JOURNAL OF INNOVATION AND TECHNOLOGY
eISSN:2805-5179 Vol.2026, Issue 2, No.5

Automated Household E-Waste Recognition and Classification Using Faster R-CNN and Modified ResNet50

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Abstract

Electronic waste (E-waste) has emerged as a major environmental challenge due to the rapid growth in electronic device consumption and the improper disposal of end-of-life equipment. Traditional E-waste collection and segregation processes are often labor-intensive, inefficient, and expose workers to hazardous materials. To address these challenges, this study proposes a vision-enabled E-waste management system that integrates Faster Region-Based Convolutional Neural Network (Faster R-CNN) and a Modified ResNet50 model for automated detection and classification of household electronic waste. The proposed framework is designed to support waste collection operations by identifying E-waste items through a vehicle-mounted camera system. Image preprocessing techniques, including resizing, normalization, and data augmentation, were employed to improve model robustness and classification performance. Faster R-CNN was utilized for object detection, while the Modified ResNet50 model was developed using transfer learning for accurate classification of multiple E-waste categories. The performance of the proposed model was evaluated and compared with AlexNet and VGG16 architectures using accuracy, precision, recall, and F1-score metrics. Experimental results demonstrated that the proposed Modified ResNet50 model achieved a classification accuracy of 97%, outperforming the comparative models. The proposed system provides an efficient and scalable solution for automated E-waste identification, reducing manual effort and supporting sustainable recycling practices in smart-city waste management applications.

Keywords

E-waste Management, Faster R-CNN, Modified ResNet50, Deep Learning, Computer Vision, Waste Classification

Introduction

Electronic waste (E-waste) has become one of the fastest-growing environmental concerns worldwide due to rapid technological development, industrialization, and increased dependence on electronic devices. Discarded electronic products such as computers, smartphones, televisions,

Submission: 6 May 2026; **Acceptance:** 3 June 2026; **Available online:** June 2026

and household appliances contain hazardous materials including lead, cadmium, mercury, nickel, and beryllium, which can negatively affect environmental sustainability and public health if improperly handled. The growing accumulation of E-waste and the limited availability of efficient recycling systems have increased the need for sustainable waste management strategies. According to Fotovvatikhah, F., et al (2025), sustainable E-waste management requires the integration of advanced recycling technologies, regulatory frameworks, and environmentally responsible disposal methods, while Singh, R. S et al. (2024) emphasized that innovative recycling approaches can improve resource recovery and reduce environmental pollution.

The rapid increase in electronic consumption has significantly contributed to the expansion of global E-waste production. It stated that the E-waste crisis demands effective recycling strategies and sustainable management practices to minimize ecological damage. Similarly, emphasized the importance of circular economy approaches in improving recycling efficiency and reducing electronic waste accumulation. India is among the top producers of E-waste due to its large population, urban growth, and digital transformation. Public awareness and social participation play important roles in improving E-waste management practices, while Öztürk-Birim, Ş., & Gündüz-Cüre, M.. (2024) discussed the importance of reliable scientific databases in enhancing research accessibility and knowledge dissemination.

Modern technological advancements such as artificial intelligence (AI), machine learning, robotics, and computer vision are increasingly being applied to automate waste collection, identification, and segregation systems. Arbeláez-Estrada et al. (2023) reported that smart technologies can significantly improve E-waste collection and classification efficiency. AI-based robotic systems can enhance automated E-waste segregation while reducing human exposure to hazardous materials. Tanvir, J., (2025) further explained that robotic and AI-enabled waste segregation methods can reduce manual labor and improve sustainable recycling operations, while Hossen, M. M.et al. (2024) highlighted the role of intelligent monitoring technologies in smart-city waste management.

Advanced robotic systems for electronic waste disassembly and material recovery are also gaining importance in sustainable recycling practices. Sallang, N. C. A et al. (2021) introduced a robot-assisted selective disassembly system for end-of-life mobile phones to improve resource recovery efficiency, while Mewada, D., et al. (2024) proposed an automated recycling identification system using deep learning techniques for accurate E-waste classification and segregation. However, limited studies have focused on integrating real-time object detection and deep learning classification for household E-waste collection in practical environments. Therefore, this study proposes a vision-enabled E-waste management system using Faster R-CNN and Modified ResNet50 to improve identification accuracy and support efficient E-waste collection and recycling operations.

