Garbage Bin Status Indicator Based on Multilayer Convolutional Neural Networks

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Abstract. Garbage is one of the most pressing issues of the 21st century. Since the world's population, urbanisation, and industrialisation have increased rapidly, so too has the amount of garbage that must be collected and disposed of each year. It doesn't matter how many people or vehicles city governments have. Garbage collection has become an absolute disaster in recent years. Throughout the city, trash cans and other forms of public garbage pickup are constantly overflowing. It creates living conditions that are unsafe for human habitation. In this study, we present a garbage bin monitoring system that takes garbage bin pictures as input. Two-dimensional photos of garbage bins are taken at regular intervals by a CCTV camera powered by solar panels and a Raspberry Pi processing device. The photos were input for three, and five-layer Convolutional Neural Network (CNN) machine learning algorithms. In accordance with the confusion matrix, the loss function, accuracy, precision, recall and F1-Score are computed. After looking at the data and results, it has been observed that the three-layer and five layers of CNN models provide 92% and 99% accuracy, respectively. On the bases of the loss graph and accuracy graph created during training and validation. this research supports that the proposed five-layer Convolutional Neural Network (CNN) model is optimal for garbage bin status identification. This technique could be adopted by the municipal government of "smart cities" to detect when bins are full and dispatch a cleaning crew to empty them.

Keywords: TensorFlow; Garbage Management system; Machine Learning; Deep Learning

INTRODUCTION

Almost 2.01 billion tonnes of municipal solid waste will be produced annually over the globe in 2021. There was likely unsafe disposal of at least 33% of that garbage. An estimated 3.4 billion tonnes of garbage will be thrown away worldwide by 2050. The garbage produced in low-income regions is projected to have multiplied by more than three. Compared to East Asia and the Pacific, which generate 23% of global garbage, the Middle East and North Africa generate only 6%. While this is generally true, Sub-Saharan Africa, the southern region of Asia, the Middle East, and North Africa are experiencing rapid growth. Garbage production in these areas is expected to more than treble, double, and double by 2050. Over half of the garbage in these locations is thrown away in the open. If something is not done soon, the increasing garbage rate will negatively impact ecology, human health, and economic development.

Table 1 shows that out of all the garbage in Europe, only 10.7% is recycled, while 25.6% is burnt. Whereas 60.5% of North American garbage is disposed of in sanitary landfills, only 50.9% of Asia's garbage is disposed of in open dumps. Garbage is gathered from homes in many Indian cities, but the country's outdated sorting and disposal infrastructure makes this method ineffective. The informal recycling business is essential in garbage management and allows low-income people to find gainful employment. They collect over 10,000 tonnes of recyclable garbage daily, barefoot and without shoes or safety gear like gloves and masks [1].

Table 1. A garbage disposal as a percentage worldwide and on a few specific continents.

Continent	Recycling	Sanitary Landfill	Open Dump	Burn	Other
Asia-Pacific	8.5%	30.9 %	50.9%	6.4%	4.5%
Africa	3.9%	29.35%	47.0%	10.6%	8.4%
European Union	10.7%	27.6%	33.0%	25.6%	4.4%
Latin America	3.2%	60.5%	34.0%	7.5%	2.0%
North America	8.1%	91.1%	0%	0%	0%

In most situations, trash spills out of the containers and covers the streets. In such areas, there needs to be recycling or waste collection infrastructure, and the government provides no service to retrieve garbage from those settlements. As a result, many towns burn it or dump it outside, see **Figure 1(a)**. Numerous studies indicate that unsafe waste disposal generates dangerous gasses and leachates due to microbial decomposition, climate conditions, refuse characteristics and land-filling operations. As previously mentioned, the garbage overflowing onto the street will undoubtedly cause several environmental issues, particularly for human health, see **Figure 1(b)**.

(a) Garbage dumpsite burning. **(b)** Overflowing garbage bin.

