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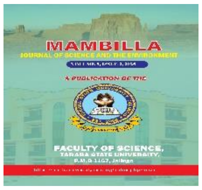

AUTOMATED ELECTRONIC WASTE IDENTIFICATION MODEL USING TRANSFER LEARNING METHOD AND YOU ONLY LOOK ONCE DETECTION ALGORITHM

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ABSTRACT

The identification of waste composition based on target-detection is crucial in promoting sustainable solid waste management. However, discrimination of different solid waste categories in the presence of incomplete and insufficient feature information remains a challenge in multi-target detection. The study aims to develop an automated model for electronic waste identification by integrating transfer learning with the YOLO (You Only Look Once) detection algorithm using kaggle repository dataset. The Model enhanced real-time object detection, improve classification accuracy, and support efficient e-waste sorting and management. By utilizing deep learning techniques, the system facilitates the rapid and accurate recognition of various electronic waste components, contributing to sustainable waste disposal and recycling efforts. The experimental results showed that the improved model achieved a mean average precision (mAP) of 0.950 which reduced incidents related to inaccurate positioning and false and missed detection. Moreover, the improved model outperformed classical detection models and is expected to be applied to intelligent monitoring for waste components in scenarios including indiscriminate waste disposal and illegal dumping, providing decision support for emergency management.

1. Introduction

With the progress in economic development and modern technology, a diverse range of new electronic and electrical equipment has been invented and is now available worldwide. The COVID-19 pandemic lockdown further amplified the demand for electronic devices, especially for health, education, entertainment, and remote work purposes. Notably, wearable healthcare devices have gained prominence during the pandemic, despite their relatively short lifespan (Janmenjoy *et al.*,2021).

As technology advances and device prices decrease, the average usage lifespan of digital gadgets is diminishing. Consequently, electronic waste (also known as waste electrical and electronic equipment WEEE) has become a critical concern. E-waste encompasses various digital devices, including mobile phones, electronic tools, household appliances like refrigerators and washing machines, telecommunication devices, computers, and health monitoring equipment (Rajesh *et al.*,2021).

The primary sources of e-waste generation are residential households, commercial establishments, and industrial facilities. As technological innovation accelerates and consumer behavior shifts towards more frequent upgrades, the global quantity of e-waste has been rising at an alarming rate. Recent reports according to the Global E-waste Monitor 2020 report by (Adrian *et al.*, 2020), estimate that approximately 53.6 million metric tons of e-waste was generated worldwide in 2019, with this figure projected to reach 74.7 million tons by 2030.

E-waste is an extremely complex mixture, composed of diverse materials including metals, plastics, glass, and hazardous substances like mercury, lead, cadmium, and chlorofluorocarbons (CFCs). Improper handling and disposal of e-waste can have severe environmental repercussions. When discarded in landfills or incinerated, the toxic materials can leach into soil and water sources, contaminating the ecosystem and posing risks to human health (Ankit *et al.*, 2021). Open burning and primitive recycling techniques release harmful pollutants into the air, contributing to

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greenhouse gas emissions and air pollution.

Moreover, the informal e-waste recycling sectors that operate in many developing nations expose workers to serious health hazards. Practices like open burning, acid baths for metal recovery, and improper dismantling put these workers at risk of poisoning, cancer, and other chronic illnesses. Addressing the e-waste crisis is therefore crucial not just from an environmental standpoint but also for protecting vulnerable communities involved in the recycling process (Muskan *et al.,* 2023).

E-waste recycling presents an opportunity for both developed and developing countries. Valuable materials can be extracted from discarded electronic items. Proper disposal and recycling are essential to prevent adverse effects on human health, natural ecosystems, and the environment. By implementing safe e-waste management techniques, we can mitigate these negative impacts (Samatha & Prajna, 2023).

The widespread adoption of digitalization has profoundly impacted various domains. Alongside the benefits, there are growing concerns surrounding urbanization, such as pollution, traffic congestion, rising welfare costs, and the alarming increase in waste streams. The concept of the Circular Economy (CE) was primarily aimed at enhancing the recovery and reuse of end-of-life products by optimizing recycling processes, using them as raw materials, and reducing the need for extracting new resources, thereby closing the product loop (Tim *et al.*, 2024).

Smart Cities have been proposed as a solution to tackle these problems, leveraging digitalization and promoting a sustainable environment through CE. In line with this, we discuss the role of digitalization, particularly Artificial Intelligence (AI), in the environmental technology domain. We investigate how automated electrical and electronic waste (e-waste) recycling can support the transition towards a sustainable environment, thus achieving CE goals.

To efficiently achieve these goals, the accurate classification of waste is crucial, as it can maximize the performance of the entire recycling process. Waste classification is a significant step in the efficient sorting and separation of different models and types of waste. Consequently, the need for smart sorting is growing to support smart recycling and the overall transition to a circular economy (Baker *et al*., 2018).

The management of electronic waste (e-waste) has become an increasingly urgent concern due to the rapid proliferation of electronic devices. This surge in e-waste generation necessitates efficient solutions. Traditional manual sorting and recycling methods are labor-intensive, time-consuming, and prone to errors. To tackle this issue, researchers are exploring automated systems and machine learning techniques for e-waste recycling. One promising approach gaining attention is transfer-based learning. By leveraging knowledge and features from pre-trained models, typically trained on extensive datasets, this method enhances e-waste detection and classification performance. It proves particularly valuable when dealing with limited training data, addressing the challenges posed by data scarcity in the e-waste recycling field (Salma & Hatem 2023).

The initial integration of technology into waste management focused primarily on basic monitoring and notification systems rather than material classification. Malapur and Pattanshetti (2017) presented a cost-effective IoT-based trash bin that used ultrasonic sensors and GSM modules to monitor fill levels and send notifications when waste exceeded threshold levels. While innovative at the time, these systems lacked classification capabilities, serving primarily as information systems rather than active sorting technologies.