Methodology

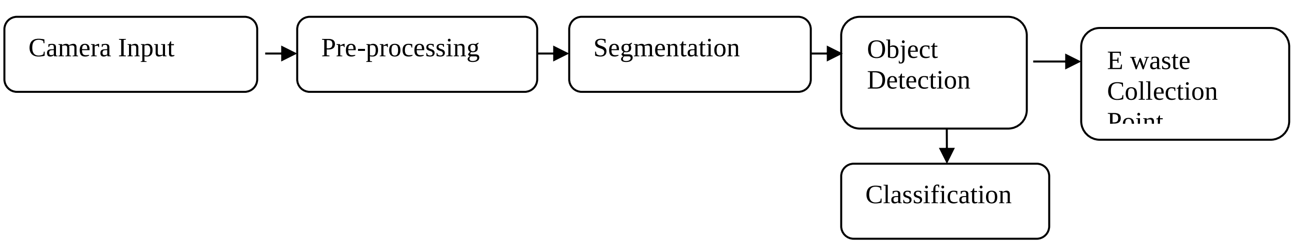

Figure 1. Proposed vision-enabled E-waste management framework

A proposed e-waste system for pinpoint and collecting household e-waste is shown in Figure 1. The proposed vision-enabled E-waste management system consists of image acquisition, preprocessing, object detection, classification, and waste identification modules. As illustrated in Figure 1, images of household electronic waste are captured using a camera mounted on a waste collection vehicle. The acquired images are preprocessed through resizing, normalization, and data augmentation techniques, including rotation, flipping, shearing, and zooming, to improve model generalization and reduce overfitting. The preprocessed images are then forwarded to the object detection and classification stages.

For object detection, a Faster Region-Based Convolutional Neural Network (Faster R-CNN) is employed to locate and identify electronic waste items within the captured images. The detected objects are subsequently classified using a Modified ResNet50 model developed through transfer learning. The original fully connected layer of ResNet50 was replaced with a customized dense classification layer corresponding to the E-waste categories. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 50 training epochs.

The dataset consists of images belonging to multiple categories of household electronic devices, including UPS, CRO, radio, tablet, keyboard, monitor, laptop, motherboard, mouse, mobile phone, refrigerator, and television. All images were resized to 224 × 224 pixels before training. The dataset was divided into training and testing sets using an 80:20 ratio. Data augmentation techniques were applied to increase dataset diversity and improve classification performance under varying environmental conditions.The performance of the proposed Modified ResNet50 model was evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results were compared with AlexNet and VGG16 architectures to assess classification effectiveness. The trained model was integrated with the proposed E-waste collection framework to enable automatic identification of household electronic waste and support efficient collection and recycling operations.

Results and Discussion

The proposed Modified ResNet50 model was trained and evaluated for the classification of household electronic waste using a dataset containing multiple E-waste categories. The dataset was divided into training and testing subsets, and all images were resized to 224 × 224 pixels before model training. Data augmentation techniques were applied to improve model robustness and reduce overfitting. The performance of the proposed model was evaluated using accuracy, precision, recall, and F1-score metrics and compared with AlexNet and VGG16 architectures.

Table 1 presents the classification results obtained from AlexNet, VGG16, and Modified ResNet50. The proposed model achieved an overall classification accuracy of 97%, outperforming AlexNet (94%) and VGG16 (95%). The improved performance can be attributed to the residual learning architecture of ResNet50, which enables deeper feature extraction while minimizing the vanishing gradient problem. Furthermore, transfer learning allowed the model to leverage pre-trained image features, improving classification efficiency even with a limited dataset.The class-wise results indicate that the Modified ResNet50 model achieved high precision, recall, and F1-

score values across most E-waste categories, including UPS, keyboard, mouse, refrigerator, and television. The model also demonstrated improved recognition of visually similar devices such as mobile phones, tablets, and laptops. The incorporation of image augmentation techniques enhanced the model’s ability to recognize devices under different orientations, lighting conditions, and background variations, thereby improving classification reliability in practical deployment scenarios.

Compared with existing AI-based E-waste identification approaches reported in recent studies, the proposed framework demonstrates competitive performance while providing an integrated solution for real-time waste collection operations. The combination of Faster R-CNN for object detection and Modified ResNet50 for classification enables accurate identification of household E-waste items captured through a vehicle-mounted camera system. The achieved accuracy of 97% confirms the effectiveness of the proposed approach and highlights its potential application in smart-city waste management systems, where automated identification can reduce manual labor, improve collection efficiency, and support sustainable recycling practices.

Table 1. Comparison of Alex Net VGG16 and Mod-ResNet50 classification report.