Figure 1. Burning and overflowing garbage images.

Improper garbage management has severe consequences for both environmental quality and public health. Sanitation workers are typically off-call 24/7 to promptly monitor garbage bins and remove overflowing garbage. Garbage pileup due to ineffective collection has the potential to have far-reaching consequences for the community. The overflowing garbage causes the area to deteriorate, infecting the surrounding neighbourhoods with the stench of liquid and solid waste. These issues range from some of those related to management and finances to those related to the environment and public health.

RELATED WORK

The aim of the paper [2] a mechanism to monitor the level of trash in the garbage bin is detected using ultrasonic and infrared sensors. The data is sent to the Raspberry Pi when a certain threshold is met, and the Raspberry Pi then sends an email and SMS alert. Along with the Raspberry Pi, Arduino also receives the data simultaneously. Following that, an ethernet shield is used to send this data to the local host. The resultant is then sent to the Microsoft Azure platforms for training to keep track of real-time garbage, and to predict future waste generation patterns in the specified area. A “Google Calendar” event and smartphone alert system are also provided using the IFTTT method.

The paper [3] proposes a public garbage bin overflow alarm and positioning system based on the STM32F103C8T6 microcontroller, which uses an infrared human body sensor mounted on the bin's surface to automatically identify who wants to throw garbage automatically open the bin cover for the convenience of users. Moreover, to avoid odour and pollutants in the immediate area after users depart, the bin cover doesn't immediately close. To accurately determine if the exterior waste can be full in all directions, the system also installed three 60-degree ultrasonic sensors on the interior wall of the lid to detect whether the internal garbage is full.

The paper [4] suggests an ideal route-detecting system and a smart bin. The Suggested smart bin uses various hardware components, including a sonar sensor, an Arduino microcontroller, a GSM/GPRS shield, and a buzzer, to monitor the garbage within the bin and convey information to a server wirelessly. To prevent bin overflow, a buzzer is utilised. A sonar sensor is employed to determine the condition of the bin and measure the echo back distance. To transfer messages via a wireless connection, GSM/GPRS shield is utilised. Path optimisation utilises a genetic algorithm based on data recorded in a database.

The paper [5] focuses on machine learning and Internet of Things-based technology, a promising perfect solution for making a smart city. As presented in the suggested framework, continually checks the metal level, noxious gas level, and dustbin capacity and then creates an alert message to handle the trash at the residential level of society immediately. Data from sensors is used to determine whether to issue an alert message. Based on test data, different supervised machine learning algorithms and techniques such as Support Vector Machine (SVM), Naive Biased (NB), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbours are matched side by side and an analysed for the categorisation and send alert messages. The appropriateness of the proposed work depends on how well the categorisation and prediction algorithms operate.

The paper [6] recommended a system where deep convolutional neural network designs would be used. Regarding transfer learning methods and fine-tuning weight parameters using ImageNet, DenseNet121 delivered the best overall performance, achieving 95% test accuracy. Our model, called RecycleNet, employs a deep convolutional neural network architecture that has been fine-tuned for sorting various recyclable materials. This cutting-edge method lowered the parameters of a 121-layer network from “7 million to around 3 million”.

The paper [7] develops a system for classifying common waste products such as newspaper/sheets, cardboard, plastic, metallic waste, and other garbage. The model was developed by transfer learning and trained on the ImageNet Large Visual Recognition Challenge dataset. After refinement and quantisation, the resulting baseline model achieved an accuracy of 87.2%.

Research [8] on a garbage classification system that uses deep learning convolutional neural networks to combine techniques from object recognition and image classification. Once the trash classification data has been trained and tested using ResNet and MobileNetV2, the garbage object data is trained and tested with three methods from the YOLOv5 family. In the end, findings from five studies on waste classification are combined. Using a consensus voting method, you can increase the rate at which your system recognises and labels image categories to 2%. A change to the Raspberry Pi CPU was made once testing showed that the recognition rate for rubbish photos had grown to roughly 98%.

