

Solid Wastes Segregation Using CNN For Smart Waste Bins: A Case Study Of The Namoo Community

Anas Musah¹ Mathew Abasagiwe Adda² Isaac Azure³

Department of Computer Science Regentropfen University College



INTRODUCTION

Issues of poor waste management are numerous and they include the destruction of life and property, removal of fertile soil that hastens crop growth, and pollution of air [1]. One of the best ways to salvage this problem is by properly disposing of waste. The advent of **'The Internet of Things**' has come to help in many ways in the areas of waste management. Among the many inventions include the use of smart bins that give alerts to waste collectors when they are full and, the use of various algorithms in finding best-optimized routes to waste sites to reduce cost. This study also focuses on the segregation of waste to enhance recycling.

Objective

- To examine the problems of waste segregation
- To develop an algorithm that automatically detects different classes of waste common in the Namoo community

Result 2: Traning vs Validation Accuracies

The model accuracies (train and validation) declined after the 15^{th} epoch with the best accuracy around 0.33 (Figure 3a). Both accuracies rose steadily in the second case, with validation accuracy fluctuating more (Figure 3b). In the third case, the best performance was at 14 and 16 epochs, but overall performance was lower (Figure 3c).



Figure 3. Training versus Validation accuracies

Method 1:MODEL USED

This work implored the use of the Convolutional Neural Network to model an algorithm that can classify different waste types based on their individual properties. CNN is one of the machine learning algorithms that is known to always give great accuracy when it comes to image classifications. The model uses convolutions that are more like filters. This study used CNN in the following layers:

- Input Layer: Normalizes grayscale or RGB images to a 0-1 range before training.;
- Convolutional Layer: Uses a kernel to perform convolutions, reducing image dimensions and extracting features.
- Pooling Layer: Reduces the size of feature maps, typically using max-pooling to create a smaller version of the input.
- Fully Connected Layer: Classifies images into labels based on features extracted by previous layers.
- Output Layer: Conducts final classification using a loss function.

Method 2: Data Collection and Preprocessing

This study utilizes primary data collected through a Sony Canon camera (150mp lens) and an Android phone (48mp camera) to identify dominant household waste types. A total of 808 images were selected from the collected data for model training and testing. Each of the four classes was represented by 202 images to ensure fairness. Factors influencing the image selection included class balance and image quality. The table below shows the breakdown of images each day:

Waste Type	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Total
Sachet of water	102	81	78	127	102	93	583
Poly bags	78	130	130	77	76	87	578
Plastic Bottles	45	36	23	34	45	78	261
Others	90	99	71	171	132	104	667
Total	315	346	302	409	355	362	2089

Result 3: Confusion Matrix

The confusion matrix shows the model's performance with predicted vs. actual data. In the first run (Figure 4a), bottles were the best-predicted class. In the second run (Figure 4b), bottles again had the highest predicted values. In the third run (Figure 4c), sachets were the best-predicted class. Misclassifications were common across all runs for other classes.



Results4: Summary of Model Performance

The model was able to give an average accuracy of 0.43. The precision on all four classes after a successful test was also 0.35 (Figure 5). These were very promising results that can go a long way to help in the segregation of waste according to the four most common classes created above.

	precision	recall	f1-score	support
class 0(satchet)	0.40	0.60	0.48	48
lass 1(polybags)	0.21	0.18	0.19	33

The combined 'others' category includes food packets, paper, glass, wood, cloth, etc.



class 2(bottles) 0.38 0.27 0.31 41 class 3(others) 0.28 0.35 0.31 40 0.35 162 accuracy 0.33 0.33 0.32 162 macro avg weighted avg 0.34 0.35 0.34 162

Figure 5. The summary of model performance

Conclusion

Waste mismanagement poses multifaceted challenges, with recycling being a promising solution reliant on effective segregation. In this study,

- 1. The highlight of the complexities of manual waste segregation was highlighted in this study
- 2. The CNN algorithm was developed and has efficiently segregated waste into four distinct classes with an average accuracy of 0.43 and precision of 0.35.

This study recommends the impact of different CNN architectures on waste segregation for future works and training and testing the model on full RGB data instead of normalising it to grayscale.

References

- [1] K Adu-Boahen, G Atampugre, KB Antwi, A Osman, KN Osei, EA Mensah, and AO Adu-Boahen. Waste management practices in ghana: challenges and prospect, jukwa central region. *International Journal of Development and Sustainability*, 3(3):530–546, 2014.
- [2] Dipesh Gyawali, Alok Regmi, Aatish Shakya, Ashish Gautam, and Surendra Shrestha. Comparative analysis of multiple deep cnn models for waste classification. *arXiv preprint arXiv:2004.02168*, 2020.
- [3] Jithina Jose and T Sasipraba. An optimal model for municipal solid waste management using hybrid dual faster r-cnn. Environmental Monitoring and Assessment, 195(4):462, 2023.

[4] Shaeke Salman and Xiuwen Liu. Overfitting mechanism and avoidance in deep neural networks. *arXiv preprint arXiv*:1901.06566, 2019.

Figure 1. Sample data for others (paper, glass, food packets, etc.

Results 1: Train loss and Validity loss

Validation loss is slightly higher than training loss, indicating the model is still learning (Figure 2a). Training loss is less than validation loss (Figure 2a), suggesting underfitting as suggested by [4]. In Figure 2a, the model performed better, with training and validation losses decreasing and stabilizing, indicating a near-good fit.



Figure 2. Training loss vs Validation loss

- [5] S Vidhya. A systematic review of machine learning approaches for trash classification. In 2023 7th International Conference on Trends in Electronics and Informatics (ICOEI), pages 996–1000. IEEE, 2023.
- [6] Cong Wang, Jiongming Qin, Cheng Qu, Xu Ran, Chuanjun Liu, and Bin Chen. A smart municipal waste management system based on deep-learning and internet of things. *Waste Management*, 135:20–29, 2021.
- [7] Hanxiang Wang, Yanfen Li, L Minh Dang, Jaesung Ko, Dongil Han, and Hyeonjoon Moon. Smartphone-based bulky waste classification using convolutional neural networks. *Multimedia Tools and Applications*, 79:29411–29431, 2020.

Acknowledgements

We express our sincere gratitude to Dr. Isaac Azure for his invaluable guidance and support during the research process. Additionally, we extend our thanks to the Department of Computer Science at Regentropfen University College (RUC). Lastly, we are grateful to the DLI Indaba Organizers for providing the funding opportunity that enabled us to publish this paper and attend this year's conference in Senegal.

Contact Information

Web: https://www.regentropfen.edu.gh/

- Email: anas.musah@regentropfen.edu.gh
- Phone: +233 (0) 555 516 90 or +233 (0) 501 374 117

5th Anniversary

IndabaX Ghana: Data Science Summit

www.indabaxghana.com