." *Procedia Manufacturing*. Elsevier B.V., Vol. **35**. pp. 607–612.

[19] Pavithra. 2014. "Smart Trash System:An Application using ZigBee", *International Journal of Innovative Science,Engineering & Technology*,Vol. **1**, pp. 319-323.

[20] Anjali Pradipbhai Anadkat, Monisha B V, Manasa Puthineedi, Ankit Kumar Patnaik, Shekhar R and Riyaz Syed. 2019. "Drone based Solid Waste Detection using Deep Learning & Image Processing", *Alliance International Conference on Artificial Intelligence and Machine Learning (AICAAM)*, pp. 357- 364.