https://doi.org/10.33472/AFJBS.6.Si3.2024.910-930

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

RECYCLERITE – AN INTELLIGENT E-WASTE DETECTOR

Shreya Patankar[1,*], Vritika Deodhar[2], Riddhi Bhogaonkar[3], Harshal Dhabale[4]

[1,2,3,4]Department of Computer Engineering, K.J Somaiya Institute of Technology, Sion, Mumbai, India

Article Info

Volume6, Issue Si3, June 2024

Received: 14 JAN 2024

Accepted: 21 April 2024

Published: 15 June 2024

doi.org/10.33472/AFJBS.6.Si3.2024.909-930

Abstract

RecycleRite addresses the pressing issue of e-waste detection by employing a groundbreaking fusion of computer vision and deep learning methodologies. We aim to revolutionize the detection process, mitigating these risks while enhancing efficiency and accuracy. Harnessing efficiency of convolutional neural networks (CNNs) and single-shot detectors (SSDs), the system automates the detection process by analyzing images of electronic devices. Multi-label detection identifies e-waste by both its name and type and optimized single-label multi-class detection, which focuses solely on identifying e-waste by its names. YOLOv8, a state-of-the-art object detection framework, excels in identifying multiple objects within an image, attaining a remarkable mean average precision at 50 (mAP@50) score of 0.97. For name-based single label detection, RTDETR, emerges as the top performer with an impressive mAP@50 score of 0.96. These methodologies not only accurately classify e-waste items but also streamline the detection process, thereby promoting sustainable waste management practices and environmental conservation.

Keywords: E-waste Detection, Recycle, Deep Learning, Computer vision

1. Introduction

In the digital age, electronic devices have become indispensable components of modern life, driving innovation, connectivity, and productivity. However, with the rapid pace of technological advancement comes a parallel challenge: electronic waste, or e-waste, has emerged as one of the most pressing environmental and public health issues of our time. As the proliferation of electronic devices continues unabated, the need for effective e-waste management strategies becomes increasingly urgent. Traditional methods of identifying and managing e-waste have proven to be laborious, error-prone, and fraught with health risks for workers. Manual sorting and classification of electronic devices not only consume valuable resources but also expose individuals to hazardous materials, leading to long-term health complications. Recognizing the shortcomings of conventional approaches, there arises a critical imperative to revolutionize the e-waste detection process through innovative technological solutions.

Enter RecycleRite, a pioneering initiative that harnesses the power of computer vision and deep learning methodologies to transform e-waste detection. By leveraging state-of-the-art techniques such as CNN and SSD, RecycleRite seeks to automate and streamline the identification of e-waste, thereby mitigating health risks for workers and enhancing efficiency and accuracy in waste management practices. At the heart of RecycleRite's approach lies a dual-pronged strategy: multi-label detection and optimized single-label multi-class detection. In multi-label detection, the system identifies e-waste items based on both their name and type, allowing for comprehensive classification and categorization. This approach is made possible by YOLOv8, a cutting-edge object detection framework renowned for its ability to identify multiple objects within an image with remarkable precision. With a mean average precision at 50 (mAP@50) score of 0.97, YOLOv8 sets a new standard for accuracy in e-waste detection, laying the groundwork for efficient waste management practices. Complementing multi-label detection is the optimized single-label multi-class detection strategy, which focuses solely on identifying e-waste items by their names. Here, RecycleRite employs RTDETR, a transformer-based architecture optimized for object detection tasks. With an impressive mAP@50 score of 0.96, RTDETR demonstrates exceptional performance in accurately classifying e-waste items, further enhancing the efficacy of RecycleRite's detection system.

1. *Problem Definition*

The challenge of managing electronic waste (e-waste) lies in the lack of automated detection methods. Manual sorting is time-consuming and error-prone, hampering effective waste management. Leveraging computer vision and deep learning can enhance identification and classification, vital for sustainability and reducing environmental and health risks.

2. *Aim and Objective*

Develop Efficient Methods for Automated Detection and Classification of E-Waste Items: E-waste presents considerable environmental and health hazards when not appropriately handled, underscoring the need for effective detection and classification methods. This research endeavors to develop automated approaches for identifying and categorizing e-waste items, aiming to streamline waste management and recycling procedures. Through automating the detection and classification tasks, the study seeks to decrease dependence on manual labor, decrease error rates, and improve the overall efficiency of e-waste management processes. Using Multi-label Multi-class Object Detection for Detection of E-Waste According to Their Types and Names: E-waste items come in various forms and classifications, ranging from electronic devices to components and accessories. Multi-label multi-class object detection allows for the simultaneous identification and categorization of multiple e-waste items within an image, considering both their types and specific names. This approach enables comprehensive inventorying of e-waste items, facilitating better sorting, recycling, and disposal practices based on their respective classifications. By employing this methodology, the study aims to provide a holistic solution to the challenges associated with e-waste detection and classification, addressing the diverse range of items encountered in e-waste management processes. The research aims to push the boundaries of e-waste management by creating strong, automated methods for detection and classification based on computer vision and deep learning. By incorporating multi-label multi-class object detection, the study seeks to offer a holistic approach to precisely identifying and sorting e-waste items, ultimately fostering sustainable and effective waste management practices.

2. Related Work

1. *Literature review*

Electronic waste (e-waste) poses a significant environmental and public health challenge worldwide due to its rapid accumulation and improper disposal. To address this pressing issue, researchers have been exploring various technological approaches, particularly leveraging advancements in deep learning and computer vision techniques, to enhance the detection and management of e-waste. Alfatmi et al. in [1] present a study focusing on the detection of common electronic devices such as phones, laptops, and keyboards using the YOLOv7 object detection model. Their work underscores the importance of efficient detection methods for prevalent e-waste items [1]. Ramya, P. et al. in [2-3] contribute to the field with two studies employing different models: FrHHGO based ShCNN and FHGO-based deep CNN. They achieve impressive accuracy, sensitivity and specificity scores of 0.95, 0.93 and 0.967 respectively for FrHHGO based ShCNN methodology. Accuracy is 19.49% privileged as compared to Neural Networks for FHGO-based deep CNN, emphasizing the significance of model selection in optimizing e-waste detection performance. Voskergian, D. et al. in [4] investigate the detection of electronic peripherals including monitors, keyboards, mice, and headphones using various YOLO models like YOLOv5s, YOLOv7-tiny and YOLOv8s. Their findings highlight YOLOv8s as the top performer, showcasing its potential for accurate detection in e-waste management applications with highest mAP@50 of 72%. Wu Q et al.in [5] focus on the detection of diverse electronic appliances such as fans, induction cookers, rice cookers, hair dryers, irons, and dust collectors. They employ the YOLO-wsee model and YOLOv5 which achieve high precision of 98.24% and mAP@0.5 scores of 99.32%, demonstrating the effectiveness of their approach in identifying e-waste items with precision.

Niful Islam in [6] explores a wide range of electronic devices, including mobile phones, televisions, laptops, keyboards, microwaves, smartwatches, and cameras. Ethan P. Zhou et al. in [7] focus on specific e-waste categories such as mobile phones, batteries, remote control devices, and light bulbs. Leveraging a Convolutional Neural Network (CNN), they achieve high validation accuracy of 93.9%, emphasizing the feasibility of deep learning approaches for accurate e-waste classification. Latha et al. in [8] extend the scope to a broader range of electronic appliances, including washing machines, refrigerators, laptops, ovens, televisions, and computers. Naushin M. et al. in [9] focus specifically on desktops, laptops, mice, batteries, and keyboards, achieving a high training accuracy of 94% using a CNN model. Their study underscores the importance of dataset quality and model training in optimizing e-waste detection performance. Ekundayo O. et al. in [10] adopt a multi-model approach, employing MobileNetV2, VGG19, DenseNet201, ResNet152V2, and Inception-ResNetV2 for e-waste detection tasks.

M. Johnson in [11] focused on the detection of batteries using Convolutional Neural Networks (CNN) and DenseNet121. Their study found that fine-tuning DenseNet121 yielded the best results, showcasing the effectiveness of transfer learning in enhancing e-waste detection accuracy. Madhav A et al. in [12] extended the scope to include a broader range of e-waste categories, including computer keyboards, motherboards, mobile phones, refrigerators, laptops, mice, radios, and televisions. Batoo K. M. et al. in[13] employed a fuzzy c-means clustering network coupled with a search and rescue (SAR) optimization algorithm to detect refrigerators, washing machines, mobile phones, bulbs, and air conditioners. Their approach minimized error rates, showcasing the potential of clustering techniques in e-waste detection. Abdelrhman M. Bassiouny et al. in [14] investigated laptop detection with and without covers using RetinaNet50 and YOLOv5 models. Their study revealed that YOLOv5 outperformed RetinaNet50, especially when transfer learning was applied, leading to improved accuracy in laptop detection. R. Dassi (2021) explored the detection of batteries, bulbs, keyboards, laptops, mobile phones, monitors, and mice using YOLOv5, CNN, and R-CNN models. Their findings indicated that the YOLOv5 model achieved a better mean average precision (mAP) value of 0.352 for intersection over union (IoU) thresholds ranging from 0.5 to 0.95.

