IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657
Volume 12, Issue 1, 2024

AUTOMATIC GARBAGE CLASSIFICATION SYSTEM BASED ON DEEP LEARNING

Ms.P.Manasa , Professor, Department Of Electonics, SICET, Hyderabad
Kondru Divya Sri, Mallela Gowthami, Janupala Vinay Kumar Reddy, Eerati Ganesh
UG Student,Department Of Electronics, SICET, Hyderabad

Abstract

The waste analysis process promotes wastetoenergy production, waste reduction, recycling and waste reduction. I mproper disposal of waste can lead to reinfestation. Contamination is a big problem for the recycling industry and can be solved with computerized destruction. The existence of patterns or techniques to help people separate waste becomes crucial for proper disposal. Although there are many types of recycling, many people are still confused o r do not know how to choose the right source to deal with all types of waste. Waste management and distribution s ystems are thought to play an important role in ecological development worldwide. Organizations should reduce w aste by recycling and reusing waste materials, thus reducing environmental problems. The project uses deep learni ng to create a waste detection system that will collect waste images or videos from cameras by recognizing, detecti ng and predicting objects and identifying waste materials such as cardboard, glass, metal, paper and plastic. . and p roper disposal of waste using recyclable and non-recyclable materials.

Keywords - Deep Learning, Object Detection, TensorFlow, Faster R-CNN, Waste Classification etc.

1. Introduction

Waste management is well known today, but unfortunately it is ignored by many and is used to describe waste cla ssification efforts to solve problems caused by improper disposal [1]. Analysis showed that 74% of the plastic leak ing into the ocean from the Philippines came from garbage [2]. To complete the recycling process, it is necessary t o find a smart idea that can distribute the waste correctly. Compared to recycling techniques, the use of waste dete ction software is an important method for waste identification because a large number of items can be identified in a limited time. Traditional methods rely on the courtesy of human labor, which often fails when it comes to waste separation and recycling [3]. Therefore, this article aims to propose and develop a framework using deep learning t hat can be effectively used in waste classification. Images will be recognized using the concept of convolutional n eural networks and with the help of image processing techniques where debris can be identified based on its shape, colour, size and size [5]. This technology will automatically help the system learn relevant features from negative images.o identify these features in new images. In this way, waste is divided into different categories. The concept used for this demonstration is used with the help of TensorFlow's object detection API and Faster RCNN technolo gy. The main aim of this research is to develop software that will detect recyclable materials in the trash and ensur e contamination (nonrecyclable materials), thus reducing human effort in separating waste and simplifying the wh ole process.

2. Literature Survey

Over the past few years, many efforts have been made to limitthe effects of improper disposal. Many image classif ication tasks based on neural networks and support vector machines have been performed [6].A comparison was m ade by Mindy Yang et al. Garbage classification of SVMs using scale-invariant feature transform (SIFT) and 11-layer CNN design such as AlexNet. The results show that SVM beats CNN. The actual rate is up to 63% [7].This next article aims to compare deep learning convolutional neural network and machine learning algorithm (SVM) r esearch on garbage classification to obtain the robustness of garbage waste. The accuracy of SVM is almost higher than CNN. However, as data and GPU usage increases, the CNN algorithm provides greater accuracy and reduces the effect of overfitting. For postprocessing in hardware, the SVM model is executed for classification. It has a Ra spberry Pi 3 and a good HD camera. The camera previews the debris and saves the image in a PNG file. Captured images are placed in preloaded groups and different LED tones shine depending on their category [8].They propos ed a Gray Level Co-
occurrence Matrix (GLCM) method for waste classification and detection by combining advanced communication technology with GLCM to improve wastewater management. The proposed system uses various communication t echnologies and performs waste monitoring, including Geographic Information System (GIS), Radio Frequency Id entification (RFID) and General Packet Radio System (GPRS) with camera integration. Key points of GLCM andI