The research [9] suggested a deep learning-powered hardware solution for elementary waste classification. It recommends using hardware based on convolutional neural network technology for deep learning. SmartBin uses image classification to determine whether a given trash item is biodegradable. This research compares and contrasts the performance of several popular pre-trained convolution neural networks, including AlexNet, ResNet, VGG-16, and others. InceptionNet is used for waste classification and efficiency testing in addition to hardware components (webCam, Raspberry Pi, infrared sensors, etc.) utilised for trash recognition in the bin. The Inception Neural Network found that the recommended model performed best, with an accuracy of 98.15% and a loss of 0.10% for the training set, and 96.2 percent and 0.13 percent for the validation data set.

Using 9,200 images of MSW, the study [10] compared the performance of four different CNN-based waste-type classifiers (such as Visual Geometry Group-16, Residual Network-50, Mobile Network V2, and DenseNet-121). The waste-type classifier can identify the sort of waste inferred from the waste-item class. A derived classifier fared better than its direct counterpart in the experiment. Of all garbage classification models, the Residual Network-50 classifier produced the highest accuracy at 94.90% [11].

This study aims to develop a method that can replace the existing laborious process with an automated one that is quicker, cleaner, and less harmful to the environment. In this paper, we propose a garbage bin identification system that uses the Convolutional Neural Network (CNN) model with three layers and five layers to determine the status of a bin (empty or full). A primary dataset in the form of a two-dimensional image is used for both model training, validation and testing purposes.

METHODOLOGY

See **Figure 2**; solar-powered CCTV cameras [12] monitor the garbage bin round-the-clock with the help of a Python application running on an online-accessible Raspberry PI processor [13]. Before being fed into the CNN machine learning model, the 2-D image undergoes a series of transformations to make it more comprehensible. The garbage bin status is checked by sending the input image to the trained model. If the garbage can reaches capacity, an alert is sent by text message or email to the relevant person.

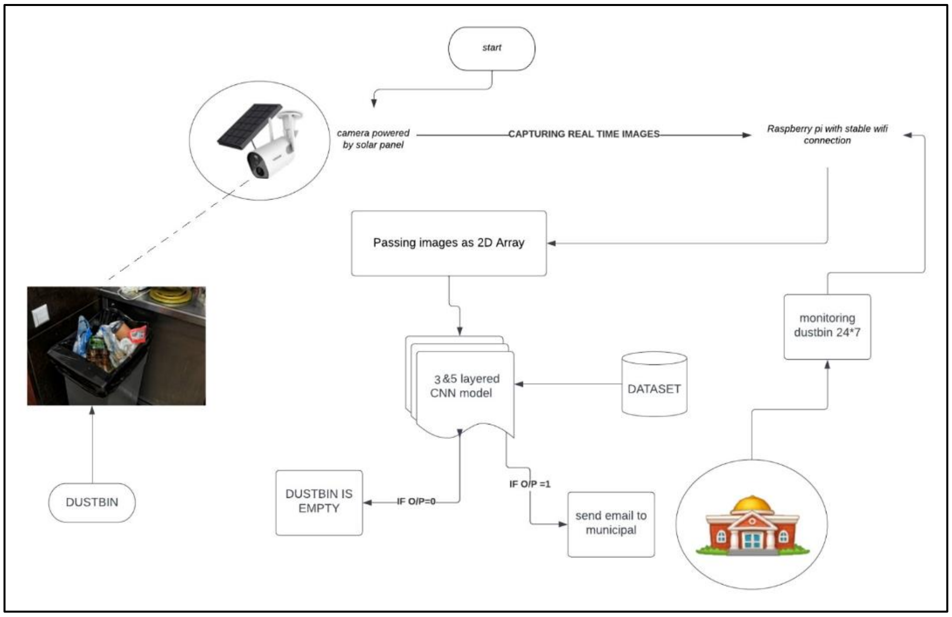

Figure 2. Proposed Methodology.