G. A. Sampedro in [16] focused on the detection of cellphones, batteries, and chargers using YOLOv4. Their study demonstrated high average precision, recall, and accuracy scores of 0.9784, 0.9713 and 0.933 respectively, highlighting the effectiveness of YOLOv4 in accurately identifying e-waste items. Abdul Rani et al. in [17] investigated the detection of microcontrollers, batteries, and electronic components using the Lite-MobileNet-v2 mode. Their study revealed that the model achieved optimal results for keyboard detection with a learning rate of 67%. Piotr Nowakowski in [18] employed a region-based convolutional neural network (R-CNN) to detect refrigerators, washing machines, and monitors or TV sets. Their study reported high recognition and classification accuracy ranging between 90% to 97% for the selected e-waste categories, underscoring the efficacy of R-CNN in accurately identifying diverse e-waste items. Hamidreza K. in [19] focused on circuit boards, plastics, and wires using the Faster R-CNN algorithm with a ResNet101 backbone. Their study reported a high purity rate of 98%, highlighting the capability of the Faster R-CNN algorithm in accurately detecting specific e-waste components.

2. *Summarized findings*

The issue of data scarcity remains a significant concern across various domains. While attempts to mitigate this challenge through the application of data augmentation techniques have been made, their efficacy is limited. Such methods primarily involve the manipulation of existing images, altering parameters such as orientation and lighting, without introducing fundamentally new data. a more robust approach entails the amalgamation of data merging and augmentation methodologies. Although the acquisition of fresh, real-time data is the preferred solution, its procurement often proves to be prohibitively expensive and time-consuming. Thus, the integration of data merging with augmentation offers a pragmatic alternative. By consolidating commonly utilized datasets, a diverse array of images representing various classes can be obtained. Additionally, the issue of class imbalance, inherent in datasets where certain categories such as mobile phones and laptops are more prevalent and readily accessible than others, can be addressed through this approach.

The survey indicates that deep learning algorithms consistently outperform traditional machine learning methods across various computer vision tasks. Deep learning excels particularly in handling complex problems such as object detection, instance segmentation, and image classification. In our specific context, where the identification of e-waste is paramount, object detection techniques assume significant importance for the correct detection and segregation of e-waste. Consequently, the authors have favored the utilization of deep learning-based neural networks for this purpose. Various deep learning architectures, including convolutional neural networks (CNNs), deep CNNs, Residual Networks (ResNet), You Only Look Once (YOLO), Recurrent Neural Networks (RNNs), and DendeNet, have been employed by different authors. Conversely, CNN architectures are prioritized for spatial data, such as images, as is the case in our scenario. Based on previous research, it can be concluded that Convolutional Neural Networks (CNNs) consistently outperform other network architectures, yielding the highest accuracy. By capturing features at various levels of abstraction, CNNs excel in detecting objects with similar visual representations. These factors collectively contribute to the superior performance of CNNs compared to traditional neural networks. All the networks that were used were mainly at default configuration; hyper-tuning parameters can help to improve the performance. Also, hybrid techniques were found more efficient than traditional techniques. A fusion residual mechanism combined with the VGG-16 network model improved classification accuracy by 5.8%

3. Methodology

The process initiates with data collection and proceeds with data processing, followed by the analysis of various object detection models. The model then generates bounding boxes around the e-waste within the image, leveraging insights gained from the training dataset.

1. *Data Preprocessing.*

Utilizing publicly available datasets previously featured in various research papers—including TRASHBOX, Starter: e-waste dataset 93b07fb8-a (Kaggle), waste_pictures (Kaggle), electronic (Kaggle), and the Roboflow dataset—the study encountered initial challenges, such as data scarcity and a limited number of classes within each dataset. Despite the valuable contributions of individual datasets, these limitations constrained the overall scope of the investigation. To address the constraints and enhance dataset diversity, the Roboflow platform served as an augmentation tool. This facilitated the generation of additional images, introducing variability to the dataset and effectively mitigating the impact of data scarcity. A systematic merging process was then employed to unify the datasets, creating a comprehensive and enriched dataset for the study. The primary aim of this merging process was to overcome the challenges posed by data scarcity and to handle class-imbalance originally present in the dataset. In order to maintain the quality and integrity of the dataset, rigorous validation processes were implemented throughout the merging and augmentation phases. The study placed a strong emphasis on minimizing bias and ensuring the reliability of the data, thus upholding ethical standards and enhancing the robustness of the experimental process.

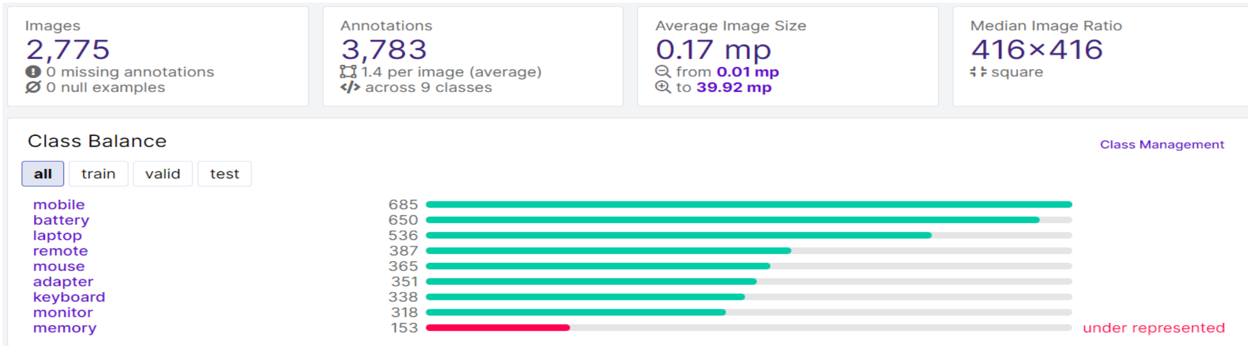


Fig. 1 Dataset Description for Single-Label Multi-Class Detection

There were around 1.4 annotations present in each image as shown in Fig 1, with a total of 3783 annotations in 2775 images. the dataset provides a foundational resource for training and evaluating E-waste classification models, facilitating the development of robust and accurate algorithms capable of effectively identifying and categorizing electronic waste items.

Fig. 2 Dataset Description for Multi-Label Multi-Class Detection

For the task of multi-label multi-class detection as seen in Fig 2, we utilized a subset of our meticulously curated dataset. This subset comprised 50 images from four distinct classes: keyboard, mobile, mouse, and laptop. To adapt this dataset for our purposes, we retained the originally annotated bounding boxes while introducing a novel approach. Specifically, we created new bounding boxes for each object by repurposing the existing coordinates. However, instead of labeling them with their original class names, we assigned them to categories related to electronic waste (E-waste). Consequently, each object in the dataset now possesses two bounding boxes: one labeled with its original class name, and another labeled with its corresponding E-waste category.

2. *Data Augmentation*

After consolidating the collected data, the next crucial phase was data augmentation, a pivotal step aimed at enhancing the dataset's diversity and robustness. This process involved the application of advanced techniques to artificially expand the dataset by introducing variations in the existing images. Several sophisticated methods were employed, including:

Image Rotation: Images were rotated at different angles to simulate variations in perspective. By rotating images, the dataset encompassed a broader range of orientations, ensuring that the model could effectively recognize e-waste items regardless of their orientation in real-world scenarios.

Scale Adjustment: Scaling adjustments were made to the images, both enlarging and reducing them. This manipulation replicated scenarios where e-waste items appear at varying distances from the camera, ensuring that the model could accurately detect and classify items irrespective of their size within the image.

Alterations in Lighting Conditions: Changes in lighting conditions were simulated to mimic real-world scenarios with diverse lighting environments. This included adjustments in brightness, contrast, and exposure levels. By exposing the model to images with different lighting conditions, it became more adept at distinguishing e-waste items under varying illumination settings.

