

Recyclable Waste Classification using Computer Vision and Deep Learning

Swathi A S
Dept of Electronics and Communication
Engineering
VTU CPGS, Mysore
Karnataka, India
swathiasmys@gmail.com

Mrs. Meghashree A C
Dept of Electronics and Communication
Engineering
VTU, CPGS, Mysore
Karnataka, India
meghashree1988@gmail.com

Abstract—Effective waste management plays an important role in reducing environmental pollution and promoting sustainable development. Analysing manual waste is a time-consuming, labour-intensive, and error-prone process. With advances in machine learning techniques, automated waste separation systems have emerged as a promising option. This article provides a comprehensive review of waste identification using machine learning, highlighting the various methods, data, and performance measures used in recent research. We discuss the challenges, opportunities, and future directions for the development of smart waste management.

Keywords—Waste management, automated systems, waste classification, machine learning, performance metrics

I. INTRODUCTION

The growing global interest in environmental sustainability and waste management has led to a growing demand for quality waste products. Traditional methods rely on manual verification, which is expensive, time consuming and prone to human error. Machine learning algorithms have shown great potential in automating waste sorting, increasing efficiency and accuracy, and reducing the environment. This article aims to review the latest developments in waste classification using machine learning, highlighting the work done and the challenges faced.

Waste management is a global problem with significant environmental and social impacts. Waste classification is an important part of waste management, which aims to separate wastes into different streams based on their properties and composition. waste segregation has many benefits that make waste management efficient. This section discusses the advantages of waste separation, including the use of recycled materials, reducing landfill use, reducing environmental pollution, conserving resources, and improving public health and safety. It demonstrates the benefits that waste segregation can provide for the environment and people in general.

Solid waste handling requires clear strategies and guidelines. This section explores various strategies to separate waste at different levels, including domestic, commercial, and industrial environments, the importance of providing appropriate structure such as individual boxes, coloured boxes, and clear labels. The role of technology and automation in supporting the disposal process is also important. Despite its importance, waste segregation faces many challenges.

II. LITERATURE REVIEW

In [1] Solid and hazardous garbage are increasing quickly in both amount and type as a result of ongoing economic expansion. According to estimates, there were 2.02 billion tons of municipal solid trash produced worldwide in 2005–2006, a rise of 7% every year since 2003. To reduce the danger to patients', the public's, and the environment's health and safety, waste must be carefully handled during collection, transportation, management, and disposal. In order to send home waste directly for processing, this study suggests an Automated Waste Segregator (AWS), which is a simple and affordable option. Its purpose is to separate the garbage into dry and moist trash. Capacitive sensors are used by the AWS to differentiate between wet and dry trash. Experimental findings demonstrate that the AWS has effectively integrated the separation of waste into moist and dry waste..

In [2] Both interior and outdoor waste disposal are largely done manually. This is unclean, and it takes a lot of expensive human resources to complete. Some outdoor garbage management is mechanized. This study discusses a plan to fully automate indoor waste management by upgrading the intelligence of the current disposal outlets and utilizing a mobile garbage collection robot. The robot is made in such a manner that it can locate a full trash can and gather rubbish in a compartment for storage..Based on the Wave Front Algorithm, the RSSI (Received Signal Strength Indicator) value from the message received is utilized to determine which trashcan is full and where it is located. The suggested system is a strong contender for waste management since it consumes electricity significantly more efficiently than the current technologies.

In [3] Along with the rapid population expansion and pollution, rubbish management has become a dangerous issue in developing nations during the past few decades. It has been discovered that most places do not promptly empty overflowing trash cans, which leads to a disease-ridden environment and weak nations. The suggested architecture creates an IOT-based

smart waste monitoring system that can determine the amount of trash in the dustbin and show the status and position of bins on a web server using Wi-Fi and GSM. The coordination between the transportation process and rubbish collection will be improved by this method.

