A Review of Embedded Systems for E-Waste Recognition

Eine Übersicht über Eingebettete Systeme zur Erkennung von Elektroschrott

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Abstract — With the global quantity of electronic waste (e-waste) rising every year comes the need for innovative solutions to the e-waste management problems. The goal of this article is to summarize the latest research in the field of e-waste recognition, with a focus on embedded systems. The summary included the following parameters for each system: recognition method, hardware implementation, dataset size, number of recognizable e-waste objects, system efficiency, goal and application. As a result of this summary, the capabilities and limitations of these systems, as well as current research trends, were revealed. The main finding of this article is that it uncovered the necessity for a complete e-waste dataset, as well as application optimized e-waste datasets, which will aid future research in this field.

Zusammenfassung — Wegen der Menge an Elektroschrott (E-Schrott), die weltweit jedes Jahr zunimmt, besteht der Bedarf an innovativen Lösungen für die Probleme des E-Schrott-Managements. Ziel dieses Artikels ist es, die neuesten Forschungsergebnisse auf dem Gebiet der E-Schrott-Erkennung zusammenzufassen, wobei der Schwerpunkt auf eingebetteten Systemen liegt. Die Zusammenfassung enthält die folgenden Parameter für jedes System: Erkennungsmethode, Hardware-Implementierung, Größe des Datensatzes, Anzahl der erkennbaren E-Schrott-Objekte, Systemeffizienz, Ziel und Anwendung. Als Ergebnis dieser Zusammenfassung wurden die Fähigkeiten und Grenzen dieser Systeme, sowie die aktuellen Forschungstrends, aufgezeigt. Das wichtigste Ergebnis dieses Artikels ist, dass er die Notwendigkeit eines vollständigen Datensatzes für Elektroschrott sowie anwendungsoptimierter Datensätze für Elektroschrott aufgedeckt hat, die die künftige Forschung auf diesem Gebiet unterstützen werden.

I. Introduction

There are many different aspects to the global e-waste problem. Firstly, e-waste has no globally accepted definition, which makes it difficult to classify. Secondly, e-waste contains a lot of hazardous materials which pose a threat to workers and the environment if not handled properly. However, e-waste also contains a lot of valuable and non-renewable materials which could be lost forever if not recycled properly. Furthermore, e-waste is difficult to track, with over 80% of the global e-waste quantity having an unknown status. What's more, the global quantity of e-waste is rising every year, with some experts estimating that it will reach 74.7 million metric tons (Mt) by the year 2030 [1]. One reason for the rising trend of the global e-waste quantity is the large amount of manual labor still required to collect, document, separate, sort, disassemble and recycle it [2]. Two of the main technical limiting factors to automating these processes are the complexity of the e-waste stream and the lack of machine-readable features on the e-waste objects. Computer vision models for e-waste recognition are one possible solution to these problems. Recent advancements in AI accelerated embedded systems and the reduced size of computer vision models have created new opportunities to tackle the global e-waste problem. Due to their small size and low power consumption, embedded systems can be installed in many different locations which is beneficial when managing e-waste, because e-waste is commonly found on the streets or improperly disposed of with general waste. The advantages of embedded computer vision systems for e-waste recognition could be used to reduce the amount of e-waste with unknown status and to actually measure how much e-waste is lost in general waste containers, instead of just relying on statistical approximations. That is why embedded computer vision systems were chosen as the focus of this article.

II. Methodology

This structured literature review was performed using the PICO framework with the goal of gaining a better understanding of how the latest embedded systems for e-waste recognition were designed. For that reason, a research annotation template was created that contained seven questions for each article that was reviewed: what method was used to recognize the e-waste, what hardware, what dataset, how many e-waste object types (i.e., classes) can the system recognize, how efficiently does the system perform its task, for what purpose was the e-waste recognition system developed and in which e-waste management process was it applied. The keyword representations of these questions were used in the header of Table I to document the respective answers for every reviewed article.

The search strategy that was utilized for this literature review involved using the following search terms: "e-waste OR WEEE AND recognition OR computer vision OR machine learning OR identification AND Embedded OR Microcontroller", where WEEE stands for Waste from Electrical and Electronic Equipment. The searches were conducted during October 2023 in the web search engine Google Scholar. During this time, the aforementioned search terms yielded 5420 results, after a search filter was applied to show results from the year 2015 or newer. However, some of the reviewed articles are older, because they were found to be appropriate for this study. These older articles were found in the reference sections of the filtered set of articles.