These augmentation techniques significantly augmented the dataset's size (roughly around three times the dataset), effectively enriching it with diverse examples of e-waste items under various conditions. The resultant augmented dataset underwent meticulous final processing, including data validation, cleaning, and normalization, to ensure its quality and consistency. Upon completion of the processing stage, the refined dataset was prepared for further analysis and model training. Its diverse composition and enhanced size provided the foundation for robust and accurate e-waste classification models, capable of effectively identifying and categorizing e-waste items in real-world scenarios.

3. *Learning Techniques.*

In the realm of e-waste classification, the superiority of deep learning techniques over traditional machine learning methods has been firmly established. As such, a comprehensive array of advanced deep learning approaches was meticulously explored to discern the most efficacious model for the task at hand. These methodologies encompassed a spectrum of cutting-edge techniques, prominently featuring Convolutional Neural Networks (CNN), YOLO models (You Only Look Once), RT-DETR (Real-Time Detection Transformer), and Transformer-based models, among others. Each of these models was rigorously scrutinized to evaluate its performance across various metrics, including accuracy, speed, and computational efficiency. This meticulous analysis sought to identify the optimal balance between accuracy and speed, a critical consideration given the project's emphasis on real-time detection capabilities. Among the array of deep learning architectures considered, YOLO models emerged as particularly compelling candidates. These models distinguished themselves through their unparalleled processing speeds, rendering them ideally suited for applications requiring rapid inference times. Despite the slight trade-off in accuracy compared to traditional CNN models, the remarkable speed of YOLO models made them the preferred choice for the project's real-time detection requirements as viewed in Fig 3.

4. *User Interface*

Usability: Usability is paramount in the UI design process, ensuring that users can easily navigate and interact with the system to accomplish their tasks efficiently. This entails intuitive layout and navigation, clear labeling of functions and features, and streamlined workflows that minimize cognitive load. Usability testing, incorporating feedback from end-users, is essential to identify and address any usability issues and refine the UI design iteratively.

Accessibility: Accessibility considerations are crucial to ensure that the UI is usable by individuals with diverse needs and abilities, including those with disabilities. This encompasses factors such as providing alternative input methods, ensuring compatibility with assistive technologies like screen readers, and adhering to accessibility standards and guidelines such as WCAG (Web Content Accessibility Guidelines). By prioritizing accessibility, the UI can accommodate a broader range of users and enhance inclusivity

Intuitiveness: Intuitiveness is essential for enabling users to interact with the UI with minimal learning curve. This involves designing interfaces that align with users' mental models and expectations, leveraging familiar patterns and conventions, and providing clear feedback and guidance throughout the interaction. Visual cues, tooltips, and contextual help can aid in guiding users through complex tasks and functionalities, enhancing the overall user experience.

Fig. 3 Methodology flow

Functionality: In crafting an efficient UI for e-waste classification models, a human-centered approach is essential, placing the needs and preferences of end-users at the forefront of the design process. Collaborative design methodologies, involving interdisciplinary teams comprising designers, developers, domain experts, and end-users, can foster empathy, creativity, and innovation in designing UIs that truly meet the needs of their intended users. Through iterative prototyping, testing, and refinement, the UI can evolve into a user-friendly, accessible, and intuitive interface that empowers users to effectively leverage the capabilities of the e-waste classification model in addressing the complex challenges of e-waste management.

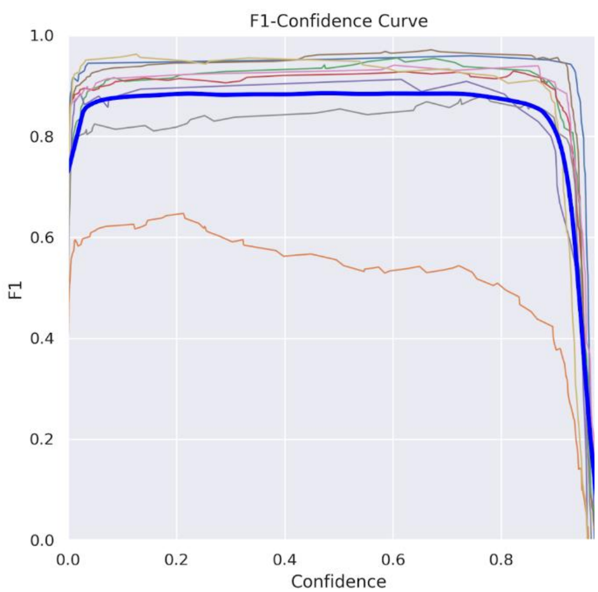
4. Results for sinlge label Multi Class Detection

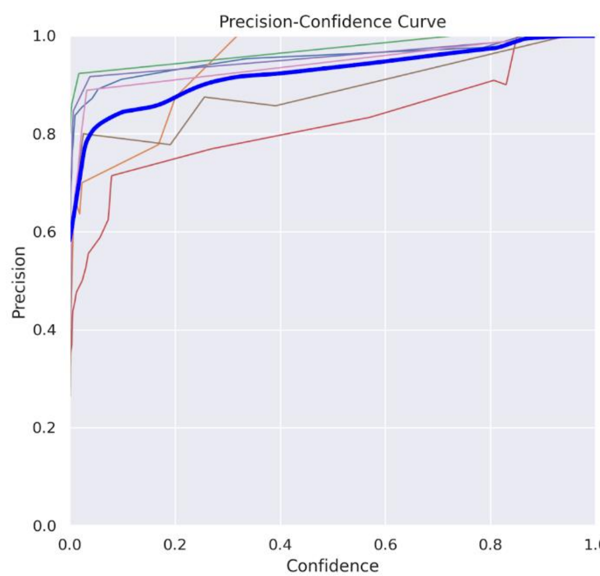
4.1 *YOLOv8*

Various evaluation metrics were used to evaluate the models. The following is the confusion matrix of YOLOv8.

Fig 4 Confusion matrix of YOLOv8

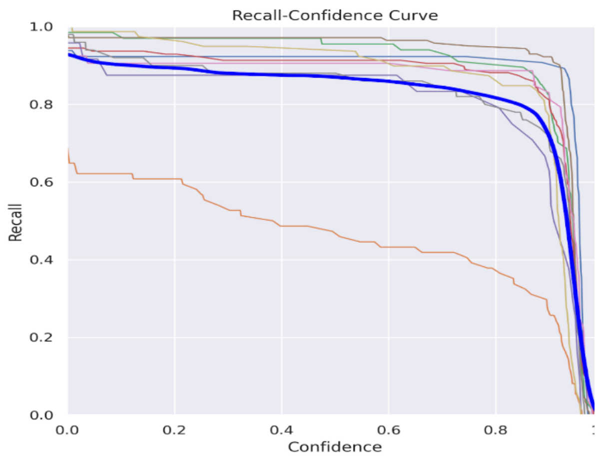
From Fig 4, We can get an overview of model performance in correctly detecting various classes of data on unseen data. The detector could efficiently detect 99% of the objects if memory class followed by keyboard and remote. It failed in correctly detecting batteries out of all the detected batteries only 55% of the objects were batteries. It gave an average accuracy of 88%.

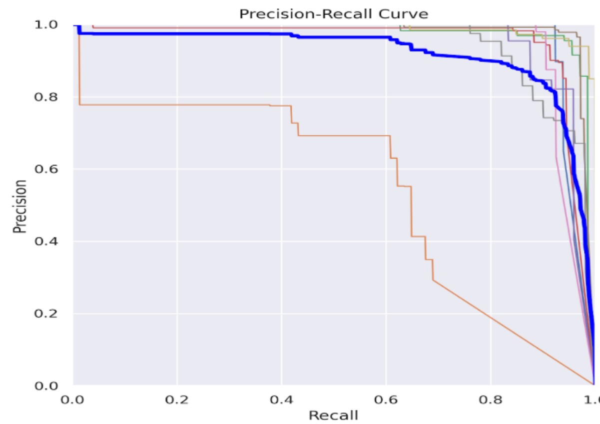




F1-Confidence Curve

Precision-Confidence Curve





Recall-Confidence Curve Precision-Recall-Confidence Curve

Fig 5 Evaluation metrics curves for YOLOv8

From Fig 5, we can observe that when the confidence level is increased the performance of the model also increases as per f1 curve but then there is a sudden drop above 0.8 confidence level. As per precision curve we can say that the precision increases with an increase in Confidence level but that is not true for Recall as the confidence level increases and recall decreases. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.6-0.7. Fig 6 shows the images of the output given by the model and the bounding box that is drawn around the object by YOLO.

4.2 *YOLOv7*

It presents a concise summary of the model's classifications, comparing actual and predicted labels within a dataset. Analyzing this matrix provides valuable insights into the model's accuracy, precision, recall, and other key metrics, aiding in pinpointing areas for improvement and refining its performance.