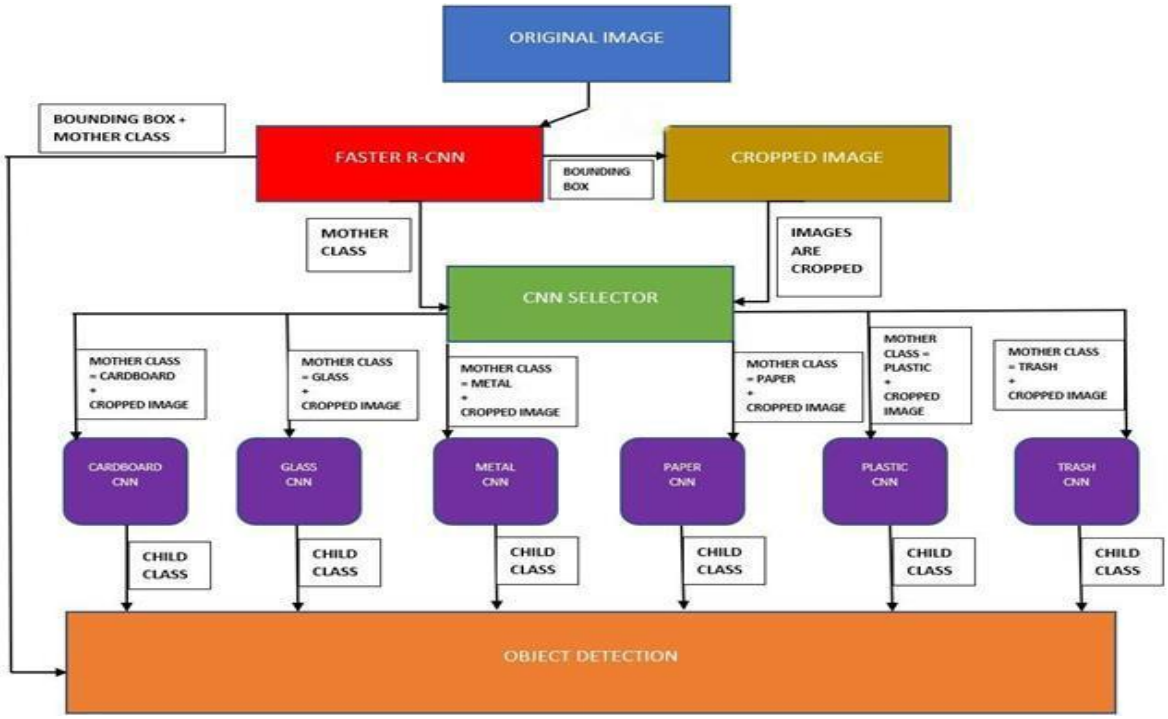
ISSN 2347–3657
Volume 12, Issue 1, 2024

t is then used as input for multilayer perceptron (MLP) and KNearest Neighbors (KNN)garbage classification tech niques. The results show that KNN performs better classification than MLP [9].The creators of Recycle Net experi mented with the widely recognized architecture of deep convolutional neural networks. Training performed witho ut preweighting,Inceptionv4 outperformed the others, achieving a testing accuracy of 90%. Developers at the time had donemodifying the learning and adjusting the weight of the weight indexusing ImageNet weights, andDenseN et121 achieved the best result, about 95%accurate. The estimated time for final editing is much slower [10].They p roposed a computer framework based on deep learning and traditional techniques to classify waste materials into f our types of recycling (paper, metal, glass, plastic). The results show that VGG-
16 technology is a good way to solve this problem, achieving 93% accuracy in the best case."Automatic Trash" wa s created by the team at the TechCrunch Disrupt Hackathon. Their frame uses a Raspberry Pi camera and has a cir cular top. The team used Google's TensorFlow AI engine and created their own setBasically, in recent years comp uter vision has been seen as a tool to help sort wasteand deep learning techniques are available< br> Appropriate r esults are achieved under control. Oluwasanya decided on Information Recognition in InsuranceAwe et al proved i ts feasibility with the help of Faster RCNN model. In the same study, the authors proposed a strategy using the Fas ter RegionBased Convolutional Neural Network (Faster RCNN) technique to obtain regional recommendations an d classify objects with an average accuracy of 68.3% [11].