III. Results

Table I. includes information that is only relevant to the process of e-waste recognition. Some of the hardware and software components of some of the referenced sources were omitted due to their functionality not being related to the process of recognizing e-waste objects.

TABLE 1 *SUMMARY OF THE EMBEDDED SYSTEMS FOR E-WASTE RECOGNITION*

Reference	Method	Hardware	Dataset	E-waste Classes	Efficiency	Goal	Application
[3]	Convolutional Neural Network (CNN): - ResNet18, retrained using transfer learning	Camera: - Logitech C615 Computer: - NVIDIA Jetson Nano Dev Kit	Custom Dataset: - 1000 labelled e-waste images	8 - Resistor - Capacitor - IC voltage regulator - LCD - Relay - Circuit board - Node MCU - Battery	Average Accuracy: 93%	E-Waste Component Recognition	E-Waste Sorting: - Sort e-waste components into two categories depending on whether they contain precious metals or not
[4]	Support Vector Machine (SVM): - contour recognition to recognize defects in the object	- 2D Camera, - 3D Camera, - RFID Scanner for object recognition - Unspecified Computer	-	5 - Li-ion car battery - Battery cell - Terminal - Terminal with connecting port - Connectors	-	E-Waste Component Recognition: - Recognize Li-ion car battery components	E-Waste Disassembly: - Automated Li-ion car battery disassembly and recycling
[5]	Contour detection, - CNN: RetinaNet50 - CNN: YOLOv5x retrained using transfer learning	- Intel Realsense D435 camera - No information on computing hardware	- COCO dataset [6] combined with custom dataset	13 - Screws - Motherboard - Connector - CPU - Fan - Hard Disk - Motherboard - RAM - SSD - Battery - WLAN - CD-ROM -Laptop-Back-Cover	Average Precision: - RetinaNet50: 69.2% - YOLOv5x: 72.2% Average Recall: - RetinaNet50: 51.3% - YOLOv5x: 55%	E-Waste Component Recognition: - Laptop components classification and localization	E-Waste Sorting and Disassembly: - Automatic disassembly of laptop components
[7]	CNN: - Mask R-CNN with FPN - Mask-R-CNN with FPN and Adaptive Pooling - Mask-R-CNN with FPN and Adaptive Pooling a nd Edge Detection	-	Custom dataset: - 533 annotated images of 10 cellphones and t heir components. After including augmented copies of these images, the dataset has a total of 4000 images	11 - Cellphone components and parts, no further details were given	Average Precision: - MASK R-CNNwith FPN: 54.9% - Mask-RCNN with FPN and Adaptive Pooling: 56.2% - Mask-RCNN with FPN and Adaptive Pooling and Edge Detection: 58.7%	E-Waste Component Recognition	E-Waste Disassembly: - Autonomous robotic disassembly of dense smartphone circuit boards
[8]	Contour detection algorithm	- Contour Vision Sensor IFM O2D220 - No information on computing hardware	-	4 Motherboard Components: - CPU -"CHIP1" -"CHIP2" -"CHIP3" -"CHIP4"	Average Accuracy: 91.75% Latency: 1.2s to recognize one component	E-Waste Component Recognition	E-Waste Sorting: - Sorting motherboard components