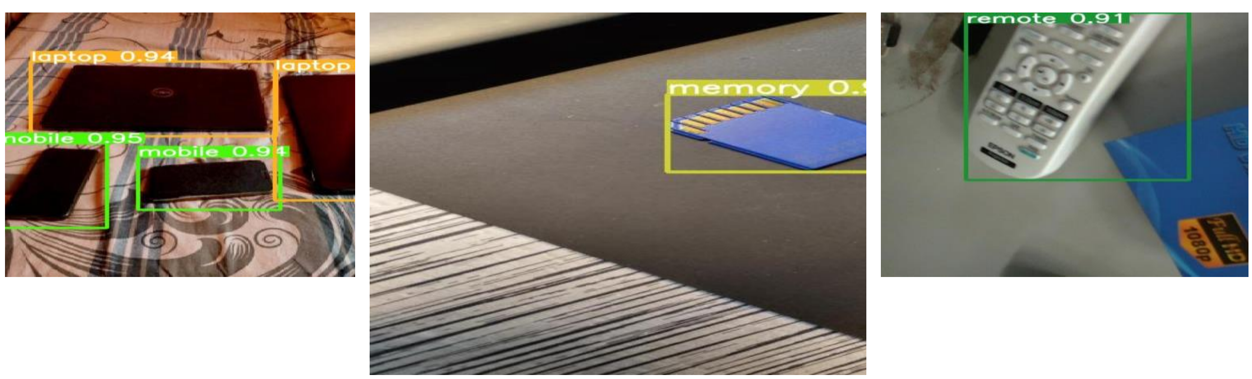


Fig 6 Output images of YOLOv8

Moreover, the confusion matrix facilitates the computation of essential metrics like accuracy, precision, recall, and F1 score, crucial for evaluating the model's efficacy across various classes. It provides valuable information about the model's ability to correctly classify instances of each class and identify any patterns or trends in misclassifications.

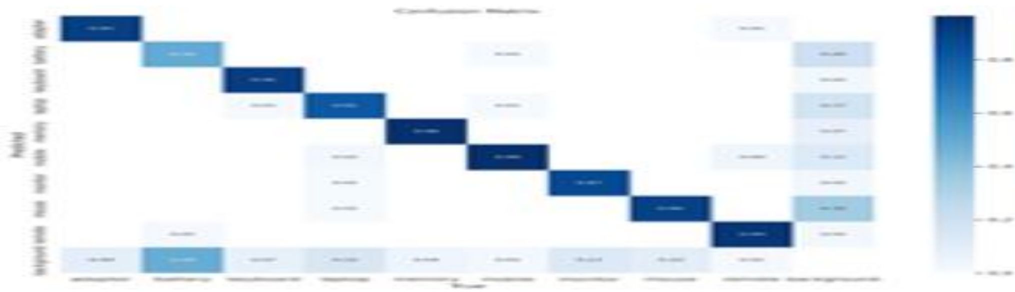
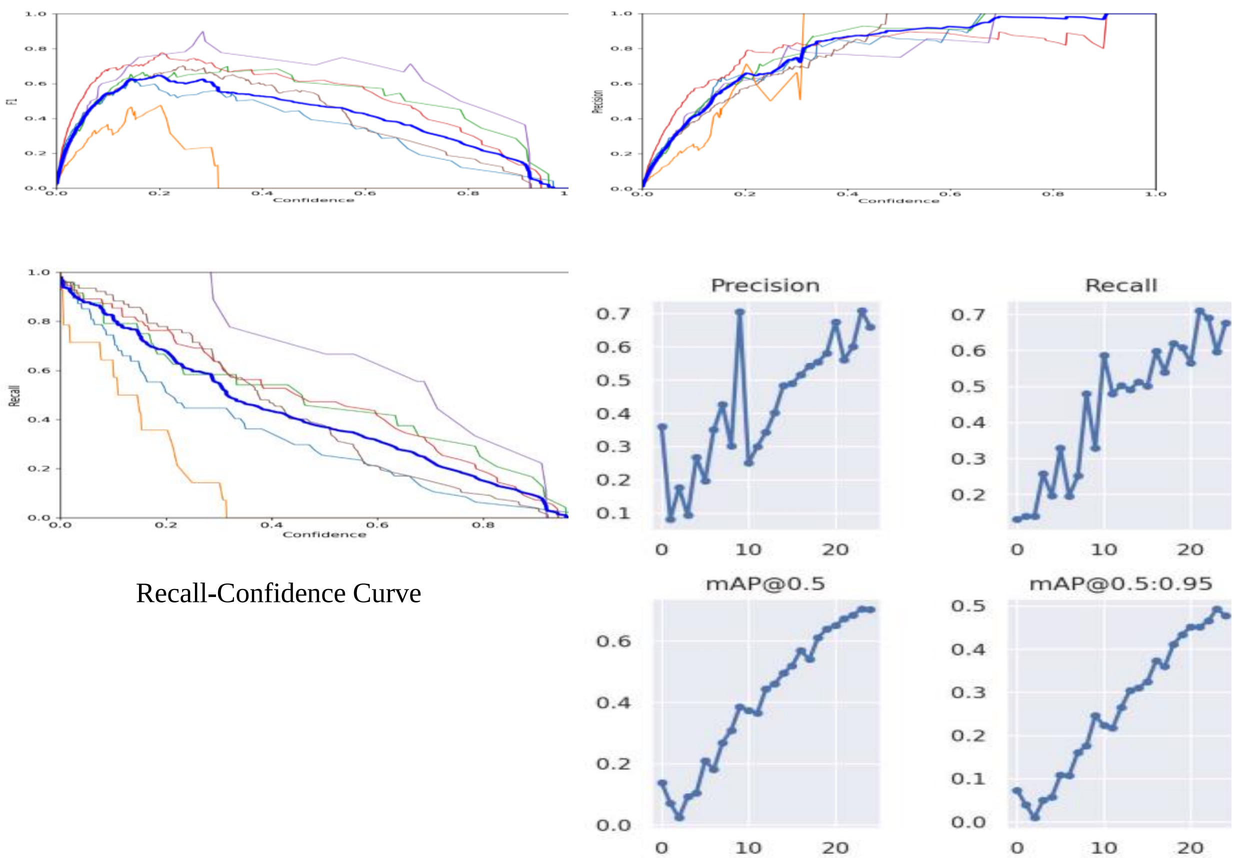


Fig 7 Confusion matrix of YOLOv7

From Fig 7, we can see that the model yields an average accuracy of 86% for all the classes and best gives accuracy for the memory and mobile class and performs worst in detecting battery class.



Recall-Confidence Curve

Curve for mAP@0.5 and mAP@0.5:0.95

Fig 8 Evaluation of YOLOv7

From Fig 8, we can observe that when the confidence level is increasing the f1 score is also increasing initially but then there is a drop in the score after 0.2 confidence. As per precision curve we can say that the precision increases with an increase in Confidence level but that is not true for Recall as the confidence level increases and recall decreases linearly. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.3-0.4. Fig 9 showcases the images are a few instances of the output given by the model on the left it classifies keyboard and on the right, it classifies mouse. A bounding box is drawn around the object by YOLO. The curve illustrates how the map metric changes as the confidence threshold for accepting detections varies.