Primary Data Collection and Pre-Processing.

In this paper, we utilise primary datasets gathered as a two-dimensional image of a garbage bin, splitting the image data into two categories (empty and full). To train a convolutional neural network (CNN) model for garbage bin classification. Using the Python library, the primary dataset transforms into a format understandable by a CNN model [14]. The transformation results in three two-dimensional arrays of numbers between 0 and 255 (see **Figure 3**). This paper incorporates normalisation, transforming the input data into uniform scales that improve model performance and convergence. The model's accuracy can increase when the input features are all on the same scale (see Eq. 1).

$$X_n = \left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) \tag{1}$$

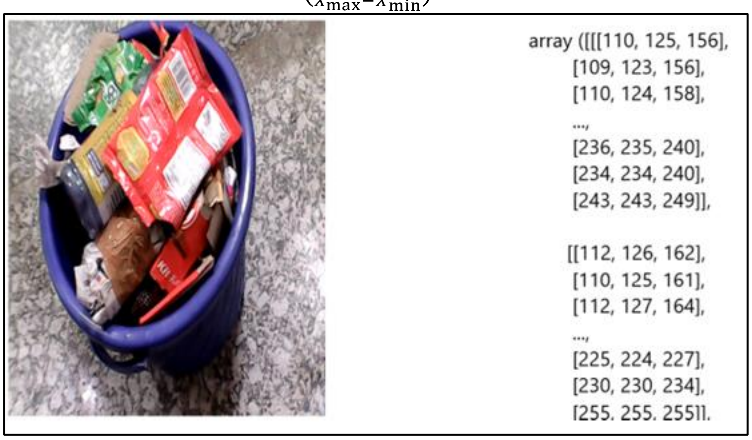

Figure 3. Image to Array of (200x200)x3.

The cleaned and standardised data is split into three sets for training, validation, and testing. The classification model is trained using the training dataset. In contrast, the validation dataset is used to verify the accuracy of the training data, examine the data fitting, and fine-tune the parameters of the CNN machine learning models so that they can effectively solve garbage bin classification problems.

Proposed CNN Models.

This paper proposes two CNN models with three (see **Figure 4**) and five convolutional layers. The model with three layers; employs the [15] ReLU activation function (see Eq. 2) with a learnable filter (kernels or weights of 3x3 size) of 32, 64 and 128 numbers, respectively. The model with five layers; employs the ReLU activation function with a learnable filter (kernels or weights of 3x3 size) of 32, 64, 128, 256 and 512 numbers, respectively.