In [4] The buildup of solid trash in metropolitan areas is becoming a major problem, resulting in environmental contamination and perhaps endangering human health if not adequately handled. To manage a range of waste products, an advanced/intelligent waste management system is required. One of the most significant phases in waste management is the separation of garbage into its many components, which is often done manually by hand-picking. To simplify the process, Using machine learning technologies, it proposed a trash categorization system that can distinguish between various waste components. Using machine learning technologies, it proposed a trash categorization system that can distinguish between various waste components. This technology can be used to classify garbage automatically, lowering the need for human intervention and reducing pollution and illness. When evaluated against the trash dataset, the outcome had an accuracy of 87%. Using our approach, the garbage will be separated more quickly and intelligently, possibly even with less input from humans. The accuracy of the system can be increased by including more images in the dataset. By adjusting some of the used parameters, it will eventually improve our system so that it can classify more trash items.

In [5] The study's results show that, compared to the 23-layer network with images of 227 x 227 pixels, our 15-layer network performs effectively with images of resolutions more than twice as low. The four primary categories of segregated rubbish are typically appropriately categorized. Our network also has the advantage of learning more quickly than the AlexNet network, especially for photos with a 120 x 120 pixel resolution. The findings of the study demonstrate that our 15-layer network performs well with images of resolutions more than twice as low as the 23-layer network with images of 227 x 227 pixels. In the majority of cases, the four basic groups of segregated trash are correctly classified. A further benefit of our network is that it learns faster than the AlexNet network, particularly for images with a resolution of 120×120 pixels.

In [6] People's everyday rubbish production is increasing by the day. How to properly identify rubbish can help you save time and money. The GC-YOLOv5 garbage categorization model is built in this paper and is based on the YOLOv5 object detection network. First, five typical types of garbage were picked based on the frequent daily garbage category, data was cleaned, categorized, and a garbage dataset was generated. Second, using

our datasets, it created and trained the GC-YOLOv5. Third, they deploy the trash classification model in the cloud due to the convenience of multi-terminal access and the reduction of processing strain on edge devices. The testing findings reveal that GC-YOLOv5 can accurately identify garbage categories and locate garbage. The GC-YOLOv5 garbage categorization model is based on the YOLOv5 object detection network. First, five typical types of garbage were picked based on the frequent daily waste category, data was cleaned, categorized, and a garbage dataset was generated. Furthermore, the GCYOLOv5 was created and trained using our datasets.

In [7] Waste management is one of contemporary society's most difficult tasks. Municipal Solid Waste (MSW) must be classified into several sorts, including bio, plastic, glass, metal, paper, and so on. Neural networks are among the most efficient approaches offered by researchers thus far. This study provides a thorough summary of the present deep learning algorithms that have been suggested to categorize garbage. This study presents a framework for categorizing trash into the categories defined in the benchmark techniques. EfficientNet-B0 was the classification architecture employed. These are Google's compound-scaling-based models that were pretrained on ImageNet and have an accuracy of 74% to 84% in top-1 over ImageNet. It used transfer learning techniques to improve the classification accuracy of a base model B0 for solid waste images, making it comparable in this domain to the B3 model, achieving an 85% image classification accuracy with a model whose upper limit of accuracy was previously 80%. However, this is just for a subset of photographs related to trash.

In [8] Waste or rubbish management is attracting growing attention in developed and emerging nations for wise and sustainable development. The waste or garbage management system is made up of multiple interconnected systems that perform a variety of complicated activities. Deep learning (DL) has recently gained popularity as an alternative computational approach for discovering the answer to various waste or rubbish management challenges. As a result of researchers focusing on this topic, important research has been published, particularly in recent years. According to the literature, a few extensive surveys on trash detection and categorization have been conducted. However, no work has studied the use of DL to tackle waste or garbage management challenges across many domains and highlighted the available datasets for waste detection and classification across several domains. This research presents a systematic and complete examination of the several existing approaches for detecting and classifying trash using machine learning and deep learning. Furthermore, it clearly discussed benchmarked datasets on garbage identification and categorization in a range of contexts. To

assist the study, the strengths and shortcomings of existing methodologies and datasets, as well as future research prospects, are emphasized. Furthermore, It are contemplating doing a comprehensive literature study on this topic, as well as experimenting with various machine learning and deep learning methods.

