

Waste Classification Using Artificial Intelligence Techniques:Literature Review.

Israa Nasir Abood, Ghaidaa Abdul Aziz Al-Talib

Department of Computer Science, College of Computer Science and Mathematics, University of Mosul, Mosul, Iraq

Israa.21csp82@student.uomosul.edu.iq

ghaydabdulaziz@uomosul.edu.iq

Abstract: waste is the total remnants of domestic, agricultural, industrial and productive human activities, all the trash left somewhere, the neglect of which threatens and harms public safety. Waste is divided into many types such as: Non-biodegradable waste, Hazardous waste, Industrial waste, Municipal solid waste, Agricultural waste.

Organic waste: It is fermentable waste such as food scraps and garden waste. Inorganic waste: It is waste that does not contain organic compounds, such as plastic, metals, and clothes. Also Solid waste: like mineral or glass materials, and it results from domestic, industrial and agricultural waste. It needs hundreds of years to decompose, and its presence poses an environmental threat. The efficiency and accuracy of conventional trash classification techniques are both low, Waste classification is the process of identifying and categorizing different types of waste based on their characteristics. Accurate waste classification is important for a number of reasons, including supporting recycling and other forms of resource recovery, protecting the environment and human health, and reducing the costs of waste management. Additionally, because of the vast amount of waste, unskilled people separate rubbish, which is less exact, takes more time, and isn't entirely practicable. Artificial intelligence and image processing, two powerful computing techniques, have advanced and now offer a variety of solutions. However, the current waste classification models still have several issues, such as poor classification accuracy or lengthy run times, because various wastes require various methods of disposal. The existing waste classification models driven by deep learning are not easy to achieve accurate results and still need to be improved due to the various architecture networks adopted. Aimed at solving these problems. Several methods and modules have been reviewed with the advantages of each are listed in Table 1.

Keywords. Waste Classification, Image processing, Machine Learning, Deep Learning, Convolutional Neural Network

1. INTRODUCTION

Recently, the production of waste has risen significantly. If waste managing is not done correctly, it may have a destructive impact on the atmosphere. Therefore, sorting the waste to optimize the number of recyclable materials should be achieved at the initial level. And there would be less likely for other items to damage the environment. It's down to a lot of pollution every year [1].

This will not only have positive environmental [2]. So, the sorting of waste should be done at the initial stage of waste management, to maximize the number of recyclable items and reduce the possibility of contamination by other items. The isolation of waste is done by unprofessional workers which is less effective, time-consuming, and not efficient because of a lot of waste. Again, the economic value of waste is huge after it is segregated. The waste becomes valuable if it is segregated and recycled using the recent advancements in technology thereby becomes a useful entity. So, the execution of Artificial Intelligence and Machine learning can carry a decent output for solving this alarming issue and to keep our environment a good place for all to live in .as well as eliminating the remains of large marine fishing nets. Burning plastic has a disastrous effect on the air. Moreover, climate change, the impact of methane and CO₂ from poorly managed waste will be a reason for up to a tenth of manmade greenhouse gas [3].

How to classify waste accurately, maximize the utilization of waste resources, and improve the quality of the living environment are urgent issues of common concern in the world. Waste classification technology is used to classify and control waste at the source, turning it into resources again through later classification and recycling.[4].

With the development of artificial intelligence, deep learning widely and intelligent technologies have been used., Therefore, an intelligent classification of wastes is the primary step to establish an advanced waste disposal system. Although the existing waste classification driven by machine learning techniques can work efficiently, the classification accuracy still needs to be improved. there are only very few waste image datasets available for model training, lack of a large-scale database like ImageNet7 (about 15 million labelled images in 22 000 classes). A small training dataset cannot accurately capture the feature of various types of garbage, and the consequence is that the classification accuracy of the model is not high. Also, since there are many types of garbage, the lack of clear and accurate classification methods will lead to low classification accuracy. For example, plastic bottles and plastic bags have different shapes and characteristics, although they are both made of plastic, the way of disposal is different. If we roughly group them into one category, the waste classification effects may be affected [5].