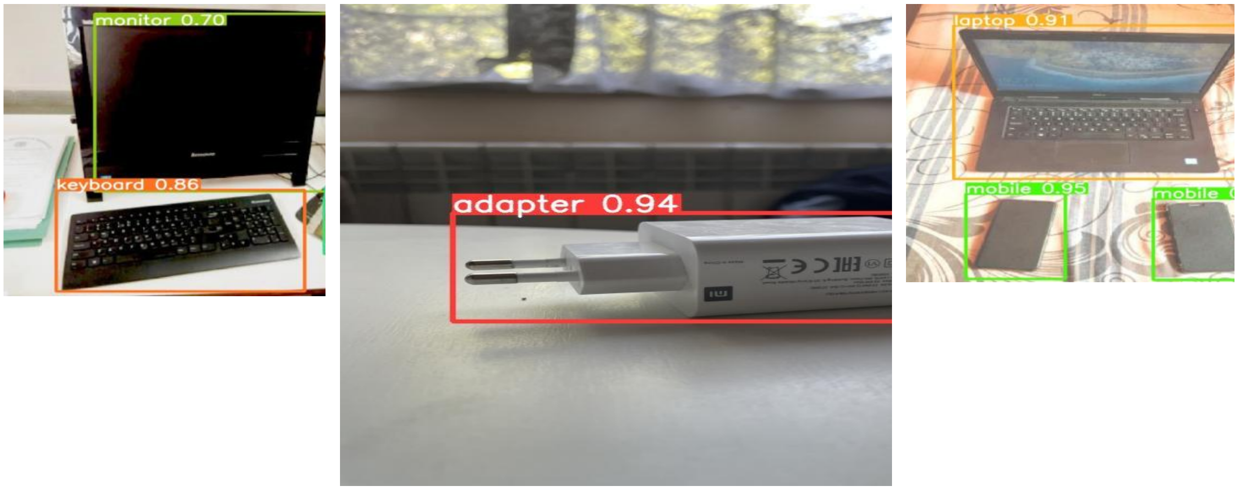


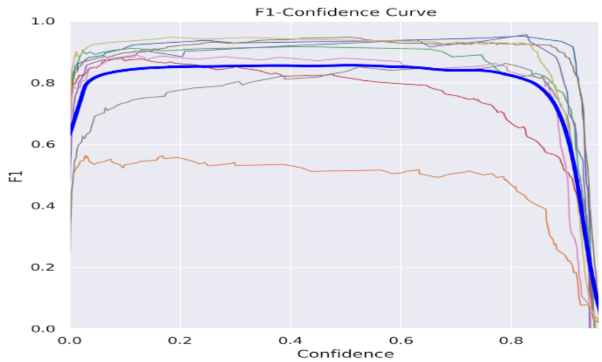
Fig 9 Output given by YOLOv7

4.3. *YOLOv5*

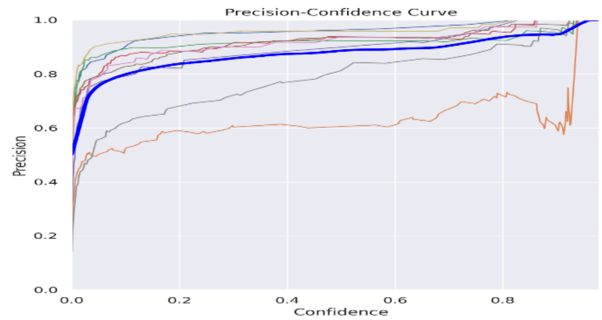
Various evaluation metrics were used to evaluate the models. The following is the confusion matrix of YOLOv5.

Fig 10 Confusion matrix of YOLOv5

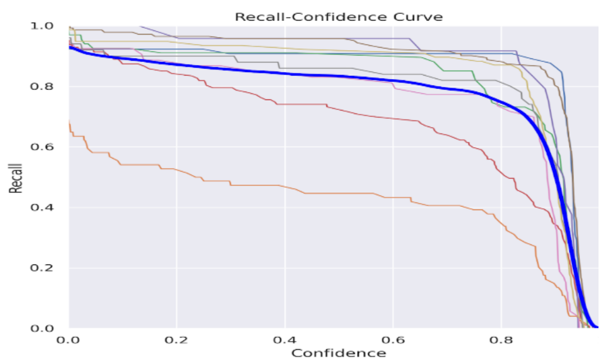
From Fig 10, we can see that the model yields an average accuracy of 91% for all the classes and best gives accuracy for the memory and mobile class and performs worst in detecting battery. It gives an accuracy of 50% for correctly detecting batteries which needs serious improvement, the reason may be that the batteries are smaller in size than the other components, so the YOLO model seems to underperform in identifying batteries correctly. From Fig 11, we can observe that when the confidence level is increased the performance of the model is not affected; it remains stagnant, as per f1 curve but then there is a sudden drop above 0.8 confidence level. Between confidence level 0.1 to 0.8 the overall F1 score is almost constant. As per precision curve we can say that the precision increases with an increase in Confidence level, it increases rapidly between confidence level 0.0 to 0.2 and then the increase is somewhat linear to confidence level. This observation is not true for Recall A recall curve, also known as a recall-precision curve or a sensitivity-specificity curve, is a graphical representation of the relationship between recall (sensitivity) and precision (positive predictive value) across different threshold values used to classify instances in a binary classification problem. Recall, also referred to as sensitivity, measures the proportion of true positive instances that are correctly identified by the model out of all actual positive instances in the dataset. As the confidence level increases the recall decreases. There is a steep decrease in recall in between confidence level 0.8 to 1.0. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.6-0.7.



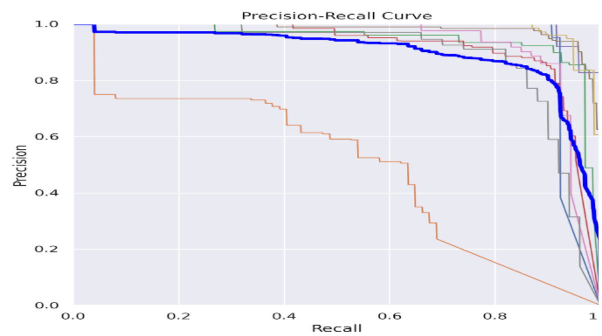
F1-Confidence Curve



Precision-Confidence Curve



Recall-Confidence Curve



Precision-Recall-Confidence Curve

Fig 11 Evaluation metrics curves for YOLOv5

In Fig 12, images are examples of the output given by the model on the left it classifies keyboard and on the right it classifies mouse. A bounding box is drawn around the object by YOLO. We can see that it is correctly identified with a confidence of 0.6, battery with confidence of 0.9 and mouse with a confidence og 0.96. The model performs well in different lighting settings observed for mouse where the lighting was darker as compared to other pictures and it also performs well with different orientations as seen in case of laptop where the orientation of the image is changed.

Fig 12 Output given by YOLOv5

4.4 *RT-DeTr*

Various evaluation metrics were used to evaluate the model performance. The following is the confusion matrix of RT-DeTr. Fig 13 provides a detailed view of the performance of a classification model for different classes. In this case, the analysis reveals that the model performs well for certain classes, such as "adaptor," "memory," and "mobile," with high numbers of true positives and low numbers of false positives.

Fig 13 Confusion matrix of RT-DeTr

However, there are classes where the model struggles, as seen with "keyboard," "laptop," "monitor," and "mouse," which have higher numbers of false negatives. This indicates that the model sometimes misclassified these classes as "background." Overall, the model's performance is decent, but there is room for improvement, particularly in reducing false negatives for these classes to enhance its overall accuracy and effectiveness in object detection tasks.

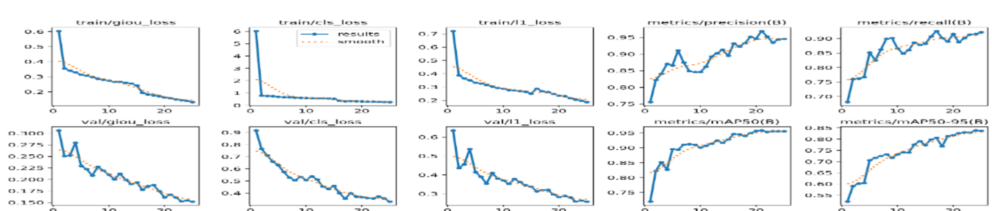


Fig 13 Analysis of training and validation error to determine early stopping

For the RT-DETR model trained on e-waste classes (adaptor, charger, keyboard, laptop, memory, mobile, monitor, mouse, background), early stopping is crucial for preventing overfitting and ensuring the model generalizes well to new instances. The training process involves splitting the dataset into training and validation sets, with the training set used for model training and the validation set used for monitoring performance. During training, the model's performance is evaluated on the validation set at regular intervals, and the validation loss is tracked. Early stopping is triggered if the validation loss does not improve for a specified number of epochs. In addition to early stopping, evaluation metrics such as precision, recall, and F1 score were used to assess the model's performance on the validation set. These metrics indicate that the RT-DETR model performs very well in terms of precision and mAP@50, indicating high accuracy and object detection performance. The mAP@50-95 metric as shown in fig 13 suggests that it maintains good performance across a range of IoU thresholds. The recall score of 0.9 indicates that it has a high rate of true positives, capturing most of the relevant objects in the images. The model weights from the epoch with the best validation performance are used as the final model, ensuring that the RT-DETR model effectively identifies e-waste classes with high accuracy and generalization.

Multi-Label Multi-Class Detection

4.5 *YOLOv8 for 200 epoch*

The following section discusses the performance of the YOLOv8 model on the same dataset using the same evaluation metrics. Training a YOLO model for 200 epochs allows for a more thorough exploration of the dataset and model optimization, potentially leading to better performance. During training, we utilized data augmentation techniques such as random horizontal flips, random scaling, and color jitter to improve the model's robustness. We also applied early stopping based on the validation loss to prevent overfitting. Our final model demonstrates strong performance in detecting objects across various classes, showcasing the effectiveness of the YOLOv8 architecture for object detection tasks.

