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An Automatic e-waste Classification Model by Improved Deep Learning Algorithm

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Abstract : Waste of Electronic and Electrical Equipment (WEEE) or e-waste is generated at an increasing rate throughout the world. The high demand for electronic devices used in daily activities led to the development of e-wastage. The improper disposal of e-waste has an adverse effect on the environment and human health. For better recycling, e-waste must be properly classified, since each electronic device contains different types of hazardous elements. Manual sorting of e-waste is a very hazardous, expensive, and time-consuming process. The need for automatic e-waste classification is addressed in this paper using YOLOv5. The dataset used for evaluation contains 1350 RGB images that are classified into 10 categories. After training the model for 50 epochs, the mAP, precision, recall and F1score are 99.6, 99.8, 95.5 and 97.6 respectively.

***IndexTerms* - E-waste classification, Deep Learning**

I. INTRODUCTION

With the advancement in economic development and modern technology, various types of new Electronic and Electrical Equipment are invented and are available in the market throughout the world. COVID-19 pandemic lockdown also boosted the demand for electronic devices to be used for health, education and entertainment purposes, and work from home scenarios. Many wearable healthcare devices are available in the market during the pandemic whose lifetime is very less. The average usage lifespan of digital devices is falling with the advancement in technology and lower prices of devices[15].

E-waste or WEEE is used to denote the obsolete, not working or end-of-life EEE. E-waste includes a wide variety of digital devices like mobile phones, electronic and electrical tools, household items like refrigerators, washing machines etc., telecommunication devices, computers, health care monitoring devices, etc. E-waste recycling is a chance for both developed and developing countries due to the valuable items that can be extracted from the e-waste. These electronic devices must be properly disposed of and recycled, otherwise will adversely affect human health, natural life and environment[16].

The adverse effects of e-waste can be reduced with safe disposal and proper e-waste management techniques. Artificial Intelligence and Deep Learning techniques can be used for smart e-waste collection. Convolution Neural Networks have been used by many researchers to detect objects in e-waste. Classification techniques can be used for automated classification of e-wastage, so that the devices can be recycled easily.

II. LITERATURE REVIEW

Abou Baker et al. examined the need for automatic recycling of e-waste. A Transfer Learning (TL) technique is proposed for automatic classification of smartphones. As a pre-trained model, AlexNet is used after fine-tuning the layers. The model is implemented on a small dataset containing 12 models of 6 smartphone brands and to reduce the overfitting problems, data augmentation is used[1]. A hybrid model, combining residual nets and inception modules is used in [2] for classifying features of smartphones. [3] examines the selection of the best pre-trained model for classifying images.

Zhang et al. developed DenseNet169 model for waste classification[13].

Hamza et al. proposed a model for identifying and classifying recyclable and non-recyclable objects in the waste. In the proposed model, Deep Consensus Network (DCN) is used for identifying objects in the image. The performance of this DCN model is further improved by whale optimization algorithm. The detected objects are classified using Naïve Bayes classifier[4]. A custom-designed CNN is used is used in [5] for classifying waste into organic and recyclable classes. Liang et al. used CNN for identifying and locating waste in the input images[14].

Chowdhury et al. used DL based approach for detecting and locating solid waste in . The model is used to detect 12 types of solid waste[8]. Artificial Intelligence and Machine Learning techniques used for recycling waste in smart cities are reviewed in [6,7]. Kumar et al. developed YOLOv3 algorithm for classifying waste of 6 classes[9]. Alsubaei et al. used arithmetic optimization algorithm for detecting objects and for improving performance of object detection, improved RefineDet model is used. Finally, the classification of waste is done using functional link neural network[10].

Li et al. proposed a cascade of detection and classification models for accurate results. In the detection model, Deconvolution Single Shot Detector, YOLOv4 and Faster-RCNN are used. ResNet is used in the classification model for category prediction[11]. Nowakowski et al. used CNN for classifying e-waste and Region-based CNN is used for detecting the type of the product in the image[12].