$$f(x) = \max(0, x)_n \quad (2)$$

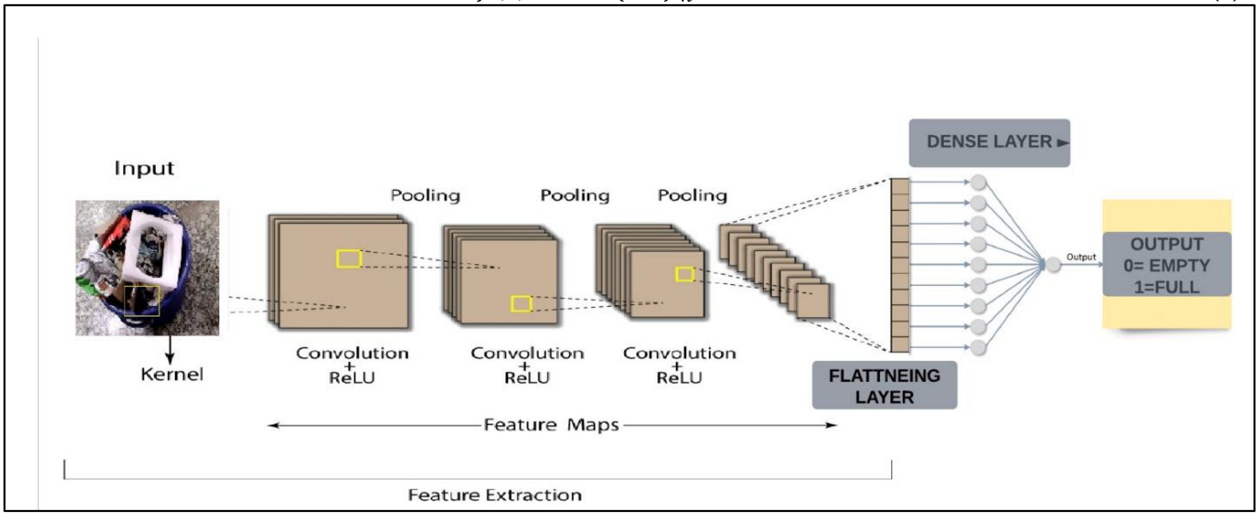

Figure 4. Proposed CNN model.

Each of our network models has 512 neurons in the dense layer, all activated using the ReLU function. The output from the dense layer will be fed into a single neuron with a [16] sigmoid activation function (see Eq. 3) to classify the empty bin or full bin.

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

Performance Evaluation

Indicators used in the confusion matrix computation include overall accuracy, recall, precision, and F1-Score, as shown in Eqs (4-7).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1 - Score = \frac{2}{\frac{1}{Recall}+\frac{1}{Precision}} \quad (7)$$

RESULTS & DISCUSSION

Of the total 150 test garbage bin images used in the experiment, 75 are from the empty bin, and 75 are from the full bin. The results showed that the 5-layer CNN model was superior to the 3-layer CNN model. According to the accuracy and loss graph derived from the training and validation dataset, the CNN model with five layers (see **Figure 6**) provides superior fitting to the CNN model with three layers (see **Figure 5**).

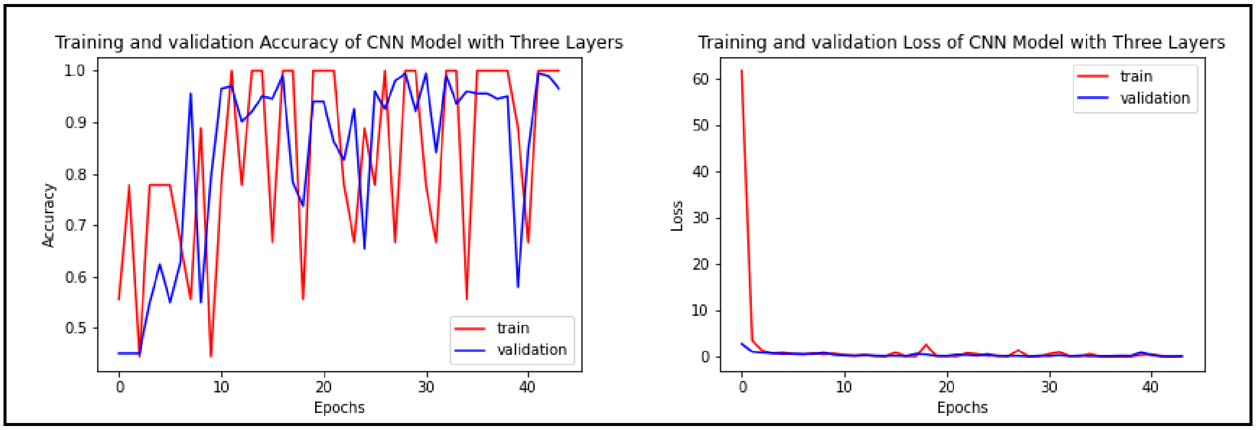

Figure 5. Accuracy and Loss graph of CNN model with three layers.