Reference	Method	Hardware	Dataset	E-waste Classes	Efficiency	Goal	Application
[9]	Combination of contour, gray value, and knowledge-based object recognition Stereo matching for position measurement with implicit detection of occlusions	- Stereo camera vision sensor - UltraSparc processor	-	2 - Car wheel - Nuts of the car wheel	Average Accuracy: 98% Latency: 15s on a wheel with four bolts	E-Waste Component Recognition	E-Waste Disassembly: - Autonomous robotic disassembly of car wheels
[10]	CNN: - Modified Residual neural network 50 (Mod-ResNet50), retrained using transfer learning	- Unspecified webcam - No information on computing hardware	Custom dataset: - 8000 images of e-waste	8 - Computers - Keyboards - Motherboards - Mobile phones - Refrigerators - Laptops - Mice - Radios - Televisions	Average Accuracy: 96%	E-Waste Device Recognition	E-Waste Collection: - Mobile robot for autonomous e-waste collection
[11]	- CNN for object recognition, - R-CNN for size estimation	- Smartphone camera for image capture and communication with server - Cloud server performs e-waste recognition	Custom dataset: - 210 images of e-waste	3 - Refrigerators - Washing machines - Monitors	Average Accuracy: 90% - 96.7%	E-Waste Device Recognition	E-Waste Collection: - Automatic classification of e-waste for improved collection planning
[12]	CNN: - Fractional Horse Herd Gas Optimization-based Shepherd Convolutional Neural Network (FrHHGO-based ShCNN)	- IoT node for image capture and communication with server - Cloud server performs e-waste recognition - Tested on PC with Intel Core i-3 CPU, and 2GB RAM	Custom dataset: - 807 E-waste images	6 - Mobile phone - Keyboard - Mouse - Monitor - Laptop - Bottles	Consumed energy: 0.301 J Delay: 0.666 s Accuracy: 0.950 Sensitivity: 0.934 Specificity: 0.967	E-Waste Device Recognition	E-waste management: - Enhance the social, environmental, and economic sustainability in emerging economies
[13]	CNN: - EfficientDet D0 512x512 [14] , retrained using few-shot learning	-	Combination of two datasets: - [15] and [16] as well as images downloaded from the internet. The resulting dataset has 990 images. After including augmented copies of these images, the dataset has a total of 2376 images - The model was pre-trained on the COCO 2017 dataset [17], [6]	7 - Battery - Bulb - Keyboard - Laptop - Monitor - Mobile Phone - Mouse	Loss: 0.227 with Adam optimizer Loss: 0.254 with Momentum optimizer	E-Waste Device Recognition	E-Waste Collection: - Safe disposing and recycling of e-waste
[18]	FAST R-CNN	Laptop - CPU: Intel Core i5 - GPU: Nvidia GeForce 940 MX 2GB	Two custom datasets called: - Standard dataset and - Non-standard Dataset	-	Accuracy with standard dataset: 88% Accuracy with non-standard dataset: 86%	E-Waste Device Recognition	E-Waste Collection: - Smartphone application which aims to help users to properly recycle their e-waste

Reference	Method	Hardware	Dataset	E-waste Classes	Efficiency	Goal	Application
[2]	Custom CNN	- Webcam Logitech C920x HD Pro - Unspecified laptop	Custom dataset: 164 images	4 - Mobile phones - Batteries - Remote control devices - Light bulbs	Training accuracy: 96.9% Validation accuracy: 93.9%.	E-Waste Device Recognition	E-Waste Sorting: - Robotic e-waste sorting system to incentivize formal recycling practices
[19]	CNN: - Single Shot Multibox Detector (SSD) Lite-MobileNet-v2	- Pi Camera 5MP - Raspberry Pi 3 Model B v1.2	MSCOCO dataset: Estimated 328000 images with 91 object types [6] , of which at least 10 are e-waste types [19]	10: - Central Processing Unit (CPU) - Motherboard - Smartphone - Microcontroller - Batteries - Laptop - Television - Mouse - Remote Control - Electronic Components	Average Accuracy: 62.2%	E-Waste Device and Component Recognition	E-Waste Collection: - Smart e-waste bin for improved e-waste collection planning
[20]	CNN: - YOLOv4	- Raspberry Pi Camera - Raspberry Pi 3 Model B	Custom dataset	4 - Cellphone - Battery - Charger - Other	Average Accuracy: 93.33% Precision: 97.84% Recall: 97.13%	E-Waste Device Recognition	E-Waste Collection and Sorting: - Smart e-waste bin which incentivizes users to recycle while also making it easier for them to do so by automating the e-waste sorting process
[21]	CNN: - YOLOv5s - YOLOv7-tiny and - YOLOv8s retrained using transfer learning	- PiCam 5MP: image capture - Raspberry Pi 4: object recognition - ThingSpeak Cloud Platform: Storage and Analysis	Subset of the Open Images Dataset v7: 4000 annotated images	4 - Monitor - Keyboard - Mouse - Headphone	Precision: - YOLOv5s: 0.752 - YOLOv7-tiny: 0.755 - YOLOv8s: 0.742 Recall: - YOLOv5s: 0.679 - YOLOv7-tiny: 0.709 - YOLOv8s: 0.708	E-Waste Device Recognition	E-Waste Collection: - Smart e-waste bin with sophisticated condition monitoring, e-waste object recognition and internet connection for improved collection planning
[22]	CNN: - AlexNet, retrained using transfer learning	Computer: - CPU: Intel Core i5, - GPU: Asus Nvidia GeForce RTX 2070S 8GB, - OS: Windows 10 x64	ImageNet combined with a custom dataset with 650 RGB images. After including augmented copies of these images, the custom dataset has a total of 5850 images	12 - Smartphone models from six different brands	Accuracy: 98%	E-Waste Device Recognition	E-Waste Sorting: - Automated e-waste classification in support of circular smart cities