3. Challenges in Waste Classification

The existence of models or techniques that help people sort waste has become crucial for proper disposal. Althoug h there are many types of recycling, many people are still confused or do not know how to choose the right bin to deal with all types of waste. Waste management and distribution systems are thought to play an important role in e cological development worldwide. Organizations should reduce waste by recycling and reusing waste materials, th us reducing environmental problems. The project uses deep learning to create a waste detection system that will co llect waste images or videos from cameras by recognizing, detecting and predicting objects and identifying waste materials such as cardboard, glass, metal, paper and plastic. . and proper disposal of waste using recyclable and no n-recyclable materials.

4. BLOCK DIAGRAM OF SYSTEM



Architecture of Faster R-CNN Model for Waste Classification

ISSN 2347–3657
Volume 12, Issue 1, 2024

5. METHODOLOGY

This section provides a brief overview of the methods used in this article. The construction process here generally consists of four main stages. The first step is importantRegarding the collection and collection of data (images), the second phase completes the model design, the third phase completes the model trai ning, and the last phase completes the model testing. In addition to this tutorial, this article describes brie f descriptions of the various libraries and tools used. The most important libraries used in this project are NumPy, Matplotlib, OS, TensorFlow, Utils and OpenCV.

5.1 Libraries used

5.1.1 NumPy

Multidimensional matrix arrays supporting advanced arithmetic operations. Array operations in mathema tics such as algebra, statistics and trigonometric formulas can be performed with the help of NumPy. The image is converted to matrix format. The matrix form of the image is used for interpretation and analysi s by neural networks [12].

5.1.2 Matplotlib

Python plotting functionality supports the Matplotlib programming language. In this project it will be use d to draw a box showing the name of the image and the number of dots. The bounding box is used to dis play the name and score of the detection object on the image. Matplotlib provides an object-oriented programming interface. Numpy is one of the code extensions of Matplotlib [4].

5.1.3 Operating System

Operating System is one of the import libraries of python. It is used to provide a method based on the op eration of the business and is also used to work on the method. Tarfiles are used to represent more data t han reading and writing. It involves reducing the size of the code used for data, writing and reading oper ations[4].

5.1.4 TensorFlow

This article provides a brief overview of the methodology used in this article. The construction process h ere generally consists of four main stages. The first step is to use TensorFlow by Google for fast calculati ons. TensorFlow helps data augmentation. It is also used

ISSN 2347–3657
Volume 12, Issue 1, 2024

The algorithm works perfectly and downloads the weights before training on the network image. In this project, TensorFlow helps analyze and classify waste in realtime video (webcam) and supports graphical data representation. It also works with a handheld camera.

5.1.5 Utilities

Part of the Python library for writing functions and classes. The main function of Utils is to support the u se of neural networks. In this project, Utils will be installed from the TensorFlow library.

5.1.6 OpenCV

OpenCV is used to analyze various images and videos. Image processing is done by OpenCV. It focuses on realtime computer vision. In this model, using the OpenCV python library, a python script will be wri tten to test the new training

[11]. These distributions are based on images located in separate folders. However, the explanation of th ese images is needed especially when the data is trained on the Faster R-CNN model. Get comments
A tool is used to label images, called the LabelIMG tool.
Images: Images of cardboard, plastic, glass, paper, metal and waste

5.3 Design Patterns

In this model, Faster RCNN Plans Cardboard, glass , 6 groups of parents who are addicted to metal, pape r, plastic and garbage. Six convolutional neural networks were prepared, one for each parent class, which also prevented recognition of nonexistent classes. For example, if the main class is cardboard, we know that the subclass cannot be bottles. First, the model currently uses images as input, Faster RCNN will pro duce a bounding box and base class as output. Using this information, the real image, which is one of the main inputs of CNNs, is cropped.