Deep learning is a subfield of machine learning that allows computers to automatically interpret representations of data by learning from examples [6]. The method used in [7]for waste classification which uses ML, combines features such as color and texture for the recognition of waste images. Now, deep learning is developing rapidly in the field of image recognition. It uses a multi-layer network to process data to achieve feature extraction. Have been built a recyclable waste image dataset, including nearly 20,000 waste images, which are divided into five categories: glass, fabric, paper, plastic, and metal. Through this dataset, a Dense Net deep learning model based on transfer learning is trained. Based on the classic pre-trained CNN classification model, DenseNet169, combined with the idea of transfer learning, the accurate recognition and classification of recyclable waste is realized [7].

2. WASTE CLASSIFICATION

Waste classification refers to the process of identifying and categorizing waste materials based on their characteristics and composition. This is typically done in order to properly dispose of the waste, recycle it, or find other ways to manage it in an environmentally responsible manner. There are various methods that can be used for waste classification, including visual inspection, chemical analysis, and the use of machine learning algorithms. Some common categories of waste that are typically classified include

municipal solid waste, hazardous waste, electronic waste, and biomedical waste [4]. In our research, we will deal with the classification of waste using intelligent methods.

3. WASTE DATASETS

Many researchers have used several different methods for classifying wastes into different categories. The use of Machine Learning and Deep Learning Algorithms are the most popular approaches for it, in one of these studies is waste image dataset which includes more than 2800 images assorted cardboard, metal, plastic, paper, bottles, metals, and e-waste.

- The Trash net + image scrapping.net dataset contains 2500 images of different garbage which are cardboards, metal, plastic, paper, glass, metals. This dataset has been used that 80%training and 20%testing [3].as figure(1).



Figure 1: Trash Net Dataset

- The trash Net dataset, has been used, which contains six types of waste images, with a total of 2527 images, including cardboard, glass, metal, paper, plastic, trash; as shown in Figure1. [8]
- Researchers In [8]collected 2313 image database as Figure 2. The average rate of recognition accuracy running on raspberry PI 3B+.
- have been grouped into1. six categories: trash, paper, glass, metal, plastic, and cardboard the dataset was split into a training set and a test set, with a ratio of 4:1. The training set was used to train a neural network model, while the test set was used to evaluate the performance of the trained model.



Figure 2. The average rate of recognition accuracy running on raspberry PI 3B+.

And 2.the original data set including batteries, bottles, paper cups, cans, milk-boxes and papers

- In other module the trash net dataset is used in [9], it is consisting of 2527 waste images classified into six classes: glass, metal, trash, paper and cardboard. TrashNet was split into three sets: training, validation and testing with ratios 70%, 13%, and 17%, respectively.
- A compose net data set, extended by the Trash Net dataset in [11] forms a total of 2751 images of waste, grouped into : Paper, Cardboard, Metal, Glass, Trash and Plastic.
- A new dataset called WasteRL, in [12] is divided into four categories: organic waste, recyclables, hazardous waste, and other wastes. Each image contains more type of waste. Figure (3) Training, validation, and testing were applied to the dataset. Models were trained in the training section and evaluated in the verification phase for a more thorough performance evaluation. Testing portion, then reviewed in the validation portion.

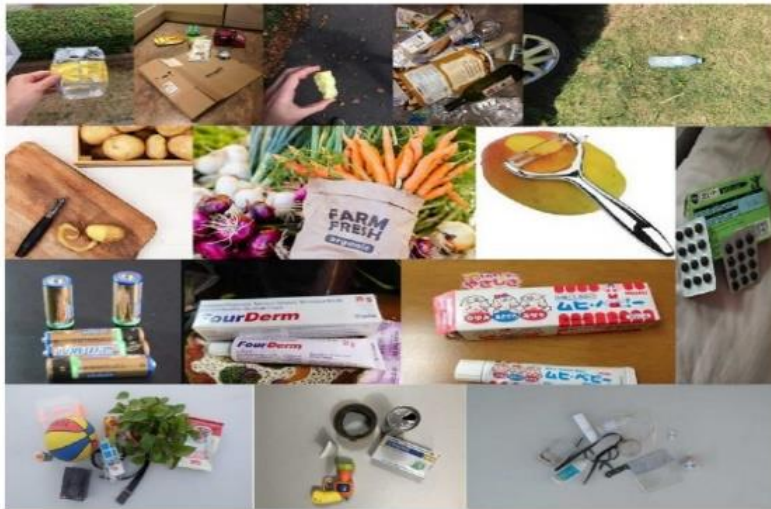


Figure. 3. images in the WasteRL dataset

Many type of algorithms have been improved in machine learning and deep learning and solve problem of classifying images such as CNN, Resnet-50, SVM, Decision Tree, Random Forest ,etc. [3]