III. RESEARCH METHODOLOGY

In this paper, data is collected at first, followed by training the model and then e-waste classification is done. The dataset used to implement the model is taken from Kaggle repository (https://www.kaggle.com/code/kerneler/starter-e-waste-dataset-93b07fb8-a) along with manually collected e-waste images. A total of 1352 RGB images are collected, which are categorized into 10 classes of e-waste as shown in the below table 1 and a sample of some of input images are shown in Fig. 2. To reduce overfitting problems, data augmentation is used to create additional copies of the taken dataset by adding more images. The final dataset after data augmentation contains 5408 RGB images and is divided into 80:20 ratio for training and testing the model respectively.

Table 1. Dataset details

Image class	Number of images
Mobile	243
Laptop	215
Mouse	63
Monitor	102
Keyboard	126
Washing machines	84
Refrigerators	113
Television	76
Printers	65
Watches	265

Fig. 2. Sample input images of e-waste

YOLOv5 is used in this paper for classification of e-waste. You Only Look Once (YOLO) is a DL technique that is used for object detection along with classifying the detected objects. YOLOv5 algorithm takes image as an input and passes it through neural network to give bounding boxes and class prediction as output[17,18].

The architecture of YOLOv5 is shown in Fig. 1, that is divided into three components. The input image is resized to 608 x 608 resolution and fed to backbone network. In the backbone, the features in the image are extracted using a pre-trained network. Cross Stage Partial Darknet53 is used as the backbone. The feature pyramids are extracted in the model neck and then final detection is done in the model head.