Model	Alex Net			VGG-16			Modified -ResNet50		
	Precision	Recall	f1-score	Precision	Recall	f1-score	Precision	Recall	f1-score
UPS	1	0.92	0.96	0.96	0.97	0.95	1	0.95	**0.95**
CRO	1	1	1	0.89	0.92	0.96	1	0.92	**1**
Radios	0.71	0.91	0.8	0.86	0.92	0.89	0.86	0.92	**0.95**
tablet	0.89	0.94	0.92	0.95	0.97	0.96	0.89	0.94	**0.95**
Keyboard	1	1	1	1	1	0.98	0.95	1	**0.98**
Mointor	1	0.8	0.95	0.97	0.96	0.92	0.95	0.94	**0.97**
Laptops	0.94	0.94	0.94	1	0.94	0.95	1	0.94	**0.97**
Motherboard	1	0.94	0.97	1	0.89	0.95	1	0.89	**0.96**
Mouse	1	1	1	1	1	1	1	1	**1**
Phones	0.89	0.94	0.92	0.95	0.97	0.96	0.95	0.97	**0.96**
Refrigerators	0.96	0.96	0.96	1	0.96	0.92	1	0.96	**0.98**
TV	1	0.8	0.89	1	1	0.97	0.94	1	**0.97**
Accuracy			**0.94**			**0.95**			**0.97**

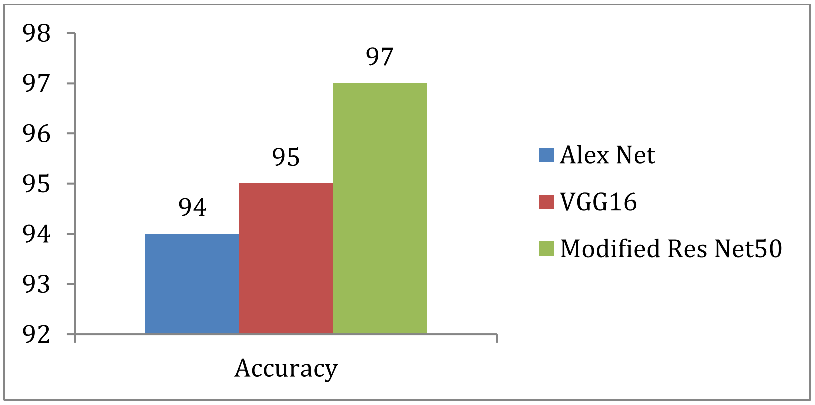

Figure 2. Alex Net, VGG16 and Mod-ResNet-50 Accuracy.

The superior performance of Modified ResNet50 is primarily due to its residual learning mechanism, which enables efficient extraction of discriminative image features. The use of transfer learning and data augmentation further improved model generalization, resulting in higher classification accuracy compared with AlexNet and VGG16. Figure 2 illustrates the classification accuracy achieved by AlexNet, VGG16, and the proposed Modified ResNet50 model for E-waste identification. The results show that the Modified ResNet50 model achieved the highest accuracy of 97%, outperforming VGG16 (95%) and AlexNet (94%). The improved performance is attributed to the residual learning architecture, which enables deeper feature extraction and efficient gradient propagation during training. Furthermore, the use of transfer learning and data augmentation techniques enhanced the model's ability to recognize E-waste objects under varying orientations and environmental conditions. These results demonstrate that the proposed Modified ResNet50 model provides superior classification performance and is suitable for practical deployment in automated E-waste collection and management systems.

Conclusion

This study presented a vision-enabled E-waste management system for the automated identification and classification of household electronic waste using deep learning techniques. The proposed framework integrates Faster R-CNN for object detection and a Modified ResNet50 model for E-waste classification, enabling efficient recognition of electronic devices during waste collection operations. Experimental results demonstrated that the proposed model achieved an overall classification accuracy of 97%, outperforming AlexNet and VGG16 in terms of classification performance.The use of transfer learning, data augmentation, and residual learning significantly improved feature extraction and classification accuracy across multiple E-waste categories. The proposed system can reduce manual effort, minimize human exposure to hazardous materials, and support sustainable recycling practices through intelligent waste segregation. Furthermore, the integration of the framework with waste collection vehicles provides a practical solution for smart-city E-waste management applications.Future work will focus on expanding the dataset with additional E-waste categories, incorporating real-time edge-based deployment, and evaluating the system under diverse environmental conditions to further improve robustness and scalability for large-scale municipal waste management systems.

Acknowledgment

The author(s) would like to thank the Department of Electrical and Electronics Engineering, AMET University, Chennai, for providing the facilities and support required to carry out this research. The author(s) also express their gratitude to all individuals who contributed to the successful completion of this work. **Funding:** The author(s) declare that no financial support, grant, or funding was received from any public, commercial, or not-for-profit organization for the conduct of this research.

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