4. WASTE CLASSIFICATION TECHNIQUES

4.1 TRADITIONAL TECHNIQUES

A. Traditional waste classification technology has low efficiency and low accuracy. To improve the efficiency and accuracy of waste classification processing Intelligent Techniques can be used Waste burial, composting and incineration are among the most important methods used for several decades. Proper handling of solid waste is essential and monitoring the whole process from waste storage to disposal is essential [3]. The use of traditional machine learning techniques often necessitates the collection and labelling of a large amount of data, which can be resource-intensive [5]. The heterogeneity of the composition and complex mechanisms of waste management systems waste (MSW) have limited not only the performance of conventional treatment approaches, which include classified recycling, landfilling, incineration, pyrolysis, gasification, composting, and anaerobic digestion, Also, in terms of waste transportation, improper and inefficient transport plans and routes consume a lot of humans, physical, and financial resources as well as increase greenhouse gas emissions [7].

B. There are several traditional methods that are commonly used for classifying waste:

- Visual inspection: This is the simplest and most straightforward method, where waste is classified based on its appearance. For example, paper, plastic, and metal can often be easily distinguished by their color, shape, and texture.

- b. **Sampling and analysis:** This method involves collecting a representative sample of the waste and analyzing it to determine its composition. This can be done through a variety of methods, such as chemical analysis or spectroscopy.
- c. **Manual sorting:** This method involves physically sorting the waste into different categories by hand. This can be done by workers at a landfill or recycling facility, or by volunteers at community clean-up events.
- d. **RFID technology:** Radio-frequency identification (RFID) technology can be used to classify waste by attaching tags to the waste that contain identifying information. This information can then be read by RFID scanners to automatically classify the waste.

4.2 INTELLIGENT TECHNIQUES

Waste classification through intelligent methods has become a key factor for human beings to achieve sustainable development. Intelligent. Waste classification can be applied to mobile devices, intelligent recyclable trash cans, etc.

It is beneficial to the environment and improves the recycling of waste resources[10].

These techniques, such as MLP, KNN, and RF, with the large amounts of data making the process very difficult and with less accuracy for waste classification takes, Neural network methods like convolutional neural networks may offer improved performance, but they also require a significant amount of training data and may experience overfitting or underfitting when fine-tuning on smaller datasets.

According to research [11], the use of supervised learning and a deep convolutional neural network resulted in record-breaking performance on a difficult dataset. Removing a single convolutional layer from the network led to a decrease in accuracy. This research also compared the performance of various machine learning models, including Decision Trees, Random Forests, and SVM, in addition to Deep Neural Networks. Among these, the CNN model demonstrated the highest accuracy rate of 90%.

In another study [12], a CNN model called Xception Net was applied to a Synthetic Aperture Radar Target Recognition Dataset, which involved a multi-class classification problem with an image dataset. The model was compared to other transfer learning models such as VGG16, Resnet152, and Inception V3. The results showed that Xception Net performed the best in terms of both Top-1 Accuracy and Top-5 Accuracy, and was the most successful among the neural network models tested that did not have any fully connected layers.

In another study [13], a multilayer hybrid deep learning method for waste classification and recycling was found to achieve up to 99% accuracy. Research comparing the number of epochs in the training set found that a deep neural approach with ten epochs produced the highest accuracy, at almost 99%. Using transfer learning methods such as mobileNetV2 and SVM resulted in an accuracy of 98.4%. Another study that used malicious software classification tasks and applied ImageNet and Resnet-50 networks found that transfer learning achieved a very high accuracy of nearly 99%.

In research [14], various sizes of decision trees and random forests were tested, as well as different combinations of SVM, Decision Tree, Random Forest, and Principal Component Analysis (PCA) applied to the trashnet dataset. A lightweight neural network called MobileNetV2 was trained through transfer learning and used to extract features, which were then incorporated into an SVM classifier. This method successfully addressed the problem of overfitting through the use of transfer learning.