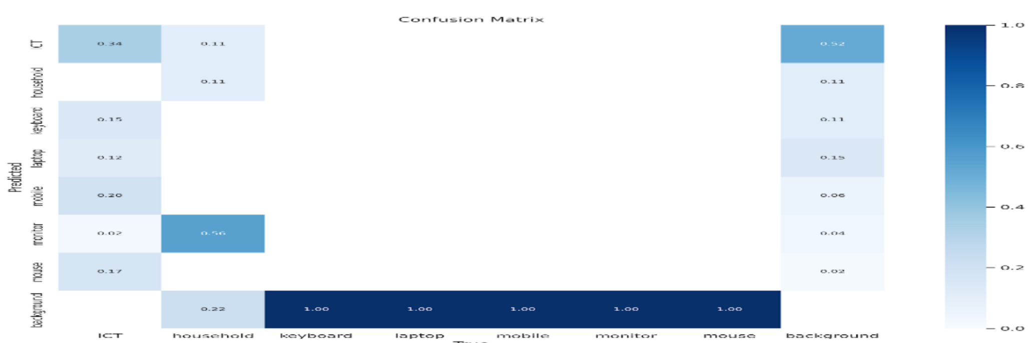
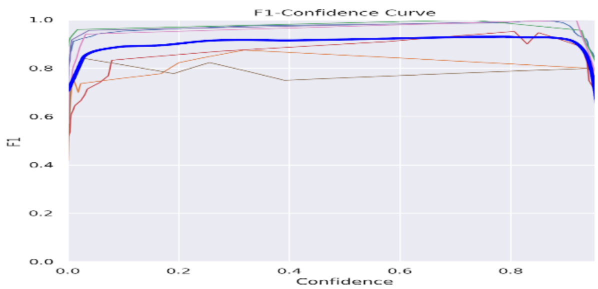
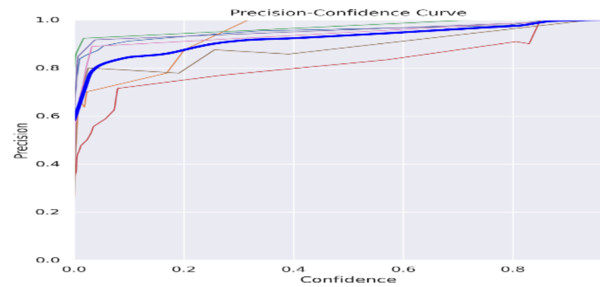


Fig 14 Confusion Matrix for YOLOv8 multi-label Detector (200 epoch)

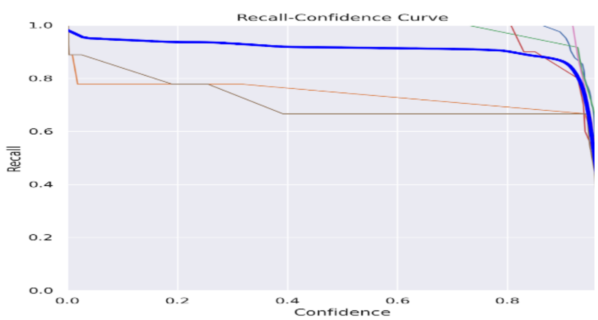
Analyzing the confusion matrix shown in Fig 14 further reveals additional insights into the model's performance. For instance, the high number of instances where keyboard, laptop, mobile, monitor, and mouse are detected in the background could indicate a challenge in distinguishing these items from clutter or other objects in the image. This suggests a potential area for improvement, such as fine-tuning the model's object detection capabilities or adjusting the training data to include more diverse backgrounds. Additionally, the correct identification of categories like ICT and household demonstrates the model's ability to understand the broader context of e-waste classification, indicating a comprehensive understanding of the e-waste domain. This analysis highlights the model's strengths and areas for enhancement, providing valuable guidance for future model iterations and training strategies. From Fig 15, we can observe that when the confidence level is increasing the f1 score is not affected much but then there is a drop in the F1 score after 0.8 confidence. As per precision curve we can say that the precision increases with an increase in Confidence level but that is not true for Recall as the confidence level increases and recall decreases. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.6-0.8



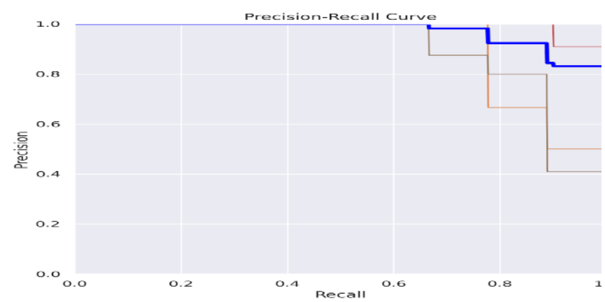
F1-Confidence Curve



Precision-Confidence Curve



Recall-Confidence Curve



Precision-Recall-Confidence Curve

Fig 15 Evaluation curves YOLOv8 multi-label Detector (200 epoch)

. Fig 16 shows a few instances of the output given by the model on the left it classifies keyboard and on the right it classifies mouse. A bounding box is drawn around the object by YOLO.

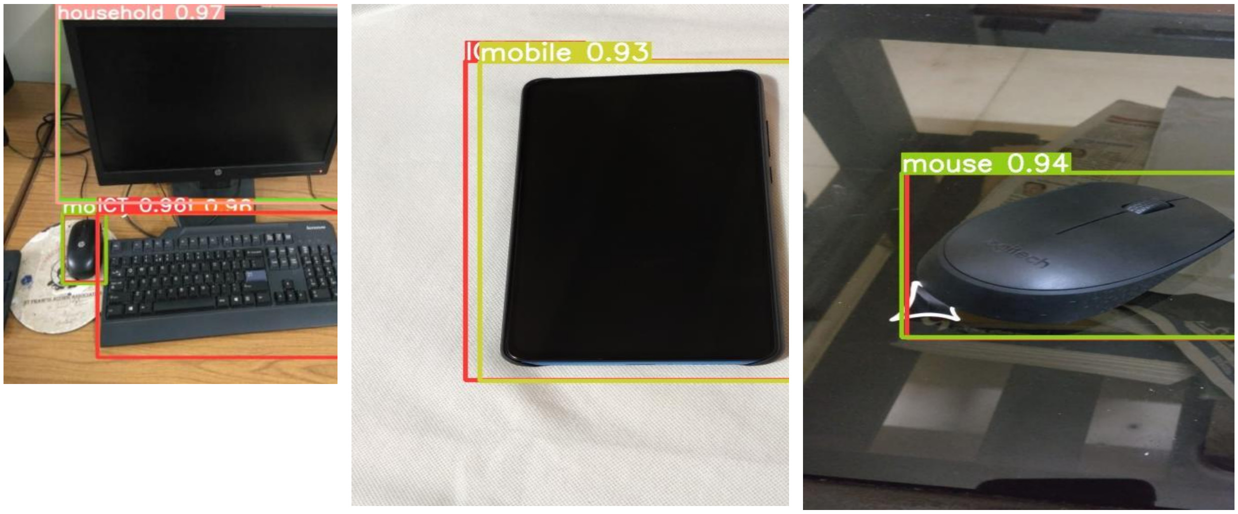


Fig 16 Output given by YOLOv8 for multi-label YOLOv8 for 200 epoch

4.6 *YOLOv8 for 150 epochs*

The following section discusses the performance of the YOLOv8 model on 150 epochs on the same dataset using the same evaluation metrics. From Fig 4.15, we can see that the model yields an average accuracy of 59% for all the classes and best gives accuracy for the 4th class that is for classifying keyboards performs worst in classifying monitors.

From Fig 17, we can observe that when the confidence level is increasing the f1 score is not affected much initially but then there is a drop in the score after 0.8 confidence. As per precision curve we can say that the precision increases with an increase in Confidence level but that is not true for Recall, as the confidence level increases, and recall decreases linearly. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.3-0.4.

