Deep Learning-based Object Detection for Smart Solid Waste Management System

Tagel Aboneh
Addis Ababa Science and Technology University, High-Performance Computing and Big data Analytics, Addis Ababa Science and Technology University, Addis Ababa, Ethiopia
+251913214122
Tagel.aboneh@aastu.edu.et

Meron Desta
Addis Ababa Science and Technology University
Addis Ababa, Ethiopia
+251926453798
destameron308@hu.edu.et
merond308@gmail.com

Bisrat Derebssa
School of Electrical and Computer Engineering, Addis Ababa Institute of Technology, Addis Ababa University, Addis Ababa, Ethiopia
+251929139442
bisrat@aait.edu.et

Abstract

Ethiopia faces increased pollution and environmental damage from waste, with improper waste sorting and classification being a challenge. A single-stage YOLOv4-waste deep neural network model is proposed for real-time object detection in image and video data. The study uses 3529 waste images divided into seven classes, and YOLOv4 outperforms YOLOv4-tiny in object detection. The best results are achieved with YOLOv4 model at mAP 91.25%, precision 0.91, recall 0.88, F1-score 0.89, and Average IoU 81.55%, while YOLOv4-tiny achieves 82.02%, precision 0.75, recall 0.76, F1-score 0.75, and Average IoU 63.59%.

Introduction

Solid waste is defined as any type of garbage, trash, refuse, or discarded material. It can be classified according to where the waste is generated, such as municipal solid waste, medical waste, and e-waste[1]. Addis Ababa's garbage management is poor, with only 65% collected and disposed of, with 5% recycled and 5% composted. 71% of solid waste is generated by households, while 26% comes from businesses. Tight cooperation between the government and households is needed to effectively manage solid waste. Municipal solid trash is delivered to Koshe, an unmanaged landfill, posing health risks to surrounding neighborhoods [3]. Traditional waste disposal methods, such as burial or landfilling, often pollute soil and air, causing long-term environmental harm. Plastic waste, which can decompose in 20 to 500 years, is a major concern. Organic waste, which decomposes anaerobically in landfills, produces methane, a greenhouse gas that can cause uncontrolled fires. Anaerobic digestion of organic waste can produce biogas, reducing greenhouse gas emissions and slowing global warming [4]. Addis Ababa's garbage management is poor, with only 65% collected and disposed of, with 5% recycled and 5% composted. 71% is generated by households, while 26% comes from businesses. Tight cooperation between the government and households is needed to effectively manage solid waste. Municipal solid trash is delivered to Koshe, an unmanaged landfill, posing health risks to surrounding neighborhoods [10].

Method

Data collection

This research uses 2529 waste images from The Stanford TrashNet Dataset and 1000 images from Repi dump sites, households, and mobile phone-collected waste. The dataset includes seven waste types and is divided into three sections for training, testing, and validation.

Labelling

Labeling dataset using LABELIMG tool, producing.txt file with graphically labeled or annotated images, is a free, open-source process.

Data Augmentation

Data-augmentation technique creates variances in data to accurately generalize unknown information. Mosaic data augmentation replicates training data and enhances context information in images, improving model learning ability.

Experiment

Subdivision and Mosaic Augmentation Parameters Tuning

Test involves tuning subdivision value and mosaic data augmentation technique in YOLOv4-tiny model to match GPU-RAM performance in Colab.

Model used

YOLO is a state-of-the-art real-time object detection algorithm using Convolutional Neural Networks. It can identify objects in images using webcam, video, and image input. Yolov4 and Yolov4-tiny models are used for lightweight deployment on edge devices.

The work utilizes deep learning-based waste object detection using Python, Anaconda IDE, TensorFlow, and Open-cv modules. Labeling is done using ImgAnnotationLab_V4.1.0.0, while training is done using Google COLAB. Digital images are collected using TCL t766S mobile phone camera and Logi Techc-720 USB camera for real-time testing.

RESULTS

Training Result for YOLOv4 Model with Sub-division Value 16 and Mosaic data Augmentation

The YOLOv4 model has the best weight values for each waste class, with AP values of 95.28% for cardboard, 94.48% for glass, 93.28% for metal, 83.28% for organic, 95.33% for paper, 88.09% for plastic, and 89.00% for trash. However, it struggles with detecting organic waste from stacks of vegetables, which may be mistakenly placed in trash classes due to mingling. The YOLOv4 model has the best mAP of 91.25 % and an average loss of 0.4679. It takes 16 hours to complete 14,000 itrations.

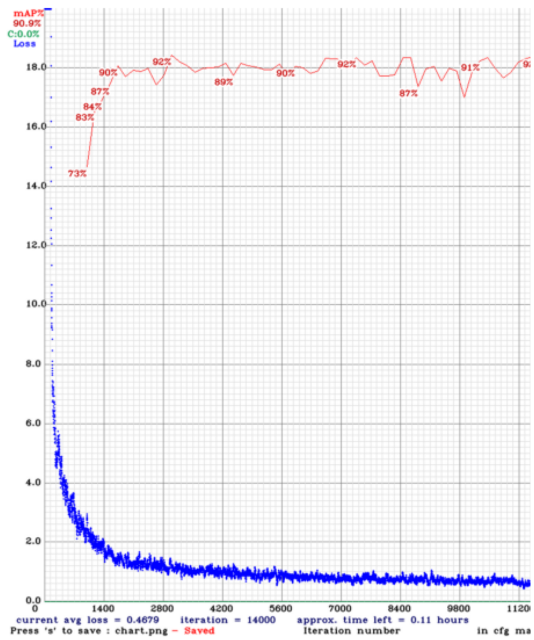

Figure 1 Average Loss and mAP for YOLOv4 iteration 1000 – 14,000 with mosaic data augmentatio.