A system was designed in study [15], a to automatically separate recyclable metal household waste using hyperspectral data to detect large-area waste distribution. A new hyperspectral image classification network was developed that performed well in this task. Another research [16] group proposed a method for waste recycling using a hybrid approach that included a radial basis function neural network classifier. They also explored the use of transfer learning with the Visual Geometry Group VGG-19

model, achieving a classification accuracy of 88.42% on waste images.[17]Another study applied a convolutional neural network model based on the 50-layer residual network pre-processing (ResNet-50) to extract features, and used a support vector machine (SVM) for classification, resulting in an accuracy of 87% on the waste image dataset.

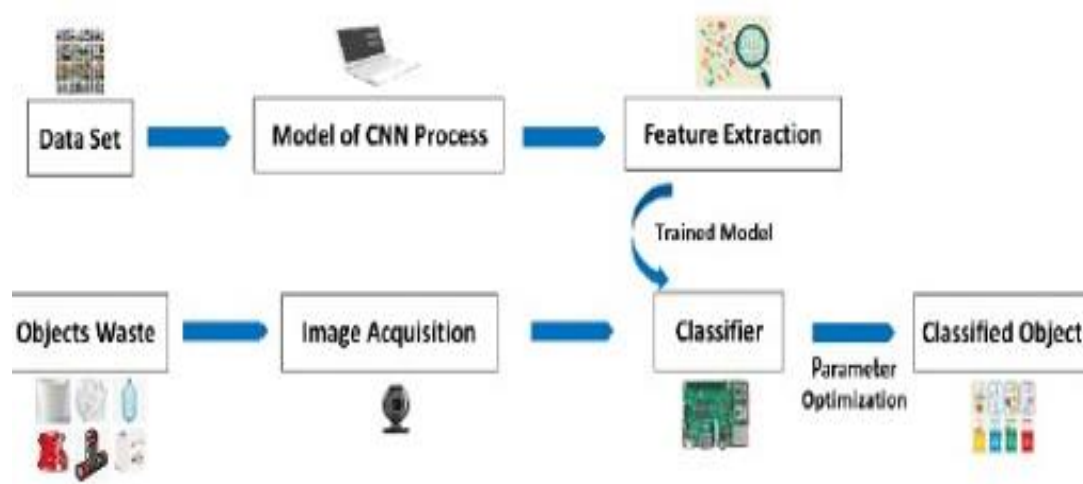
Another study applied[18] the MobileNet model, which was trained through transfer learning on the Imagenet large-scale visual recognition challenge, and achieved an accuracy of 87.2%. After optimization and quantification, the accuracy rate increased to 89.34% and the model was successfully deployed on mobile devices. However, the literature suggests that pre-training models and fine-tuning on small datasets may not always produce the best results, One research [27] group proposed a multi-task detection system for garbage classification using the region proposal network (RPN) and the VGG-16 model. Another study[27] designed a trash detection and classification system using the Support Vector Machines (SVM) method to classify features. However, offline testing of the system on organic waste resulted in an accuracy of 82.7%.

Researchers have proposed various models for waste segregation. One study found that the InceptionNet Neural Network achieved the best performance, with an accuracy of 98.15% and a loss of 0.10 on the training set, and 96.23% and 0.13 on the validation set[12].in Another [19] model proposed using a convolutional neural network to classify waste into three categories: compostable, recyclable, and reject. Yinghao proposed a method called the Multilayer hybrid deep learning method (MHS), which used a combination of CNN and MLP to extract features from sensor data and sort waste into two categories: recyclable and others. The MHS method achieved an overall accuracy of over 90%.[20] Another study compared the performance of Support Vector Machines (SVM) with Scale-Invariant Feature Transformation (SIFT) and a Convolutional Neural System (CNN) on a six-class classification task for glass, metal, paper, cardboard, plastic, and refuse. The results showed that SVM outperformed CNN due to the limited number of images, with accuracies of 63% and 22%, respectively.[20]

The researchers have proposed frameworks for automated waste segregation using computer vision techniques. One study proposed a system that uses a canny algorithm for border detection and gaussian blur to filter noise to visually classify types of waste and control an automated arm and transport line. Another group developed an app called SpotGarbage that uses CNN to detect pools of waste in images taken by users and geotagged on a smartphone. The app achieved a mean accuracy of 87.69%.[20]Another model used CNN to classify garbage images into five categories, and SVM to extract SIFT features [21]. proposed a model that uses two different approaches to detect different types of garbage containers: feature detectors/descriptors with a vector of locally aggregated descriptors, and CNN with You Only Look Once (YOLO). The model achieved an accuracy of 90%.