In [9] Information and communications technology (ICT) is primarily used in conjunction with "smart cities" to offer services that improve internal living circumstances. The Internet of Things (IoT) has recently made significant strides, providing researchers and developers with several chances to build a range of ITS and smart city systems and applications. It is a broad topic of study with many potential applications, including intelligent traffic management, intelligent street lighting, and the detection of gas and water leaks. Efficient Waste Collection (WC), one of these applications, is regarded as a crucial service for assisting in maintaining a healthy environment for the residents while lowering operational expenses. In order to achieve a high Quality of Service (QoS) in garbage collection, this article offers a novel architecture for a smart waste management system based on artificial intelligence approaches. It emphasizes the combined use of surveillance and Internet of Things (IoT) technologies. Deep learning techniques may be used in this industry to significantly cut costs while retaining optimal performance. Based on Deep Learning and pattern recognition, this research provides a novel technique for smart waste management systems. This technology may be linked with current solutions to assist in cost reduction and process automation. As an example, it intends to collect real-world data in order to run the experiment and evaluate the generalization ability of the developed model.

III. METHODOLOGY

Classification is a technique used to categorize data based on their distinct features. It involves dividing the data into different clusters, each representing specific characteristics. In this context, a novel model is developed, capable of making predictions and classifying data by learning from known examples.

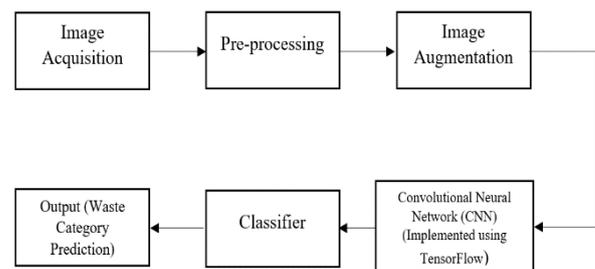
The proposed system comprises three fundamental modules: pre-processing, image augmentation, and feature extraction. Pre-processing involves preparing the data by applying various techniques to enhance its quality and remove noise. Image augmentation is employed to generate additional images by resizing, zooming, rotating, and other transformations. This process helps in creating a more diverse and comprehensive

dataset, allowing the model to capture a broader range of features and improve its ability to predict images accurately.

During the feature extraction phase, the system analyzes the unlabeled data to identify and characterize its essential attributes with the highest possible precision. This process aids in uncovering relevant patterns and distinctions within the data, facilitating accurate classification.

By integrating these modules into the system, it becomes proficient in classifying data efficiently, contributing to enhanced performance and better decision-making. The model's ability to recognize and interpret features from the dataset is instrumental in achieving successful predictions and accurate classifications. Ensuring proper waste disposal by identifying the appropriate trash bin for each waste type is crucial for effective waste management. To achieve this, we conducted experiments with various neural network approaches to determine the most accurate method for waste classification.

Figure 1: Methodology of proposed system.



1. **Image Acquisition:** In this stage, images of waste items are captured using a camera module or other image acquisition methods.
2. **Pre-processing:** The captured images undergo pre-processing to enhance their quality, remove noise, and standardize their format, making them suitable for input to the CNN model.
3. **Image Augmentation:** Additional images are created by applying image augmentation techniques such as resizing, rotation, flipping, etc. This increases the diversity of the dataset and helps improve the CNN model's performance.
4. **Convolutional Neural Network (CNN):** The core of the system, the CNN model, is implemented using TensorFlow, a deep learning framework. It consists of multiple convolutional and pooling layers that learn to extract features from the waste images.
5. **Waste Identification/Classification:** The CNN model processes the pre-processed and augmented images and identifies the category of each waste item, classifying them into different groups like plastic, metal, glass, etc.

6. **Output (Waste Category Prediction):** The output of the CNN model provides predictions of the waste category for each input image, enabling waste identification and proper waste sorting.

Our evaluation utilized an image database compiled by Yang et al. [Yang and Thung], which consists of approximately 2,400 images across six classes of recycled objects. Each class contains around 400-500 images. The authors' data acquisition process involved using a white poster-board as a background, resulting in variations in lighting and pose among the photos. Figure 1 displays sample images from the six classes of recycled objects. Through our experiments, we aimed to identify the neural network approach that performs best in determining the appropriate trash bin for waste disposal. By leveraging the diverse dataset and exploring various network architectures, we sought to contribute to improve waste sorting and recycling practices.