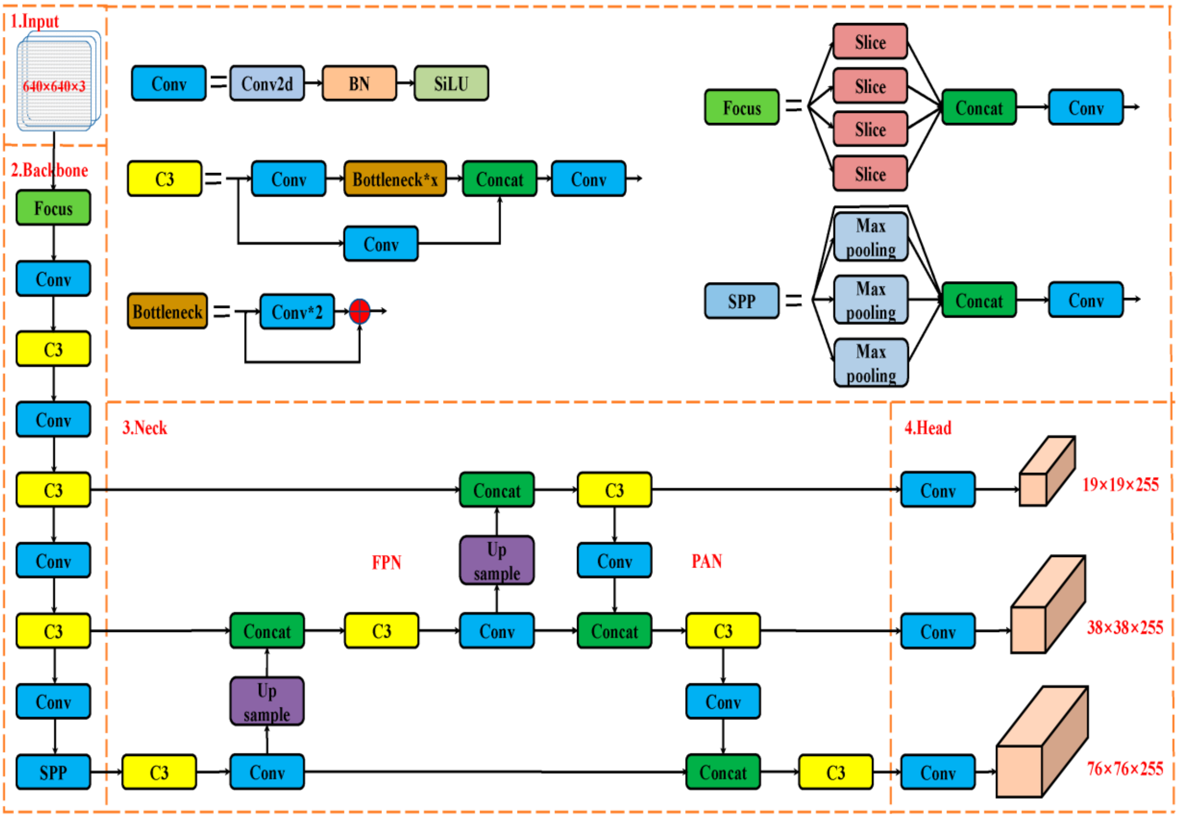

Fig. 1. Architecture of YOLOv5

The Focus layer is used to reduce the number of parameters by slicing and concatenating the input. This layer along with CSP structure reduces the feature map by using a series of convolution, max pooling, and subsampling operations. Spatial Pyramid Pooling (SPP) aggregates the input information and produces fixed length output. Path Aggregation Network (PANet) is a feature pyramid network used for proper localization of pixels.
Sigmoid Linear Unit (SiLU) activation function used along with the convolution operations in hidden layers. The model is trained to identify classes of e-waste items from the input image. The network gives bounding boxes along with the identified class and its confidence score as the output.

IV. RESULTS AND DISCUSSION

The model is trained and tested using 1350 RGB images. Matlab with Deep Learning toolbox is used as a computing environment. Windows 10 with i5 processor is used which has access to NVIDIA GPU. The performance of the model is evaluated using mean average precision (mAP), f1score, precision and recall. The mAP score is determined by comparing the detected box to the corresponding ground truth box. mAP is averaged over average precision. Intersection over Union (IoU) gives the connection between the coordinates of predicted and actual bounding boxes.

$$\mathrm{IoU} = \frac{\text{area of overlap}}{\text{area of union}}$$

Precision is used to evaluate how accurately the model classifies a sample as positive. It measures the accuracy of our predictions. True positives are the samples predicted positive and correct, whereas false positives are the samples predicted as positive but incorrect.

$$\text{Precision} = \frac{true\ positives}{true\ positives + false\ positives}$$

Recall is used to evaluate how accurately the model can find positive samples. False negatives are the objects that were there but not predicted.

$$\text{Recall} = \frac{true\ positives}{true\ positives + false\ negatives}$$

Average Precision is the summation of the difference between the kth and (k − 1)th recall, multiplied with the kth precision for n number of thresholds.

$$Average\ Precision(AP) = \sum_{k=0}^{k=n-1} [Recall(k) - Recall(k-1)] * Precision(k)$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} APi$$

F1 score is used to indicate how well the classification models can anticipate outcomes. It is calculated using the harmonic mean of recall and accuracy.

$$F1score = 2 * \frac{Recall * Precision}{Recall + Precision}$$

The YOLOv5 model is trained for 50 epochs, which are small batches of the training set. Before each epoch the training set is shuffled. During the training phase, the model undergone 50 epochs to learn from the dataset to minimize the training loss and improve accuracy. The model is fine-tuned gradually with the increasing epochs and the accuracy is increased steadily. After 50 epochs, the validation loss increased. Hence, to reduce overfitting, the model is trained for 50 epochs to attain better accuracy. Fig. 3 and 4 show the accuracy and loss values for training and validation or test data respectively. The mAP, precision, recall and F1score of YOLOv5 on the dataset are 99.6, 99.8, 95.5 and 97.6 respectively.