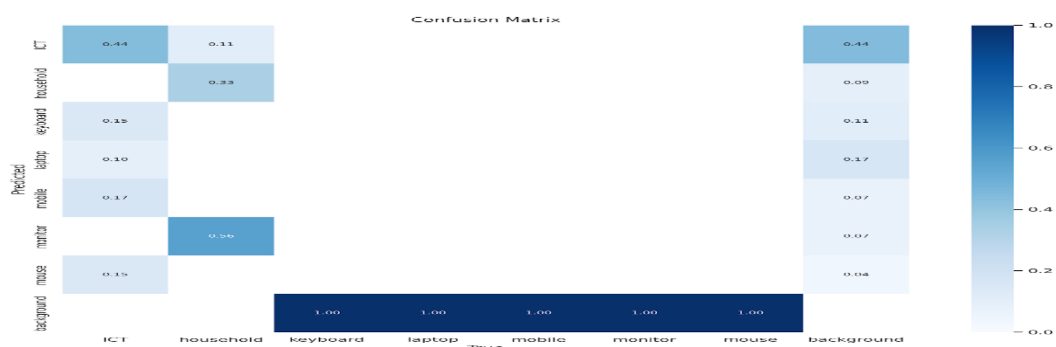
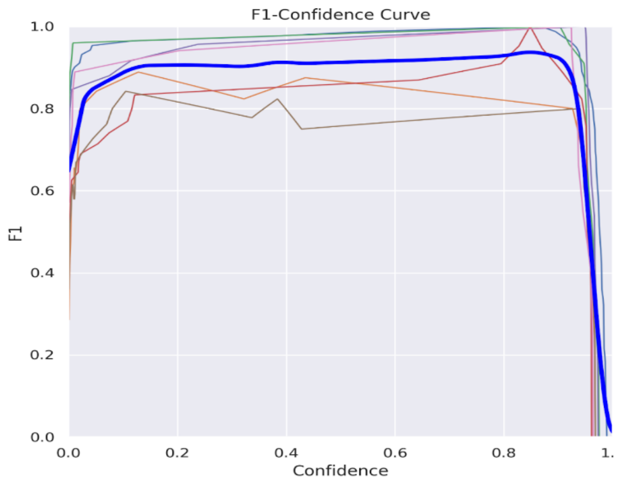
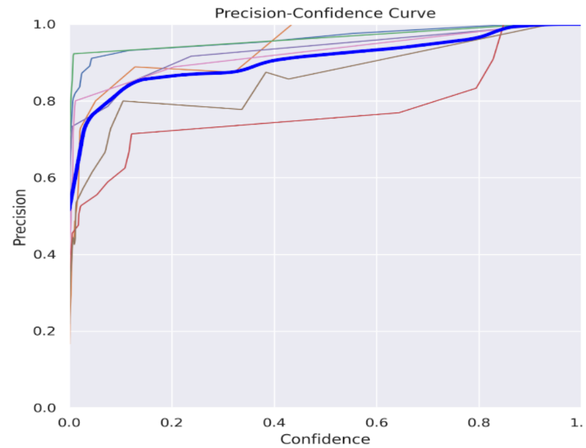


Fig 17 Confusion matrix of YOLOv8 multi-label (150 epoch)

The F1-confidence in Fig 18 score serves as a comprehensive metric for evaluating object detection models, blending the F1 score, which captures the balance between precision and recall, with the confidence score provided by the model's predictions. The F1 score represents the harmonic mean of precision and recall, offering a unified measure of the model's accuracy. Meanwhile, the confidence score reflects the model's certainty in its predictions, typically represented as a probability or confidence level associated with each detected object. By combining these metrics, the F1-confidence score provides a nuanced assessment of the model's performance, considering both its precision-recall trade-off and its confidence in its predictions.

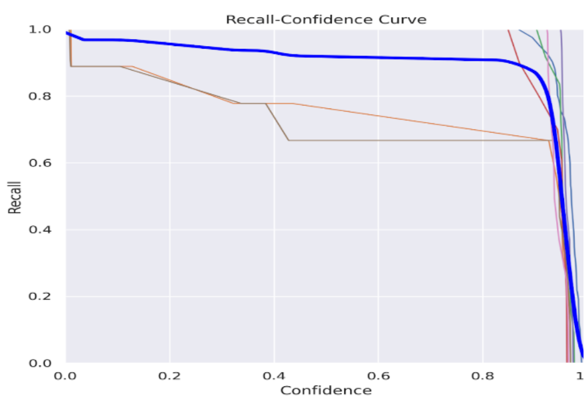


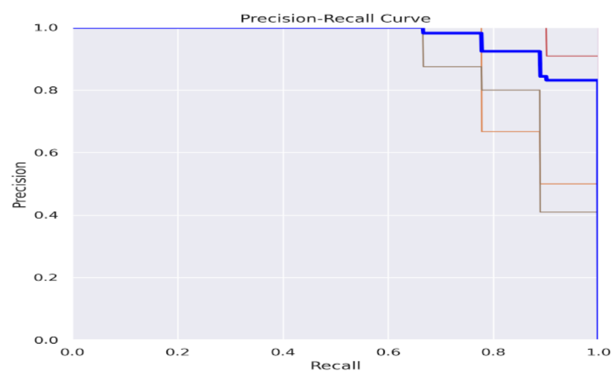


F1-Confidence Curve Precision-Confidence Curve

Fig 18 Evaluation curves for YOLOv8(150 epoch)

In Fig 19, the recall curve is plotted by varying the threshold used to classify instances as positive, which influences the trade-off between recall and precision. A higher threshold may result in fewer positive predictions with higher precision but lower recall, while a lower threshold may lead to more positive predictions with higher recall but lower precision. The curve illustrates how recall and precision change as the classification threshold is adjusted, providing insights into the model's performance across different operating points.





Recall-Confidence Curve Precision-Recall-Confidence Curve

Fig 19 Evaluation metrics curves for YOLOv8 (150 epochs)

The following images in Fig 20 are a few instances of the output given by the model on the left it classifies keyboard and on the right, it classifies mouse. A bounding box is drawn around the object by YOLO.

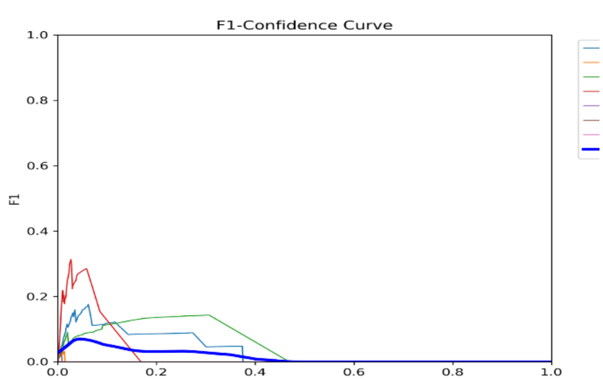
Fig 20 Output given by YOLOv8(150 epoch) for multi-label

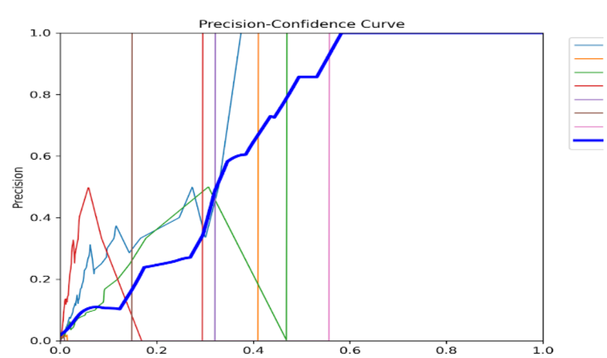
4.7 *YOLOv5 for 150 epoch*

The following section discussed the performance of the YOLOv7 model on the same dataset using the same evaluation metrics.

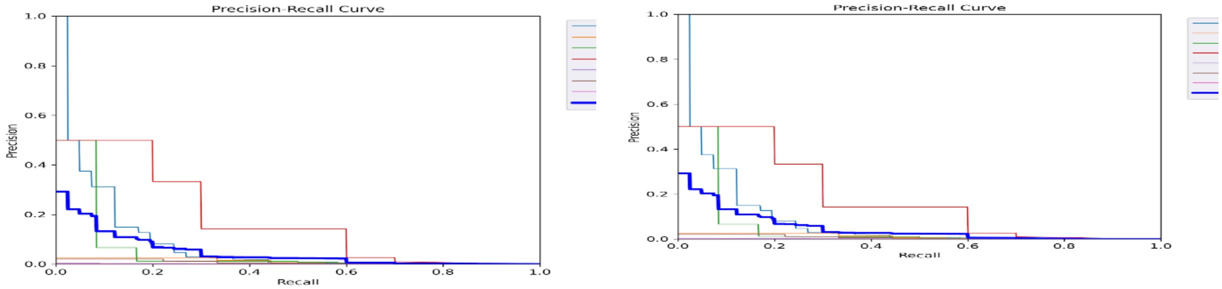
Fig 21 Confusion matrix of YOLOv5 for multi-label

From Fig 21 we can see that all the classes detected in the background including their categories as per confusion matrix. This is because the model got confused as there are two bounding boxes for each object and things consider them under the background section.