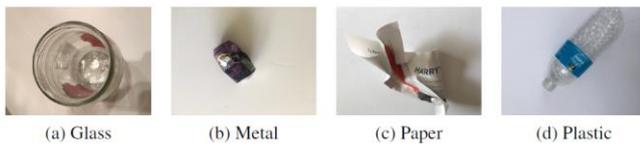


Figure 2: Samples of images used for classification

To assess the performance of each neural network, we utilized the Pearson correlation coefficient (PCC) and the Spearman Rank Order Correlation Coefficient (SCC) as evaluation metrics. In our experiments, we employed several models, namely the VGG-16 model (VGG16), AlexNet, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF).

The VGG16 model is a pre-trained Convolutional Neural Network (CNN) trained on around 1.2 million images from the ImageNet Dataset. With 16 layers, this model is capable of classifying images into 1000 object categories. VGG16 has demonstrated outstanding accuracy in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) classification and localization tasks. Moreover, it performs excellently in other image recognition datasets, even when integrated into relatively simple pipelines, such as using deep features classified by a linear SVM without fine-tuning. Both VGG-16 and AlexNet are commonly employed in photo classification, as ImageNet primarily comprises photos. AlexNet, the first widely known CNN, incorporates repeated convolutional layers followed by max-poolings.

In addition to the CNN models, we adopted three distinct classification algorithms: SVM, KNN, and RF. SVM is a

supervised machine learning algorithm used for classification and regression tasks. It aims to find a hyperplane that optimally separates a dataset into two classes (support vectors). The support vectors are the data points closest to the hyperplane, and their removal would alter the position of the dividing hyperplane.

KNN is an early supervised classifier that predicts the target label by identifying the nearest neighbor class. This is achieved using distance measures like Euclidean distance.

RF, a supervised classification algorithm, forms a robust forest by combining multiple decision trees. The higher the number of trees in the forest, the more accurate the results tend to be.

By employing these models and algorithms and evaluating their performance using PCC and SCC, we aimed to identify the most effective approach for waste classification and bin assignment, contributing to improved waste management practices.

IV. EXPERIMENTAL RESULTS

In this section of the paper, we will evaluate the outcomes of the model that was developed. The model performs satisfactorily on the test data, accurately classifying the type of waste materials by detecting the objects present in the images. For evaluation purposes, the model was tested on a dataset of waste material images. The testing code specifically incorporates these images to assess the model's performance in waste material detection.

During the testing phase, the model's detection time for predicting the type of waste material in a single object from an image averaged around 60 milliseconds. To determine the actual accuracy of the model, the image names were manually cross-referenced to observe how precisely the model functions on these specific images. The prediction results of multiple wastes are shown below.