One research group proposed a conveyor belt system that uses a camera array and robotic arms to detect garbage and estimate their poses using deep neural networks (RPN with VGG-16 model). [22]

A system for intelligent classification of garbage can show in Figure 4



(Figure 4) the design of intelligent classification garbage can

5. EVALUATION METRICS

a-Accuracy (confusion matrix)

Accuracy is how close a measured value is to the actual value[1, 3].

It is the ratio between the total number of accurate predictions and the total number of predictions. Using accuracy as a determining criterion for the model makes good sense, but it is often advised to use Precision and Recall. This is because there may be other cases in which precision is relatively high, but recall or accuracy is comparatively poor.

$$b - Precision = \frac{\text{actual positives}}{(\text{true positives} + \text{false positives})}$$

$$c - Recall = \frac{\text{True positive}}{(\text{true positives} + \text{false positives})}$$

$$d - F1 - Score = \frac{(2 * Precision * Recall)}{(Precision + Recall)}$$

Finally Several intelligent methods were listed in Table 1 showing the advantages of each model with the size of data used in every reference as well as the number of categories and the accuracy of results

Table 1 Waste Classification modules using AI techniques

| AI Model | Advantage | Reference | Data size | No. of class | Accuracy |
|---------------|---|-----------|----------------|--------------|----------|
| (SVM) | <ul style="list-style-type: none"> Solve binary classification problem high-dimensional, of non-linear element Effective memory | [3] | 2.5 k | 6 | 85% |
| Random Forest | <ul style="list-style-type: none"> It lessens decision tree overfitting and enhances accuracy. It can be applied for solving problems of classification and regression. It is a very useful for classification to multiclass | [3] | 2.5 k | 6 | 55% |
| | | [23] | 8.6 K | 5 | 93.73% |
| Decision Tree | extremely intuitive and simple to understand | [3] | 2.5 k | 6 | 65% |
| Xception | <ul style="list-style-type: none"> Simple to explain. achieving good accuracy by utilizing library like Keras or TensorFlow. | [1] | 2.8k | 7 | 92.5% |
| DenseNet121 | <ul style="list-style-type: none"> can improve parameters to get easy training of networks. Reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. Best performance for the classification of organic and residual waste. | [1] | 2.8k | 7 | 93.3% |
| | | [24] | 2.751k | 7 | 96.42 |
| Resnet-50 | <ul style="list-style-type: none"> reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers best performance for the classification of organic and residual waste. | [1] | 2.8k 22.01k | | 92% |
| | | [25] | 20k | 2 | 97.8% |
| MobilenetV2 | <ul style="list-style-type: none"> quick training and heigh precision. Higher Model accuracy upon test data. Detection of object and segmentation. | [1] | 2.8k | 7 | 93% |
| | | [24] | 2.751k | 2 | 96.27% |
| | | [26] | 2.75k | 6 | 98.4% |

| | | | | | |
|---------------|--|------|--------|---|----------------------------|
| EfficienNetB7 | <ul style="list-style-type: none"> • Lightweight • compatible with mobile -devices. | [1] | 2.8k | 7 | 87% |
| DNN-TC | Out performs with Trash Net dataset and VN-Trash datasets. | [2] | 5.9k | 3 | 94%Trashnet 98%VN-trash |
| CNN | <ul style="list-style-type: none"> • simple structure. • Heigh performance for waste image classification. • don't need a human supervision for identification of important features. • They are very accurate at image recognition and classification. • minimize computation in comparison with a regular neural network. | [1] | 2.8k | 7 | 90% |
| | | [4] | 2.5k | 6 | 92.6% |
| | | [8] | 2.3k | 6 | 95.33% |
| | | [27] | 2.34k | 7 | 81.50% |
| | | [28] | 2.35k | 6 | 98.15% |
| [29] | 2.3k | 6 | 93.97% | | |
| VGGNet-16 | <ul style="list-style-type: none"> • increases the perception field of each layer for the feature map. • Suitable for image categorization, and transfer learning makes it simple to utilize • Appropriate for classification of images when using transfer learning. | [25] | 2.5k | 2 | %95 |
| ResNet34 | <ul style="list-style-type: none"> • remarkable accuracy. • Finding a good learning rate for the model improved training efficiency. | [24] | 2.7k | 7 | 96.27% |