Reference	Method	Hardware	Dataset	E-waste Classes	Efficiency	Goal	Application
[23]	CNN: - MobileNetV2 - VGG19 - DenseNet201 - ResNet152V2 - InceptionResNetV2 retrained using transfer learning	Android smartphone	WasteNet: 33520 images. It is a combination of these six datasets: - Trashnet [24] - Drinking waste classification [25] - Waste Classification Data [26] - Open Recycle Dataset [27] - Garbage In Images (GINI) Dataset [28], [29] - E-waste stock photos from Getty Images [30]	7 - E-waste - Garbage - Glass - Metal - Organic - Paper - Plastic	Highest Accuracy: InceptionResNetV2 at 90% Lowest Loss: InceptionResNetV2 at 0.38 Smallest Size: MobileNetV2 at 2.6 MB Lowest Latency: MobileNetV2 at 521 ms	E-Waste Material Recognition	E-Waste Collection: - Smartphone application that combines e-waste recognition with gamification elements to motivate users to recycle their e-waste
[31]	Triangulation scan	- BASLER avA1000-120 km/kc 3D color area scan camera, - Laser emitter	-	5 kinds of waste mixtures: - non-ferrous metal mixture which contains copper, brass and aluminum particles - polymer mixture which contains polypropylene (PP) particles - polymer mixture which contains Acrylonitrile butadiene styrene (ABS) particles - standard particles which contain euro coins - standard particles which contain bottle covers	Sorting rate for non-ferrous metal mixture: 98% Sorting rate for the two polymer mixtures: 99% *except for black colored particles which absorbed part of the red laser Sorting rate for euro coins: 99% Sorting rate for bottle covers: 91%	E-Waste Material Recognition	E-Waste Sorting: - Mechanical separating system for shredded e-waste particles

A. *E-Waste Recognition Methods*

As shown in Fig. 1, the most common method for e-waste recognition is by training a convolutional neural network (CNN) to do so.

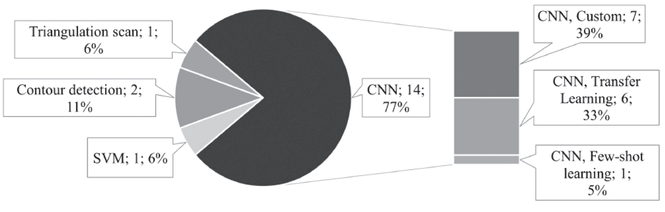

Fig 1. Methods for e-waste recognition, their number of occurrences in the reviewed literature and overall percentage.

From the 14 reviewed systems that rely on a CNN, nearly half of them, six to be exact, have been trained on some large generic dataset and then re-trained with the transfer learning technique on a small e-waste dataset, thus gaining the ability to recognize these e-waste objects. The majority of the reviewed CNNs, seven, were trained on a small custom e-waste dataset or a large dataset which contains many object types, some of which are e-waste (e.g., [19]). Dassi and Sundareson demonstrated in [13] the use of the few-shot learning technique to train their EfficientDet CNN to recognize seven types of e-waste.

B. *E-Waste Recognition Goals*

Three main goals were identified for the e-waste recognition systems in the reviewed literature: Material Recognition, Component Recognition and Device Recognition. Their proportions are shown in Fig. 2.

The majority of the reviewed systems, ten, aim at recognizing e-waste devices, however the system capable of recognizing the most devices is only capable of recognizing 12 e-waste devices [22].

E-waste component recognition is less popular, but this category contains the system with the most classes, 13, presented by Bassiouny et al., [5].