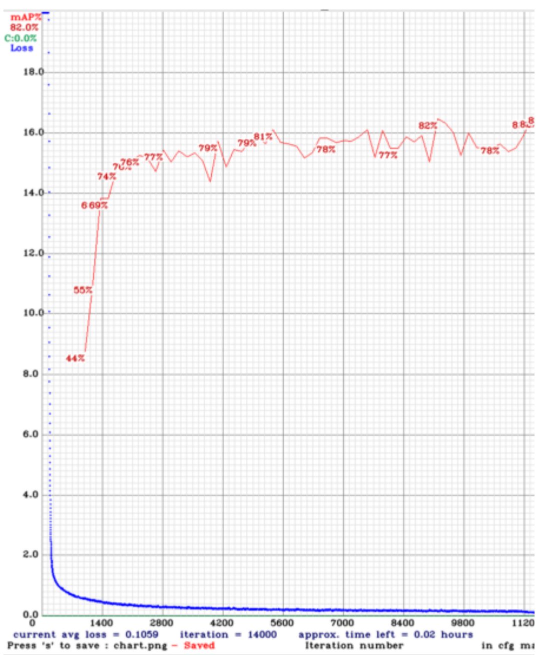

Figure 2 Average Loss and mAP for YOLOv4-tiny iteration 1000 – 14,000 with mosaic data augmentatio.

YOLOv4-tiny model achieves best weight value in various classes, except organic, with high AP values in cardboard, glass, metal, organic, paper, plastic, and trash. effectively on a *never-before-seen dataset* or *validation set.* The YOLOv4-tiny model has the best mAP of 82.02 % and an average loss of 0.1059. It takes 3 hours (13 hours faster than the YOLOv4 model inference time) to complete 14,000 iterations.

Subdivision and Mosaic Augmentation Parameters Tuning

The test involves tuning parameters in a YOLOv4-tiny model, adjusting subdivision values and mosaic data augmentation techniques to match GPU-RAM performance in Colab.

Conclusion

This paper presents a classification model and real-time object detection system for image bounding box and prediction probability. The YOLOv4-tiny architecture, simpler than the YOLOV4 design, improves the algorithm's performance in prediction probability and time. YOLOv4 outperforms in prediction probability with a 91.25% mAP value, 0.99% precision, 0.88% recall, 0.89 F1-Score, and average IOU of 80.47%. However, YOLOv4-tiny has faster computing speed but lacks the same detection capabilities and prediction probability.

Subdivision	Mosaic	mAP	Time
16	Without mosaic	77.35	150 minutes
16	With mosaic	79.86	180 minutes
8	Without mosaic	80.06	120 minutes
8	With mosaic	82.02	185 minutes

Table 1 Effect of Mosaic Data Augmentation and Subdivision Parameters.

ACKNOWLEDGMENTS

Department of Electromechanical Engineering, Department of Software Engineering College of Electrical and Mechanical Engineering, High-Performance Computing and Big data Analytics, Addis Ababa Science and Technology University, Addis Ababa, Ethiopia. Hawassa University for the platform they provide while conducting the project.

Reference

[1] W. H. O. WHO, "Compendium of WHO and other UN guidance on health and environment: 2022 update," *WHO Fact Sheet*, vol. 2019, no. December, p. 5, 2022, [Online]. Available: https://www.who.int/en/news-room/fact-sheets/detail/arsenic.

[2] S. Meng and W. T. Chu, "A Study of Garbage Classification with Convolutional Neural Networks," *Indo - Taiwan 2nd Int. Conf. Comput. Anal. Networks, Indo-Taiwan ICAN 2020 - Proc.*, pp. 152–157, 2020, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181311.

[3] D. M. Chen, B. Leon, and T. Krueger, "Smart Waste Management for Smart City : Impact on Industrialization Smart Waste Management for Smart City : Impact on Industrialization," 2021, doi: 10.1088/1755-1315/655/1/012040.

[4] & R. Nahman, A., Yonli, A.H., Fisseha, G.G., Katima, Jamidu H.Y., Kidane, G.G., Osman, Mohamed Abdelnaem M., Ahmed, M.T., Mohammed, M.A., Loutfy, N.M., Osibanjo, O., Oelofse, S., *Africa Waste Management Outlook. UN Environment Programme, Nairobi, Kenya.*, vol. 123, no. 3. 2018.

[5] World Health Organization. Regional Office for the Western Pacific., "Guides for municipal solid waste management in Pacific Island countries," *Heal. Cities - Heal. Islands Doc. Ser.*, no. no.6., p. 183 p., 1996.

[6] (constructed in 1965)., "OpenLitterMap . com – Open Data on Plastic Pollution with Blockchain Rewards (Littercoin)," 2018.

[7] C. L. Bjerkli, *Camilla Louise Bjerkli Urban services and governance*, no. April. 2013.

[8] E. Gelan, "Municipal Solid Waste Management Practices for Achieving Green Architecture Concepts in Addis Ababa, Ethiopia," *Technologies*, vol. 9, no. 3, p. 48, 2021, doi: 10.3390/technologies9030048.

[9] G. P. Cambridge Industries Limited Profile, "Africa ' s First Facility," *Reppie Waste to Energy Facil.*, no. Cil, pp. 7–10, 2017.

[10] M. Paananen-porkka, "Solid Waste Management in Addis Ababa," 2016.

[11] M. Zoppi, "Real Life Smart Waste Management System," vol. 3307, pp. 631–640.

[12] Aditya Hosamani, "Decoding the dichotomy: Traditional Image Processing vs. Deep Learning Whitepaper," pp. 1–6, 2020, [Online]. Available: https://www.imveurope.com/sites/default/files/content/white-paper/pdfs/HCL_IMVE_WP-ImageProcessing_vs_DL.pdf.