6.CONCLUSIONS

Deep learning techniques have shown promising results for waste classification tasks. These techniques can accurately classify different types of waste, including plastic, paper, and metal, and can also identify specific subcategories within these broad classes. Deep learning algorithms can be trained on large datasets of images or other types of data, allowing them to learn complex patterns and features that are difficult to identify using traditional methods. Overall, the use of deep learning techniques can improve the efficiency and accuracy of waste classification systems, making it easier to properly manage and recycle different types of waste.

The main objective of this study is to study the properties of solid waste some of the intelligent methods used to classify waste, including deep learning, were mentioned and analyzed Several of the model techniques for managing waste classification in daily life. Intelligent trash classification is essential because of the growing amount of waste. We reviewed the most popular smart methods used for waste classification and make a comparision between them. The types of classification focused on a section of solid waste It included Multi-class and use the best solutions through In varying proportions, it is well observed that the CNN, Mobile net, Resnet achieved high rates, while the decision tree and random forest lagged behind Using a transfer learning technique, the convolutional neural networks is enhanced to better detect the various types of waste.The model's efficacy and accuracy can still be improved. Transfer learning technique is used to enhance the convolutional neural network so that model could more accurately and efficiently detect the different forms of waste. Future work should focus on further improving the classification performance of the model. More importantly, further studies should aim to ensure classification accuracy, Still, use transfer learning with higher accuracy than normal deep learning algorithm.

REFERENCES

- [1] Amin, Z.M.A., Sami, K.N., and Hassan, R.: 'An approach of classifying waste using transfer learning method', *International Journal on Perceptive and Cognitive Computing*, 2021, 7, (1), pp. 41-52
- [2] Vo, A.H., Vo, M.T., and Le, T.: 'A novel framework for trash classification using deep transfer learning', *IEEE Access*, 2019, 7, pp. 178631-178639
- [3] Sami, K.N., Amin, Z.M.A., and Hassan, R.: 'Waste Management Using Machine Learning and Deep Learning Algorithms', *International Journal on Perceptive and Cognitive Computing*, 2020, 6, (2), pp. 97-106
- [4] Shi, C., Tan, C., Wang, T., and Wang, L.: 'A waste classification method based on a multilayer hybrid convolution neural network', *Applied Sciences*, 2021, 11, (18), pp. 8572
- [5] Huang, G.L., He, J., Xu, Z., and Huang, G.: 'A combination model based on transfer learning for waste classification', *Concurrency and Computation: Practice and Experience*, 2020, 32, (19), pp. e5751
- [6] Abou Baker, N., Zengeler, N., and Handmann, U.: 'A Transfer Learning Evaluation of Deep Neural Networks for Image Classification', *Machine Learning and Knowledge Extraction*, 2022, 4, (1), pp. 22-41
- [7] Zhang, Q., Yang, Q., Zhang, X., Bao, Q., Su, J., and Liu, X.: 'Waste image classification based on transfer learning and convolutional neural network', *Waste Management*, 2021, 135, pp. 150-157
- [8] Feng, J.-w., and Tang, X.-y.: 'Office garbage intelligent classification based on inception-v3 transfer learning model', in Editor (Ed.)^(Eds.): 'Book Office garbage intelligent classification based on inception-v3 transfer learning model' (IOP Publishing, 2020, edn.), pp. 012008
- [9] Alsabei, A., Alsayed, A., Alzahrani, M., and Al-Shareef, S.: 'Waste Classification by Fine-Tuning Pre-trained CNN and GAN', *International Journal of Computer Science & Network Security*, 2021, 21, (8), pp. 65-70
- [10] Carreira, J., Madeira, H., and Silva, J.G.: 'Xception: A technique for the experimental evaluation of dependability in modern computers', *IEEE Transactions on Software Engineering*, 1998, 24, (2), pp. 125-136
- [11] Zhao, J., Guo, W., Cui, S., Zhang, Z., and Yu, W.: 'Convolutional neural network for SAR image classification at patch level', in Editor (Ed.)^(Eds.): 'Book Convolutional neural network for SAR image classification at patch level' (IEEE, 2016, edn.), pp. 945-948
- [12] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., and Chen, L.-C.: 'Mobilenetv2: Inverted residuals and linear bottlenecks', in Editor (Ed.)^(Eds.): 'Book Mobilenetv2: Inverted residuals and linear bottlenecks' (2018, edn.), pp. 4510-4520
- [13] Kalvankar, S., Pandit, H., and Parwate, P.: 'Galaxy morphology classification using efficientnet architectures', *arXiv preprint arXiv:2008.13611*, 2020
- [14] ICp, P., Narayanan, S., Kommuri, V.S., Subramanian, S., Bijlani, K., Nagendra, S., and Podila, N.: 'ICACCI-02 (A): Artificial Intelligence and Machine Learning/Data Engineering/Biocomputing (Regular Papers)'
- [15] Costa, B.S., Bernardes, A.C., Pereira, J.V., Zampa, V.H., Pereira, V.A., Matos, G.F., Soares, E.A., Soares, C.L., and Silva, A.F.: 'Artificial intelligence in automated sorting in trash recycling', in Editor (Ed.)^(Eds.): 'Book Artificial intelligence in automated sorting in trash recycling' (SBC, 2018, edn.), pp. 198-205
- [16] IAgarwal, C., and Sharma, A.: 'Image understanding using decision tree based machine learning', in Editor (Ed.)^(Eds.): 'Book Image understanding using decision tree based machine learning' (IEEE, 2011, edn.), pp. 1-8
- [17] Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., and Adam, H.: 'Mobilenets: Efficient convolutional neural networks for mobile vision applications', *arXiv preprint arXiv:1704.04861*, 2017