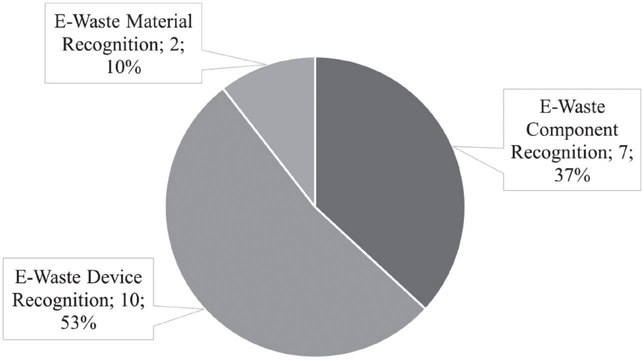

Fig 2. Goals of the reviewed e-waste recognition systems, their number of occurrences in the reviewed literature and overall percentage.

IV. E-WASTE RECOGNITION APPLICATIONS

Electronic waste management has three main stages: pre-processing, processing and post-processing. Each stage has its own e-waste management processes, described in Table II.

TABLE I. E-Waste Management Processes Overview

Stage	E-Waste Management Process				
Pre-Processing	Collection				
	Transportation				
Processing	Separation (from general waste)				
	Documentation				
	Sorting	Shredding	Incineration	Acid leaching	Bio-leaching
	Disassembling	Sorting fractions	-	-	-
Post-Processing	Component recovery	-	-	-	-
	Material recovery				

The success of any given system depends on how well it has been optimized for its specific application. E-waste recognition systems can be applied in any of the processes mentioned in Table II, however most of the reviewed systems were designed for the purposes of three e-waste management processes: collection, sorting and disassembly, as it is shown in Fig. 3.

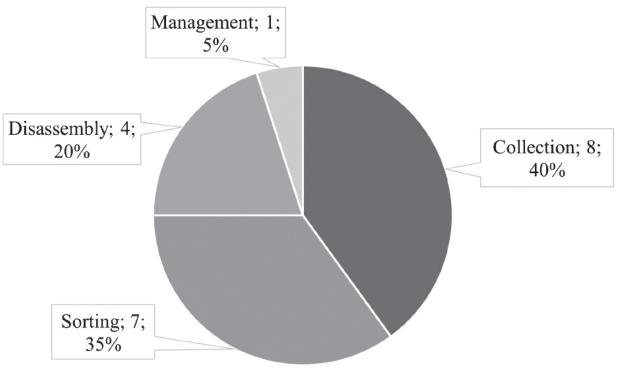

Fig 3. E-waste management processes where the reviewed e-waste recognition systems are applied, their number of occurrences in the reviewed literature and overall percentage.

A. *E-Waste Classes*

The size of the dataset has no apparent influence on the number of e-waste object types (i.e., classes) that the system can recognize. The correlation between these two system parameters can be seen in Fig. 4. There are systems trained on a dataset with a couple of hundred images which can recognize more e-waste objects than a system trained on a dataset with a couple of thousand images and vice versa. This is due to the fact that some convolutional neural networks are trained using the transfer learning technique. This technique allows the developer to re-train a CNN on a new dataset, which in the reviewed cases was smaller than the base dataset the CNN was originally trained on.

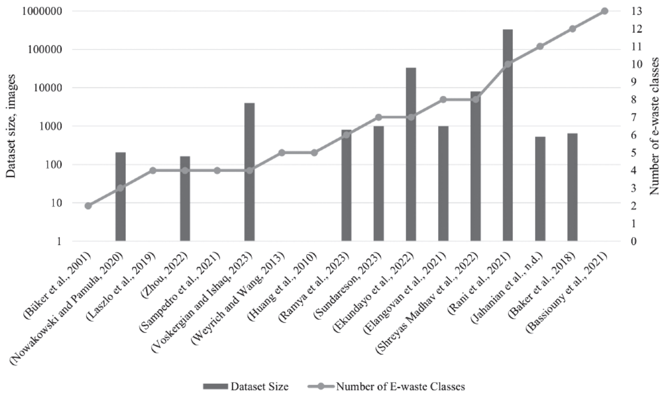

Fig 4. Correlation between the dataset size and the number of recognizable e-waste object types (i.e., classes) for each system in the reviewed literature, where this information was available.