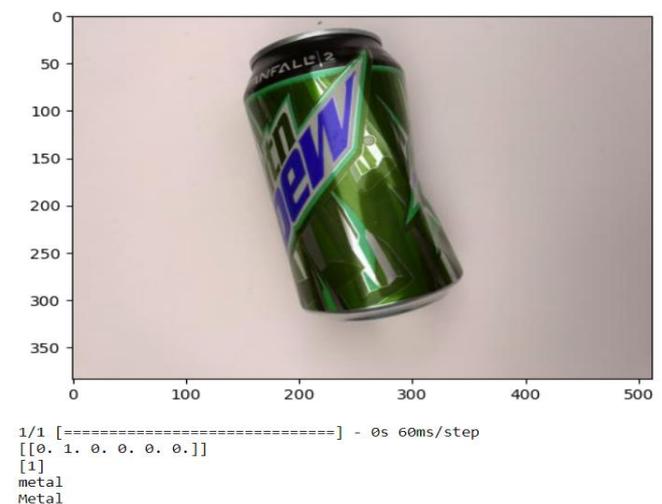
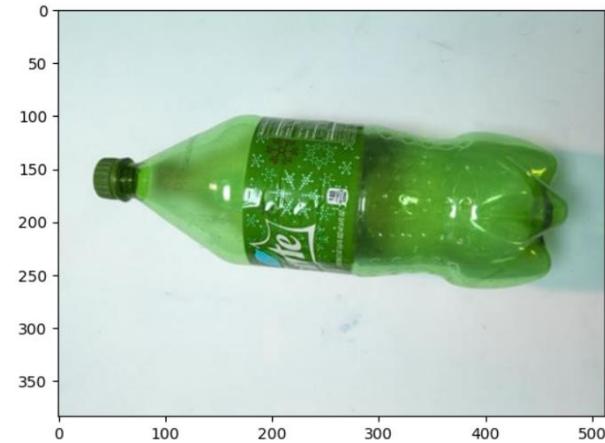
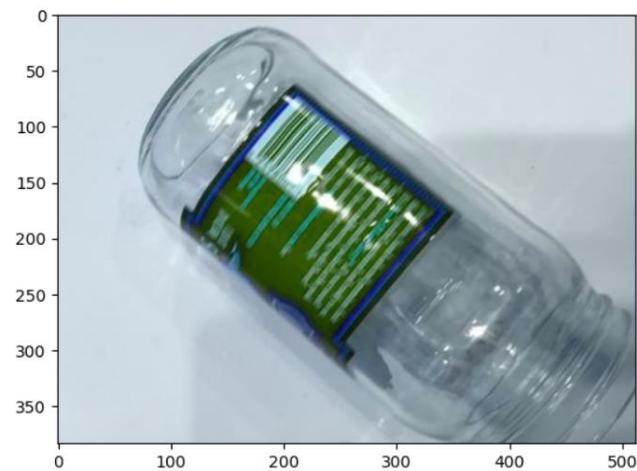


Figure 3: Prediction result of Metal



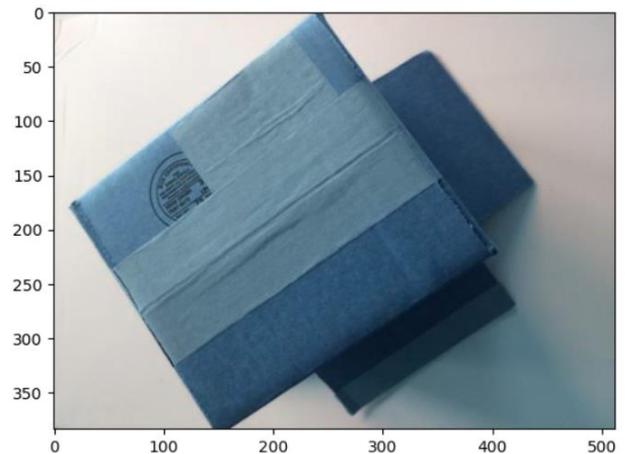
```
1/1 [=====] - 0s 61ms/step
[[0.00000e+00 7.31337e-15 1.00000e+00 0.00000e+00 0.00000e+00 0.00000e+00]]
[2]
plastic
Plastic
```

Figure 4: Prediction result of Plastic



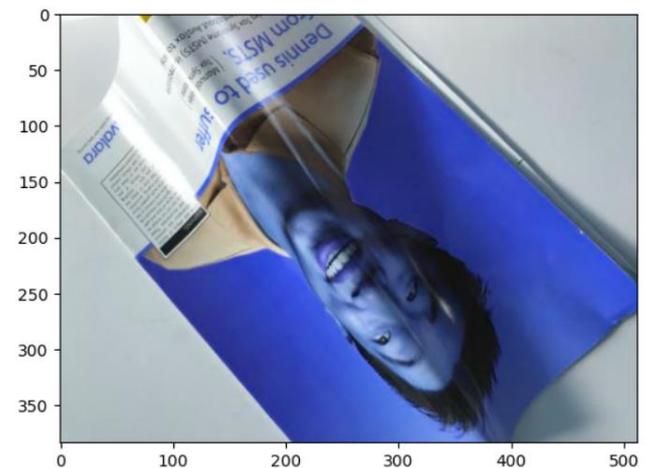
```
1/1 [=====] - 0s 60ms/step
[[0. 1. 0. 0. 0. 0.]]
[1]
Glass
```