F1-Confidence Curve Precision-Confidence Curve



Recall-Confidence Curve Precision-Recall-Confidence Curve

Fig 22 Evaluation metrics curves for YOLOv5 multi-label

From Fig 22, we can observe that when the confidence level is increasing the f1 score is also increasing initially but then there is a drop in the score after 0.2 confidence. As per precision curve we can say that the precision increases with an increase in Confidence level but that is not true for Recall as the confidence level increases and recall decreases linearly. So we select a value that gives good precision, recall as well as f1 score so we select a value between 0.3-0.4.

Fig 23 Output given by YOLOv5 for multi-label

Fig 23 shows a few instances of the output given by the model on the left it classifies mobile as ICT as well and on the right it classifies mouse as ICT as well . In the middle it identifies the monitor as a household also. A bounding box is drawn around the object by YOLO. Since these instances are for multi-label multi-class detection the boxes overlap due to similarity in size of bounding boxes.

4.8 *Comparative Analysis*

Table 1 compares the performance of both the models YOLOv7 and YOLOv8. By using the evaluation metrics mAP score, accuracy, Precision and Recall we compared both the models. From the above results we can conclude that YOLOv8 outperformed YOLOv7. For all the evaluation metrics YOLOv8 gave better results than YOLOv7.

Table 1 Comparative Analysis for Single label detection

Evaluation Metrices	RT-DETR	YOLOv8	YOLOv7	YOLOv5
mAP@50	0.96	0.915	0.73	0.89
mAP@50-95	0.83	0.803	0.48	0.76
precision	0.95	0.905	0.66	0.86
recall	0.9	0.871	0.676	0.85

Table 2 compares evaluation metrics for three versions of YOLO models trained for multi-label object detection. YOLOv8-MultiLabel consistently outperforms YOLOv8-MultiLabel and YOLOv5-MultiLabel across metrics such as mAP@50, mAP@50-95, precision, and recall, indicating its superior performance in accurately detecting and classifying objects within images.

Table 2 Comparative Analysis for Multi label detection

Evaluation Metrices	YOLOv8-MultiLabel	YOLOv8-MultiLabel	YOLOv5-MultiLabel
Epoch	200	150	200
mAP@50	0.97	0.93	0.05
mAP@50-95	0.86	0.81	0.02
precision	0.97	0.95	0.12
recall	0.91	0.89	0.05

5. Conclusion and Future Scope

This paper showcases the pivotal role of automated e-waste classification systems employing artificial intelligence and machine learning techniques, specifically deep learning, in addressing these challenges. It highlights the significant diversity in model architecture, with studies exploring multiple models, including Inception, ResNet, VGG, and YOLO, in an effort to optimize classification accuracy. Deep learning algorithms, particularly convolutional neural networks (CNNs) and their variants, outperform machine learning algorithms in e-waste classification tasks, by consistently achieving accuracy rates exceeding 90%, thereby emphasizing their superiority over traditional machine learning models. Recurrent neural networks (RNNs) were found to be less effective for e-waste classification, especially compared to CNNs. YOLO models, known for their real-time object detection capabilities, have been used for fast e-waste identification and achieved high accuracy. Furthermore, clustering and fuzzy optimization algorithms improve classification accuracy, contributing to safer and more efficient e-waste management. In addition, the integration of Internet of Things (IoT) with deep learning models shows great promise in improving e-waste management by using such advanced object detection models to identify electronic objects, thereby contributing to more sustainable waste management. Moreover, it discusses the role of transfer learning, data augmentation, and real-time monitoring in enhancing the accuracy and efficiency of e-waste classification systems. As the e-waste problem continues to grow, the future scope presents numerous opportunities for further research, including the expansion of datasets, hyperparameter optimization, real-time monitoring, safety measures, regulatory compliance, and public awareness campaigns.

Conflicts of Interest

No Conflict of Interest

References

[01] K. Alfatmi, F. S. Shinde, M. Shahade, S. S. Sharma, S. S. Aruja and T. Y. Chaudhari, "ESafe: An E-waste Management and Awareness Application using YOLO Object Detection," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 1061-1066,

[02] Ramya, P., Ramya, V., & M, B. R. (2023, February 1). E-waste management using hybrid optimization-enabled deep learning in IoT-cloud platform. Advances in Engineering Software; Elsevier BV.
[03] Puppala Ramya, V. Ramya & M. Babu Rao (2023) Optimized Deep Learning-Based EWaste Management in IoT Application via Energy-Aware Routing, Cybernetics and Systems,
[04] Voskergian, D., & Ishaq, I. (2023, August 23). Smart e-waste management system utilizing Internet of Things and Deep Learning approaches. Journal of Smart Cities and Society; IOS Press.
[05] Wu, Q., Wang, N., Fang, H., & He, D. (2023, June 20). A novel object detection method to facilitate the recycling of waste small electrical and electronic equipment. Journal of Material Cycles and Waste Management; Springer Science+Business Media.
[06] Islam, N.; Jony, M.H.; Hasan, E.; Sutradhar, S.; Rahman, A.; Islam, M. EWasteNet: A Two-Stream Data Efficient Image Transformer Approach for E-Waste Classification. In Proceedings of the 2023 IEEE 8th International Conference on Software Engineering and Computer Systems (ICSECS), Penang, Malaysia, 25–27 August 2023.
[07] E. P. Zhou, "Machine Learning For The Classification And Separation Of E-Waste," 2022 IEEE MIT Undergraduate Research Technology Conference (URTC), Cambridge, MA, USA, 2022, pp. 1-5,
[08] Latha, CJ, Kalaiselvi, K, Ramanarayan, S, Srivel, R, Vani, S, Sairam, TVM. Dynamic convolutional neural network based e-waste management and optimized collection planning. Concurrency Computat Pract Exper. 2022;
[09] Naushin, M., Saraswat, A., & Abhishek, K. (2022). Deep Learning Approach to Deal with E-Waste. Advanced Machine Intelligence and Signal Processing, 123–136.
[10] Ekundayo, O., Murphy, L., Pathak, P., & Stynes, P. (2022). An On-Device Deep Learning Framework to Encourage the Recycling of Waste. Intelligent Systems and Applications, 405– 417.
[11] M. Johnson, A. Khatoon and C. Fitzpatrick, "Application of AI and Machine Vision to improve battery detection and recovery in E-Waste Management," 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Maldives, Maldives, 2022, pp. 1-6,
[12] Madhav, A. V. S., Rajaraman, R., Harini, S., & Kiliroor, C. C. (2021, November 2). Application of artificial intelligence to enhance collection of E-waste: A potential solution for household WEEE collection and segregation in India. Waste Management & Research; SAGE Publishing.
[13] Batoo, K. M., Pandiaraj, S., Muthuramamoorthy, M., Raslan, E. H., & Krishnamoorthy, S. (2021, October 1). Fuzzy-based adaptive learning network using search and rescue optimization for e-waste management model: case study. Environmental Science and Pollution Research; Springer Science+Business Media.
[14] Abdelrhman M. Bassiouny, Abdelrahman S. Farhan, Shady A. Maged, Mohammed I. Awaad(2021), "Comparison of Different Computer Vision Approaches for E-waste Components Detection to Automate E-waste Disassembly"
[15] R. Dassi, S. Kamal and B. S. Babu, "E-Waste Detection and Collection assistance system using YOLOv5," 2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India, 2021, pp. 1-6,
[16] 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," 2021 1st International Conference in Information and Computing Research (iCORE), Manila, Philippines, 2021, pp. 125-128,
[17] Abdul Rani, Khairul Najmy & Rahim, Hishamuddin & Ong, Boon & Jusoh, Muzammil & Yasin, Najib & Sabapathy, Thennarasan & Mustafa, Wan & Jamlos, Mohd & Ahmad, R.Badlishah & Hammood, Dalal. (2021). Mobile Green E-Waste Management Systems using IoT for Smart Campus. Journal of Physics: Conference Series. 1962.
[18] Nowakowski, P., & Pamuła, T. (2020, May 1). Application of deep learning object classifier to improve e-waste collection planning. Waste Management; Elsevier BV.
[19] U. Shafi, R. Mumtaz, H. Anwar, A. M. Qamar and H. Khurshid, "Surface Water Pollution Detection using Internet of Things," 2018 15th International Conference on Smart Cities: Improving Quality of Life Using ICT & IoT (HONET-ICT), Islamabad, Pakistan, 2018, pp. 92- 96.