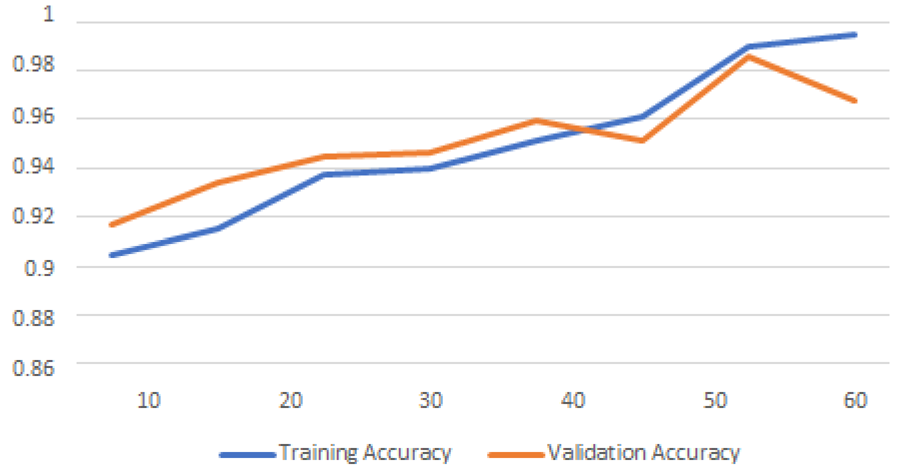

Fig. 3. Accuracy values for training and validation data

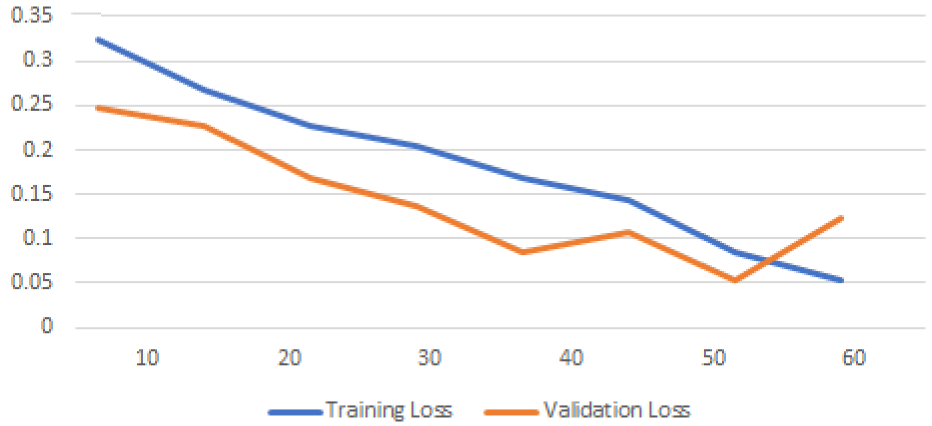

Fig. 4. Loss values for training and validation data

V. CONCLUSION

Artificial Intelligence and Deep Learning play a major role in proper management of e-waste. The YOLOv5 model is used in this paper to detect and classify e-waste. The mAP, precision, recall and F1score of YOLOv5 on the dataset are 99.6, 99.8, 95.5 and 97.6 respectively, after training for 50 epochs. Further research can be done by implementing the model on large datasets and real-world data. The model can be enhanced by incorporating it with other Deep Learning models.

REFERENCES

[1] Abou Baker, Nermeen & Szabo-Müller, Paul & Handmann, Uwe. (2021). Transfer learning-based method for automated e-waste recycling in smart cities. EAI Endorsed Transactions on Smart Cities. 5. 169337. 10.4108/eai.16-4-2021.169337.

[2] Abou Baker, Nermeen & Stehr, Jonas & Handmann, Uwe. (2022). Transfer Learning Approach Towards a Smarter Recycling. 10.1007/978-3-031-15919-0_57.

[3] Abou Baker, Nermeen & Zengeler, Nico & Handmann, Uwe. (2022). A Transfer Learning Evaluation of Deep Neural Networks for Image Classification. Machine Learning and Knowledge Extraction. 4. 22-41. 10.3390/make4010002.