It is apparent, however, that systems using convolutional neural networks for e-waste recognition are capable of recognizing more e-waste objects than systems which use other recognition methods, as shown in Fig. 5.

Fig 5. Correlation between the recognition method and the number of recognizable e-waste object types (i.e., classes) for each system in the reviewed literature.

V. DISCUSSION

From the reviewed literature, the system capable of recognizing the most e-waste devices is only capable of recognizing 12 e-waste devices. This is significantly less than the approximately 900 e-waste product types described in the UNU-KEYS classification [32]. If a system's goal is to recognize individual devices, the number of classes must be many times higher in order to achieve practical results. This would require a larger dataset. The reviewed systems demonstrate that it is possible to train small models on large datasets and run them on embedded hardware (e.g., [19]), however, a complete e-waste dataset, containing images of every e-waste device type, does not yet exist. One possible solution might be to use the UNU-KEYS classification [32] to build such a dataset, where each class represents one UNU-KEY. The benefits of using the UNU-KEYS classification are that it covers all possible e-waste devices and that the UNU-KEYS are cross-referenced to other notable classifications such as the Harmonized Commodity Description and Coding System (HS) and the European Union's WEEE directive [33].

An alternative approach to solving the e-waste recognition problem might be to infer the type of e-waste device based on its composition. For example, instead of training a CNN to recognize specific devices, it can be trained to recognize specific materials or components in order to infer what the device that contains them actually is. Currently, all of the reviewed systems for e-waste material recognition are focused on the collection or sorting of the recognized materials, whereas all of the reviewed systems for e-waste component recognition are focused on the collection, sorting or disassembly of the recognized components. No examples were found of an embedded system which is able to infer the e-waste device type based on its material composition or its components. The assumed benefit of this generic approach is that it might be more reliable than direct device recognition when the e-waste device is deformed. Furthermore, a dataset of e-waste materials or components might be smaller, and therefore easier to create, than a dataset containing all possible e-waste device types.

With regards to direct device recognition using a CNN, the size and structure of the dataset depends on the application of the system. If the system is expected to work in an environment where only small e-waste devices can be found, the model could just be trained on this type of e-waste. For that purpose, a dataset of only small e-waste devices should be created.

The e-waste dataset structure also depends on geographical location because different countries have different definitions for e-waste. For example, in the European Union, the WEEE directive covers six categories of e-waste: temperature exchange equipment, screens, lamps, large equipment, small equipment and small IT and telecommunication equipment [34]. In the Japan however, the Home Appliance Recycling Law defines four categories for e-waste: air conditioners, televisions (CRT, LCD/plasma), refrigerators/freezers and washing machines/clothes dryers, machine translated from [35].

In summary, building a complete e-waste dataset would be beneficial for e-waste recognition systems, regardless of their application, however that would be a very large undertaking. Alternative approaches are to create application specific datasets, location specific datasets or to use alternative e-waste recognition methods, such as inferring the type of e-waste device based on its material or component composition.

VI. CONCLUSION

In this article, 18 embedded systems for e-waste recognition were analyzed and compared according to the method they used, their hardware implementation, dataset size, number of recognizable e-waste objects, efficiency, goal and application. The key takeaway from the performed literature review is that embedded systems are capable of recognizing e-waste efficiently, however they are limited in their recognition capabilities by the lack of a complete e-waste dataset. Although creating such a dataset is possible, it would be a large undertaking considering the many different types of e-waste devices. Therefore, alternative methods were also suggested such as creating application specific e-waste datasets and location specific e-waste datasets. Lastly, an alternative method for e-waste recognition was proposed which suggests recognizing the material or component composition of an e-waste device in order to infer its type.

VII. ACKNOWLEDGEMENT

This research is within the frames of the contract № 232ПД0007-03, Scientific and Research Sector at the Technical University of Sofia.

VIII.REFERENCES

[1] V. Forti, C. P. Baldé, R. Kuehr, and G. Bel, "The Global E-waste Monitor 2020," p. 121.

[2] E. P. Zhou, "Machine Learning For The Classification And Separation Of E-Waste," in 2022 IEEE MIT Undergraduate Research Technology Conference (URTC), Cambridge, MA, USA: IEEE, Sep. 2022, pp. 1–5. doi: 10.1109/URTC56832.2022.10002242.