- [18] Rishma, G., and Aarthi, R.: 'Classification of Waste Objects Using Deep Convolutional Neural Networks': 'ICDSMLA 2020' (Springer, 2022), pp. 533-542
- [19] Yang, M., and Thung, G.: 'Classification of trash for recyclability status', CS229 project report, 2016, 2016, (1), pp. 3
- [20] Salmador, A., Pérez Cid, J., and Rodríguez Novelle, I.: 'Intelligent garbage classifier', 2008
- [21] Valente, M., Silva, H., Caldeira, J.M., Soares, V.N., and Gaspar, P.D.: 'Detection of waste containers using computer vision', Applied System Innovation, 2019, 2, (1), pp. 11
- [22] Bansal, S., Patel, S., Shah, I., Patel, P., Makwana, P., and Thakker, D.: 'AGDC: Automatic garbage detection and collection', arXiv preprint arXiv:1908.05849, 2019
- [23] Bansal, M., Kumar, M., Sachdeva, M., and Mittal, A.: 'Transfer learning for image classification using VGG19: Caltech-101 image data set', Journal of Ambient Intelligence and Humanized Computing, 2021, pp. 1-12
- [24] Srivatsan, K., Dhiman, S., and Jain, A.: 'Waste Classification using Transfer Learning with Convolutional Neural Networks', in Editor (Ed.) (Eds.): 'Book Waste Classification using Transfer Learning with Convolutional Neural Networks' (IOP Publishing, 2021, edn.), pp. 012010
- [25] Wu, F., and Lin, H.: 'Effect of transfer learning on the performance of VGGNet-16 and ResNet-50 for the classification of organic and residual waste', Frontiers in Environmental Science, 2022, 10, pp. 2129
- [26] Xu, X., Qi, X., and Diao, X.: 'Reach on waste classification and identification by transfer learning and lightweight neural network', 2020
- [27] Liang, S., and Gu, Y.: 'A deep convolutional neural network to simultaneously localize and recognize waste types in images', Waste Management, 2021, 126, pp. 247-257
- [28] Gupta, T., Joshi, R., Mukhopadhyay, D., Sachdeva, K., Jain, N., Virmani, D., and Garcia-Hernandez, L.: 'A deep learning approach based hardware solution to categorise garbage in environment', Complex & Intelligent Systems, 2022, 8, (2), pp. 1129-1152
- [29] Yusiong, J.P.T.: 'An Ensemble of CNN-ELM Models for Trash Classification', Bulletin on Innovative Computing, Information and Control, 2022, 16, (09), pp. 943