[4] Hamza, Manar & Mengash, Hanan & Negm, Noha & Marzouk, Radwa & Motwakel, Abdelwahed & Zamani, Abu. (2023). Deep Consensus Network for Recycling Waste Detection in Smart Cities. Computers, Materials & Continua. 75. 4191-4205. 10.32604/cmc.2023.027050.

[5] Salunke, Aatmaj. (2023). WasteSegNet: A Deep Learning Approach for Smart Waste Segregation in Urban Environments. 10.13140/RG.2.2.17592.93442.

[6] Chen, Xiangru. (2022). Machine learning approach for a circular economy with waste recycling in smart cities. Energy Reports. 8. 3127-3140. 10.1016/j.egyr.2022.01.193.

[7] Fang, Bingbing & Yu, Jiacheng & Chen, Zhonghao & Osman, Ahmed & Farghali, Mohamed & Ihara, Ikko & Hamza, Essam & Rooney, David & Yap, Pow Seng. (2023). Artificial intelligence for waste management in smart cities: a review. Environmental Chemistry Letters. 21. 10.1007/s10311-023-01604-3.

[8] Chowdhury, Tanvir & Sinthiya, Nusrat & Shanta, S M. Sajid & Hasan, Md & Habib, Mubassir & Rahman, Mohammad. (2022). Object Detection Based Management System of Solid Waste Using Artificial Intelligence Techniques. 0019-0023. 10.1109/UEMCON54665.2022.9965643.

[9] Kumar, Saurav & Yadav, Drishti & Gupta, Himanshu & Verma, Om & Ansari, Irshad & Ahn, Chang Wook. (2020). A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation: Towards Smart Waste Management. Electronics. 10. 14. 10.3390/electronics10010014.

[10] Alsubaei, Faisal & Al-Wesabi, Fahd & Hilal, Anwer. (2022). Deep Learning-Based Small Object Detection and Classification Model for Garbage Waste Management in Smart Cities and IoT Environment. Applied Sciences. 12. 2281. 10.3390/app12052281.

[11] Li, Jiajia & Chen, Jie & Sheng, Bin & Li, Ping & Yang, Po & Feng, David Dagan Feng & Qi, Jun. (2021). Automatic Detection and Classification System of Domestic Waste via Multi-model Cascaded Convolutional Neural Network. IEEE Transactions on Industrial Informatics. PP. 10.1109/TII.2021.3085669.

[12] Nowakowski, Piotr & Pamuła, Teresa. (2020). Application of deep learning object classifier to improve e-waste collection planning. Waste Management. 109. 1-9. 10.1016/j.wasman.2020.04.041.

[13] Zhang, Qiang & Yang, Qifan & Zhang, Xujuan & Bao, Qiang & Su, Jinqi & Liu, Xueyan. (2021). Waste image classification based on transfer learning and convolutional neural network. Waste Management. 135. 150-157. 10.1016/j.wasman.2021.08.038.

[14] Liang, Shuang & Gu, Yu. (2021). A deep convolutional neural network to simultaneously localize and recognize waste types in images. Waste Management. 126. 247-257. 10.1016/j.wasman.2021.03.017.

[15] Chatterjee, S & Kumar, Krishna. (2009). Effective electronic waste management and recycling process involving formal and non-formal sectors. International Journal of Physical Sciences. 4.

[16] Robinson, Brett. (2009). E-waste: An Assessment of Global Production and Environmental Impacts. Science of The Total Environment. 408. 183-191. 10.1016/j.scitotenv.2009.09.044.

[17] Geetha S, Saha J, Dasgupta I, Bera R, Lawal IA, Kadry S. Design of Waste Management System Using Ensemble Neural Networks. *Designs*. 2022; 6(2):27. https://doi.org/10.3390/designs6020027

[18] Chen, Zhangyi, Xiaoling Li, Long Wang, Yueyang Shi, Zhipeng Sun, and Wei Sun. 2022. "An Object Detection and Localization Method Based on Improved YOLOv5 for the Teleoperated Robot" *Applied Sciences* 12, no. 22: 11441. https://doi.org/10.3390/app122211441