[3] S. Elangovan, S. Sasikala, S. Arun Kumar, M. Bharathi, E. Naveen Sangath', and T. Subashini, "A Deep Learning Based Multiclass Segregation of E-waste using Hardware Software Co-Simulation," J. Phys. Conf. Ser., vol. 1997, no. 1, p. 012039, Aug. 2021, doi: 10.1088/1742-6596/1997/1/012039.

[4] M. Weyrich and Y. Wang, "Architecture design of a vision-based intelligent system for automated disassembly of E-waste with a case study of traction batteries," in 2013 IEEE 18th Conference on Emerging Technologies & Factory Automation (ETFA), Cagliari, Italy: IEEE, Sep. 2013, pp. 1–8. doi: 10.1109/ETFA.2013.6648043.

[5] A. M. Bassiouny, A. S. Farhan, S. A. Maged, and M. I. Awaad, "Comparison of Different Computer Vision Approaches for E-waste Components Detection to Automate E-waste Disassembly," in 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), Cairo, Egypt: IEEE, May 2021, pp. 17–23. doi: 10.1109/MIUCC52538.2021.9447637.

[6] T.-Y. Lin et al., "Microsoft COCO: Common Objects in Context." arXiv, Feb. 20, 2015. Accessed: Oct. 30, 2023. [Online]. Available: http://arxiv.org/abs/1405.0312

[7] A. Jahanian, Q. H. Le, K. Youcef-Toumi, and D. Tsetserukou, "See the E-Waste! Training Visual Intelligence to See Dense Circuit Boards for Recycling".

[8] R. Laszlo, R. Holonec, R. Copindean, and F. Dragan, "Sorting System for e-Waste Recycling using Contour Vision Sensors," in 2019 8th International Conference on Modern Power Systems (MPS), Cluj Napoca, Romania: IEEE, May 2019, pp. 1–4. doi: 10.1109/MPS.2019.8759739.

[9] U. Büker et al., "Vision-based control of an autonomous disassembly station," Robot. Auton. Syst., vol. 35, no. 3–4, pp. 179–189, Jun. 2001, doi: 10.1016/S0921-8890(01)00121-X.

[10] A. Shreyas Madhav, R. Rajaraman, S. Harini, and C. C. Kiliroor, "Application of artificial intelligence to enhance collection of E-waste: A potential solution for household WEEE collection and segregation in India," Waste Manag. Res. J. Sustain. Circ. Econ., vol. 40, no. 7, pp. 1047–1053, Jul. 2022, doi: 10.1177/0734242X211052846.

[11] P. Nowakowski and T. Pamuła, "Application of deep learning object classifier to improve e-waste collection planning," Waste Manag., vol. 109, pp. 1–9, May 2020, doi: 10.1016/j.wasman.2020.04.041.

[12] P. Ramya, R. V, and B. R. M, “E-waste management using hybrid optimization-enabled deep learning in IoT-cloud platform,” Adv. Eng. Softw., vol. 176, p. 103353, Feb. 2023, doi: 10.1016/j.advengsoft.2022.103353.

[13] R. Dassi and P. Sundareson, “IEEE CTSoc 2020 Remote Internship Project- Object detection for E-waste in Indian context.” Oct. 11, 2023. Accessed: Oct. 11, 2023. [Online]. Available: https://github.com/prabindh/ctsoc-ewaste

[14] M. Tan, R. Pang, and Q. V. Le, “EfficientDet: Scalable and Efficient Object Detection.” arXiv, Jul. 27, 2020. Accessed: Oct. 30, 2023. [Online]. Available: http://arxiv.org/abs/1911.09070

[15] “waste_pictures.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.kaggle.com/datasets/wangziang/waste-pictures

[16] “Starter: e-waste dataset 93b07fb8-a.” Accessed: Oct. 30, 2023. [Online]. Available: https://kaggle.com/code/kerneler/starter-e-waste-dataset-93b07fb8-a

[17] “COCO 2017 Dataset.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.kaggle.com/datasets/awsaf49/coco-2017-dataset

[18] K. Acharekar, P. Khedekar, J. Dsouza, and S. Vaidya, “Machine Learning based RecyClick: Recycle At A Click,” in 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), Tirunelveli, India: IEEE, Jun. 2020, pp. 927–933. doi: 10.1109/ICOEI48184.2020.9142933.