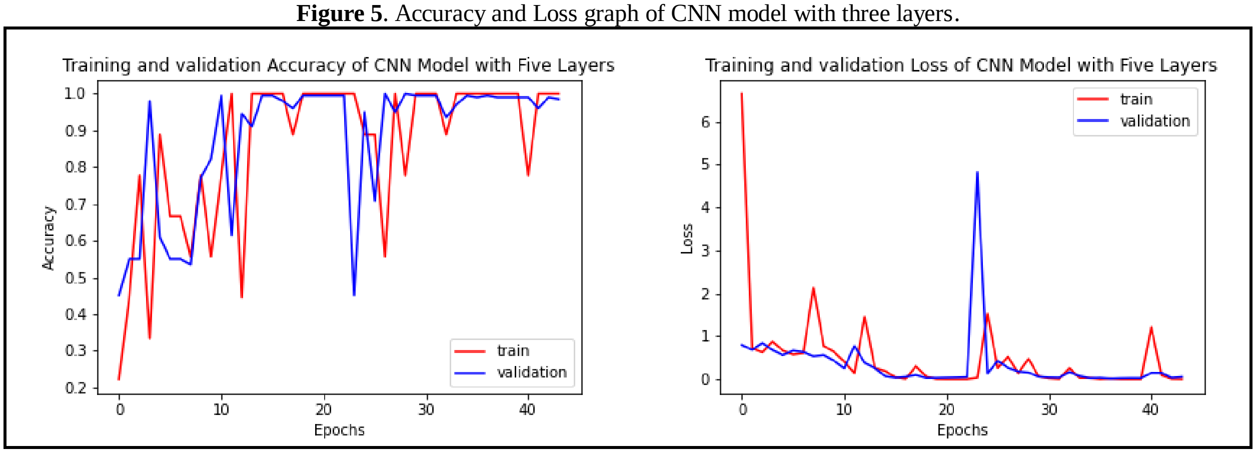

Figure 6. Accuracy and Loss graph of CNN model with five layers.

The confusion matrix [17] is calculated for the models in the discussion. There is a calculation of the F1-Score, along with accuracy, recall, precision, and accuracy. A five-layer CNN model performs better in accuracy, precision, and F1-Score than a three-layer CNN model. As seen in **Table 2**, the recall is identical in both models.

Table 2. Results of Confusion Matrix Analysis.

S. No	Parameters	CNN Model with three Layers	CNN Model with five Layers
1.	True Positive	75	75
2.	False Positive	0	0
3.	True Negative	63	74
4.	False Negative	12	1
5.	Accuracy	0.92	0.99
6.	Precision	0.86	0.99
7.	Recall	1.0	1.0
8.	F1-Score	0.93	0.99

CONCLUSIONS

As shown in **Figure 5** & **Figure 6**, the five-layer CNN model outperformed the three-layer CNN model regarding cross-entropy loss. CNN models with five layers have an accuracy of 99%, but CNN models with three layers only achieve 92%. According to this research, a five-layer CNN model is optimal for determining whether a garbage bin is full or empty. The system may send a text message or other alert to the concert staff based on the status to remind them to empty the garbage bin. This study's findings may be used for smart city initiatives, such as improved waste management.

REFERENCES

[1] "Solid Waste Management in Urban India: Imperatives for Improvement," *Journal of Contemporary Issues in Business and Government*, vol. 25, no. 1, 2019, doi: 10.47750/cibg.2019.25.01.001.

[2] C. J. Baby, H. Singh, A. Srivastava, R. Dhawan, and P. Mahalakshmi, "Smart bin: An intelligent waste alert and prediction system using machine learning approach," *Proceedings of the 2017 International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET 2017*, vol. 2018-Janua, pp. 771–774, 2018, doi: 10.1109/WiSPNET.2017.8299865.

[3] L. Yu, Y. Wang, M. Deng, and X. Gong, "Design of Public Garbage Can Overflow Alarm and Positioning System based on NB-IoT," vol. 6, no. 7, pp. 132–141, 2020, doi: 10.6919/ICJE.202007.