5.4 Model Training

Training data is created by creating TF records [14] and converting XML files (description of images col lected by the LabelIMG tool) into CSV files containing the training images and all data. Try the images. Once the training data is created, a map is created that tells the system what each object is by describing t he mapping of the category ID to the category name. Once the creation and configuration of the training method is completed, TensorFlow starts training the model.Training a large network in Faster RCNN req uires a lot of energy. Additional software requirements include installation of the CUDA® Deep Neural Network library CUDNN SDK for Windows 10 computers and use of Compute Unified Device Architec ture (CUDA). TensorFlow GPU version 1.4.0 with Python version 3.5 is open source software for high p erformance computing. Its adaptable architecture allows computing to be easily distributed at different le vels.

5.5 Model Testing

Testing the training model is the end of the process. Send the still image after the training is completed. This is used to identify and classify objects in real time using webcams, photos and videos. This project uses protobuf to predict objects detected by videos, photos or webcams. At this stage, the design is tested using test data. The framework manages evaluation data as well as training data. Finally, the framework separates waste into 6 categories (cardboard, plastic, metal, paper, glass and garbage).

ISSN 2347–3657
Volume 12, Issue 1, 2024

6. Conclusion and

Next ScopeTo limit the impact of improper disposal, the project introduced the use of waste materials usi ng crossfunctional technology. energy absorption studies and imagesas a search engine process. Therefor e, in its implementation, the framework uses large image datasets, training algorithms, and prediction mo dels for detection and classification. In this article, we show with an image how to use the FasterR-CNN method to classify six waste categories (cardboard, metal, glass, paper, plastic, garbage) into vario us products. high level of accuracy. Litter detection is not limited to images; scraps can be detected and i solated from a video stream or live camera network stream. The approach used in this article will help re duce pollution and focus on advancing global waste management in the long term. Therefore, it can be c oncluded that this project is an important tool for people.The main problem of this project is the dataset, which has a slightly different appearance than the local dump data. This is why the model is not accurate for some local abandoned images. Future work to consider is a similar approach but improving the data by including local images of waste products. Need to add photoWaste materials from the education proc ess look unhealthy and dirty. This will help the model predict local waste, including mostly dirty househ old items. Further research in this project should consider including more types of other bulk waste in th e database. By strengthening the list of categories, the framework will be further developed and will help in proper development of the waste management process. In the future, various models such as Faster R-CNN, SSD Mobile Net and YOLO will also be able to be analyzed and compared. This analysis can be d one using various classification algorithms separately from the base for each model, and eventually arriv e at the most appropriate model to use to obtain realistic targets and forecasts in the short term. Future w ork is also focusing on using this technology on a mobile phone, so users can easily separate waste and d ispose of it in the correct bin to prevent environmental pollution and reduce pollution.

7. References

1. Singh, S.; Mamasa, K.; Ragosaman, S.; Raj, K.D.; Anusha, N.; Sumi Sar Gallia. Garbage classificatio n using neural networks. Spiral July 2017, 2053-2058.

2. Ranada, P. Why the Philippines is the world's third largest ocean plastic dump. Rapper Blog. Access d ate: 6 October 2015.

3. Sousa, J.; Rebello, A.; Cardoso, J.S. Automating shelf sorting using deep learning. 2019 15th Worksh op on Computer Vision (WVC). IB, 2019, page 17. 43a48 ib.

4. Devi, R.S.; Vijaykumar, V.; Mutumena, M. Use deep learning for waste classification.

5. Bircanoğlu, C.; Tay, M.; Bessel, F.; Genko, Ö.; Kä±zrak, M.A. Recyclenet:

Smart waste classification using deep neural networks. Innovations in Intelligent Systems and Applicatio ns (INISTA) 2018. IEEE, 2018, p. 1-7.