[19] K. N. A. Rani et al., “Mobile Green E-Waste Management Systems using IoT for Smart Campus,” J. Phys. Conf. Ser., vol. 1962, no. 1, p. 012056, Jul. 2021, doi: 10.1088/1742-6596/1962/1/012056.

[20] G. A. Sampedro, R. G. C. Kim, Y. J. Aruan, D.-S. Kim, and J.-M. Lee, “Smart E-Waste Bin Development Based on YOLOv4 Model,” in 2021 1st International Conference in Information and Computing Research (iCORE), Manila, Philippines: IEEE, Dec. 2021, pp. 125–128. doi: 10.1109/iCORE54267.2021.00041.

[21] D. Voskergian and I. Ishaq, “Smart e-waste management system utilizing Internet of Things and Deep Learning approaches,” J. Smart Cities Soc., vol. 2, no. 2, pp. 77–98, Aug. 2023, doi: 10.3233/SCS-230007.

[22] N. Baker, P. Szabo-Müller, and U. Handmann, “Transfer learning-based method for automated e-waste recycling in smart cities,” EAI Endorsed Trans. Smart Cities, p. 169337, Jul. 2018, doi: 10.4108/eai.16-4-2021.169337.

[23][23] O. Ekundayo, L. Murphy, P. Pathak, and P. Stynes, “An On-Device Deep Learning Framework to Encourage the Recycling of Waste,” in Intelligent Systems and Applications, vol. 296, K. Arai, Ed., in Lecture Notes in Networks and Systems, vol. 296. , Cham: Springer International Publishing, 2022, pp. 405–417. doi: 10.1007/978-3-030-82199-9_26.

[24] G. Thung, “trashnet.” Sep. 27, 2023. Accessed: Oct. 16, 2023. [Online]. Available: https://github.com/garythung/trashnet

[25] A. Serezhkin, “Drinking Waste Classification.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.kaggle.com/datasets/arkadiyhacks/drinking-waste-classification

[26] S. Sekar, “Waste Classification Data.” Accessed: Sep. 22, 2023. [Online]. Available: https://www.kaggle.com/datasets/techsash/waste-classification-data

[27] V. Evard and M. Smirnov, “Open Recycle Dataset.” Open Recycle Community, Sep. 17, 2023. Accessed: Oct. 30, 2023. [Online]. Available: https://github.com/openrecycle/dataset

[28] G. Mittal, K. B. Yagnik, M. Garg, and N. C. Krishnan, “Garbage In Images (GINI) Dataset.” Aug. 30, 2023. Accessed: Oct. 30, 2023. [Online]. Available: https://github.com/spotgarbage/spotgarbage-GINI

[29] G. Mittal, K. B. Yagnik, M. Garg, and N. C. Krishnan, “SpotGarbage: smartphone app to detect garbage using deep learning,” in Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Heidelberg Germany: ACM, Sep. 2016, pp. 940–945. doi: 10.1145/2971648.2971731.

[30] “3,800 E Waste Stock Photos - Getty Images.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.gettyimages.ie/photos/e-waste

[31] J. Huang, T. Pretz, and Z. Bian, “Intelligent solid waste processing using optical sensor based sorting technology,” in 2010 3rd International Congress on Image and Signal Processing, Yantai, China: IEEE, Oct. 2010, pp. 1657–1661. doi: 10.1109/CISP.2010.5647729.

[32] F. Wang, J. Huisman, K. Balde, and A. Stevels, “A systematic and compatible classification of WEEE,” p. 6.

[33] Vanessa Forti, Kees Baldé, and Ruediger Kuehr, “E-waste Statistics: Guidelines on Classifications, Reporting and Indicators, second edition.,” United Nations University, ViE – SCYCLE, Bonn, Germany, 2018.

[34] “Directive 2012/19/EU of the European Parliament and of the Council of 4 July 2012 on waste electrical and electronic equipment (WEEE) (recast).” Accessed: Oct. 20, 2022. [Online]. Available: http://data.europa.eu/eli/dir/2012/19/2018-07-04

[35] “Home Appliance Recycling Law.” Accessed: Nov. 10, 2023. [Online]. Available: https://www.meti.go.jp/policy/it_policy/kaden_recycle/index.html