[4] [4] B. S. Malapur and V. R. Pattanshetti, "IoT based waste management: An application to smart city," *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing, ICECDS 2017*, pp. 2476–2479, 2018, doi: 10.1109/ICECDS.2017.8389897.

[5] S. Dubey, M. K. Singh, P. Singh, and S. Aggarwal, "Waste Management of Residential Society using Machine Learning and IoT Approach," *2020 International Conference on Emerging Smart Computing and Informatics, ESCI 2020*, pp. 293–297, 2020, doi: 10.1109/ESCI48226.2020.9167526.

[6] C. Bircanoglu, M. Atay, F. Beser, O. Genc, and M. A. Kizrak, "RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks," *2018 IEEE (SMC) International Conference on Innovations in Intelligent Systems and Applications, INISTA 2018*, 2018, doi: 10.1109/INISTA.2018.8466276.

[7] S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios, and E. J. Calilung, "Common garbage classification using mobilenet," *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management, HNICEM 2018*, pp. 1–4, 2018, doi: 10.1109/HNICEM.2018.8666300.

[8] Z. Yang, Y. Bao, Y. Liu, Q. Zhao, H. Zheng, and Y. L. Bao, "Research on deep learning garbage classification system based on fusion of image classification and object detection classification," *Mathematical Biosciences and Engineering*, vol. 20, no. 3, pp. 4741–4759, 2023, doi: 10.3934/mbe.2023219.

[9] T. Gupta *et al.*, "A deep learning approach based hardware solution to categorise garbage in environment," *Complex and Intelligent Systems*, vol. 8, no. 2, pp. 1129–1152, 2022, doi: 10.1007/s40747-021-00529-0.

[10] C. Srinilta and S. Kanharattanachai, "Municipal solid waste segregation with CNN," *Proceeding - 5th International Conference on Engineering, Applied Sciences and Technology, ICEAST 2019*, pp. 1–4, 2019, doi: 10.1109/ICEAST.2019.8802522.

[11] S. Sudha, M. Vidhyalakshmi, K. Pavithra, K. Sangeetha, and V. Swaathi, "An automatic classification method for environment: Friendly waste segregation using deep learning," *Proceedings - 2016 IEEE International Conference on Technological Innovations in ICT for Agriculture and Rural Development, TIAR 2016*, no. Tiar, pp. 65–70, 2016, doi: 10.1109/TIAR.2016.7801215.

[12] S. Madakam, R. Ramaswamy, and S. Tripathi, "Internet of Things (IoT): A Literature Review," *Journal of Computer and Communications*, vol. 03, no. 05, pp. 164–173, 2015, doi: 10.4236/jcc.2015.35021.

[13] M. Gopal, V. Masane, and R. A. Naphade, "International Research Smart Garbage Monitoring System." [Online]. Available: www.ijtsrd.com

[14] I. Mittal, A. Tiwari, B. Rana, and P. Singh, "Trash Classification: Classifying garbage using Deep Learning," vol. 11, no. July, 2020, doi: 10.13140/RG.2.2.19452.56969.

[15] C. C. J. Kuo, "Understanding convolutional neural networks with a mathematical model," *J Vis Commun Image Represent*, vol. 41, pp. 406–413, Nov. 2016, doi: 10.1016/j.jvcir.2016.11.003.

[16] A. Patil and M. Rane, "Convolutional Neural Networks: An Overview and Its Applications in Pattern Recognition," *Smart Innovation, Systems and Technologies*, vol. 195, pp. 21–30, 2021, doi: 10.1007/978-981-15-7078-0_3.

[17] B. N. Silva, M. Khan, and K. Han, "Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities," *Sustainable Cities and Society*, vol. 38. Elsevier Ltd, pp. 697–713, Apr. 01, 2018. doi: 10.1016/j.scs.2018.01.053.