Figure 5: Prediction result of Glass



```
1/1 [=====] - 0s 61ms/step
[[1.5815711e-32 0.0000000e+00 1.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00]]
[2]
Cardboard
```

Figure 6: Prediction result of Cardboard



```
1/1 [=====] - 0s 61ms/step
[[1. 0. 0. 0. 0. 0.]]
[0]
Paper
```

Figure 3: Prediction result of Paper

The classification accuracies achieved by the Convolutional Neural Network (CNN) surpassed those attained by traditional machine learning approaches. However, it is worth noting that CNN requires a larger number of algebraic calculations, which results in slower processing compared to the traditional methods. Nevertheless, CNN can enhance its classification accuracies by leveraging various techniques, such as data augmentation and fine-tuning. These methods offer opportunities for further refinement and improvement of the model's performance.

V. CONCLUSION

This paper demonstrates the effectiveness of CNNs in waste segregation tasks. The use of pre-trained CNN models, such as VGG16 or AlexNet, has proven to be particularly beneficial in achieving accurate waste classification. The proposed waste segregation system performs real-time image processing using TensorFlow, allowing for quick and efficient waste classification. This ensures that the system can be deployed in real-world scenarios with timely sorting capabilities. The CNN-based waste segregation system offers the potential to significantly enhance waste management practices. By automating the process of waste classification, it streamlines recycling efforts and promotes efficient resource utilization. Efficient waste segregation and recycling contribute to reducing environmental pollution and conserving natural resources. The adoption of such advanced technologies can have a positive impact on the environment and sustainability.

Moreover, the paper opens avenues for future research, such as exploring more sophisticated CNN architectures or applying transfer learning to adapt the model to specific waste types.

REFERENCES

- [1] Dimitris Ziouzos, Dimitris Tsiktsiris, Nikolaos Baras and Minas Dasygenis "A Distributed Architecture for Smart Recycling Using Machine Learning" Department of Electrical and Computer Engineering, University of Western Macedonia(2020).
- [2] "Object Detection and Recognition for a Pick and Place Robot" Rahul Kumar The University of the South Pacific Suva, Sanjesh Kumar The University of the South Pacific Suva, Sunil Lal The University of the South Pacific Suva(2019).
- [3] Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik, UC Berkeley and ICSI "Rich feature hierarchies for accurate object detection and semantic segmentation" provided by computer vision foundation(2019).
- [4] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, F. A. Wichmann, and W. Brendel, "Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness," arXiv preprint arXiv:1811.12231, 2018.
- [5] C. Bircanog˘lu, M. Atay, F. Bes,er, O˘ .Genc., and M. A. Kızrak, "Recyclenet: Intelligent waste sorting using deep neural networks," in 2018 Innovations in Intelligent Systems and Applications (INISTA), IEEE, 2018, pp. 1–7.
- [6] Chandaluru Priyanka, Sri Ramya P. 2020. Image Based Classification of Waste Material Using Convolution Neural Network, International Journal of Advanced Science and Technology Vol.
- [7] 29, 5, pp. 2967 - 2975
- [8] 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
- [9] Bakator M, Radosav D. 2018. "Deep Learning and Medical Diagnosis: A Review of Literature", Multimodal Technologies and Interaction. Vol. 2, 47, pp. 1-12.
- [10] 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
- [11] 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
- [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] Anjali Pradiphai 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.
- [15] 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.
- [16] 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.
- [17] G. Suddul and N. Nedoomaren, "An Energy Efficient and Low-Cost Smart Recycling Bin," International Journal of Computer Applications, vol. 180, no. 29, pp. 18–22, 2018. doi:10.5120/ijca2018916698.
- [18] G. Thung and M. Yang. "Classification of Trash for Recyclability Status". CS229 Course Report, 2016, <http://cs229.stanford.edu/proj2016/report/ThungYang-ClassificationOfTrashForRecyclabilityStatusreport.pdf>. Accessed 08 Jun. 2020.