6. . Singh, S.; Mamasa, K.; Ragosaman, S.; Raj, K.D.; Anusha, N.; Sumi Zacharias. Wastebr> Separate t he system using artificial materials. Spiral July 2017, 2053-2058.

7. Ranada, P. Why are the Philippines the world's third largest ocean plastic dump? Rapper Blog. Access date: 6 October 2015, 2015.

8. Sousa, J.; Rebelo, A.; Cardoso, J.S. Automating shelf sorting through deep learning. 2019, XV Works hop on Visual Computing (WVC). IB, 2019, page 17. 43 → 48.

ISSN 2347–3657
Volume 12, Issue 1, 2024

9. Devi, R.S.; Vijaykumar, V.; Muthumeena, M. Garbage classification using deep learning algorithms.

10. Bircanoğlu, C.; Tay, M.; Bessel, F.; Genko, Ö.; Kä±zrak, MA Recyclenet: Smart waste classification using deep neural networks. Innovations in Intelligent Systems and Applications (INISTA) 2018. IEEE, 2018, p. 1-7.

11. Yaj, M. Thung, G. Garbage recyclability classification. 2016 CS229 Project Report.

12. Lowe, D.G. Unique image features from different contents. International Journal of Computer Vision 2004, 60, 91–110.

13. Huang, J. Rathod, V.; Güneş, C.; Zhu, M. Koratikara, A.; Fati, A.; Fisher, I.; Wojna, Z.; Song, Y. Gu adarrama, S.; Other things. Quick/accurate replacement for today's electronics. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, p. 123. 7310 → 7311.

14. Thomas Gamauf, TensorFlow
wanting logging? What are these and how to use them

? Blog (https://medium.com/mostly-ai/tensorflow-records-what-they-are-and-how-to-use-them-c46bc4bbb564), 20 March 2018.

15. Simonyan , K.; Ziserman, A. Deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 2014.

16. Donovan, J. Automatic trash bin collects trash at techcrunch effect Hackathon
Techcrunch Impact Hackathon, San Francisco, CA, USA. Rep Disrupt SF 2016, 2016.

17. Awe, O.; Mengistu, R.; Sreedhar, V. Smart Garbage Network: Garbage Localization and Classificati on. Arxiv preprint 2017.

18. Dabulkar, A.; Muthyan, B.; Srinivasan, S.; Ravi, S.; Quan, H.; Gao, J. Ntse pov tseg pov tseg tsis rau g cai. 2017 IEEE 3rd International Conference on Big Data Computing
Services and Applications (BigDataService). IEEE, 2017, pp.255–260.

19. Zhao, ZQ; Zheng, P. Xu Sheng; Wu, X. Object detection using deep learning: a review.

IEEE Transactions on ntawm Neural Networks thiab Learning Systems 2019, 30, 3212–3232.

20. Evik, E.; Zengin, K. Classification of skin lesions in dermoscopic images using deep convolutional n etworks. European Journal of Science and Technology 2019, p. 309-318.

21. Aled, H., Alkharaf, A.A., Themis, AH, Almurihid, H.S., Alharbi, K.A., Aranazi, NH, Others. A fram ework for classifying and analyzing social media content. Social Networks 2018,7,79.

22. Arcos-Garcia, A.; Alvarez-Garcia, J.A.; Soria-
Morillo, L.M. Deep neural network for traffic sign detection system Evaluate. Neural Computing 2018, 3 16, 332–344.

ISSN 2347–3657
Volume 12, Issue 1, 2024

23. John, NE; Srilakshmi, R.; Menon, S.R.; Santosh, V. Smart garbage classifier raw li cov khoom siv ne ural network.

24. Ladd. International Conference on Computer Vision Systems. Springer, 2017, p. 195-204.

25. Dewanan, S.K. The importance and use of digital image processing. International Journal of Comput er Science and Engineering Technology (IJCSET) 2016, 7, 316–320.