More sophisticated approaches began to emerge as researchers applied machine learning to waste classification. Gan and Zhang (2020) developed a CNN-based garbage classification model that compared a traditional BP neural network with a migrated CNN based on AlexNet. Their results showed dramatic improvement from 76% accuracy with the BP model to 100% accuracy with the CNN approach. Niu *et al.* (2020) introduced a deep learning-based trash classification model, exploring four approaches: training from scratch, using standard architectures, applying transfer learning, and developing custom models. Their DeepCoral-ResNet model achieved 96% accuracy on the TrashNet dataset, demonstrating the effectiveness of transfer learning for waste management and environmental monitoring.

Lin *et al.* (2022) introduced RWNet, an architecture based on ResNet variants optimized for recyclable waste sorting through transfer learning. Their RWNet-152 achieved 88.8% accuracy, demonstrating how specialized architectures could improve performance on waste classification tasks. These advancements significantly improved classification accuracy but still faced challenges in processing speed, real-time application, and adaptation to the specific characteristics of e-waste components.

Fan *et al.* (2023) proposed a novel system integrating data augmentation with an enhanced YOLO algorithm (YOLO_EC) for efficient waste detection during sorting processes. Their system achieved 96.35% mAP (a 4.54% improvement over baseline), 74.05% model size reduction, and real-time performance at 24 FPS, making it suitable for practical deployment in waste management settings.

Mohammed *et al.* (2023) developed an automated waste sorting system using an Artificial Neural Network (ANN) with feature fusion, achieving 91.7% accuracy in categorizing waste into paper, glass, plastic, and metal. Their approach demonstrated how feature fusion could enhance classification performance without requiring more complex network architectures.

Specialized approaches for challenging conditions emerged during this period. Qiao *et al.* (2023) identified a critical limitation in existing waste classification systems—poor performance in low-light conditions. Their Dark-Waste classification model incorporated an innovative Illumination Conversion technique to generate synthetic low-light training images, addressing data scarcity while enabling effective classification in challenging visual environments. Dataset standardization also received attention, with (Majchrowska *et al.,* 2022) developing two new benchmark datasets: "detect-waste" and "classify-waste" to address the absence of standardized evaluation resources. Their two-stage detection methodology using EfficientDet-D2 for identifying litter locations and EfficientNet-B2 for waste classification achieved up to 70% average precision in waste detection and approximately 75% accuracy in waste classification. E-waste specific applications also advanced during this period. (Bassiouny *et al.,* 2021) implemented a methodology for e-waste component detection using YOLOv5x, demonstrating superior precision and spatial localization abilities compared to traditional image processing techniques. Their approach validated YOLOv5x's effectiveness for identifying intricate features such as screw holes in laptop components, highlighting the potential for automated disassembly applications.

2. Methodology

2.1 Model Flow

The automated e-waste identification model, is designed to efficiently and accurately classify electronic waste for improved recycling processes. The model development follows a structured workflow encompassing several key stages: data collection, preprocessing and annotation, data splitting, model training, and model evaluation as demonstrated in Figure 1.

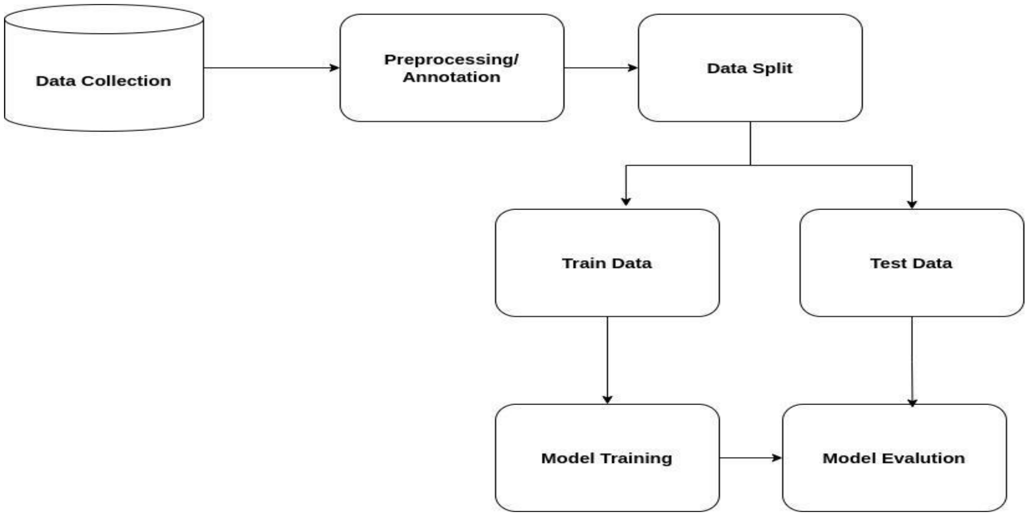


Figure 1: Model Flow for E-waste

2.2 Data Collection

The dataset used in this research was sourced from the Kaggle e-waste dataset repository, specifically designed for electronic waste detection and classification. The dataset comprises images of five distinct categories of electronic waste commonly found in recycling streams:

1. Laptops: End-of-life portable computers and their components
2. Monitors: Various types of display screens and monitors
3. Mice: Computer mice of different designs and manufacturers
4. Mobile Phones: Various models of mobile phones and smartphones
5. Keyboards: Computer keyboards in different conditions and styles

2.3 YOLOv8 Architecture

1. *Powerful Backbone*

YOLOv8 uses pre-trained convolutional neural networks, such as Darknet or Efficient-53Det, to extract valuable features from input images. These features are designed to capture essential information about the content of the image and to lay the foundation for object detection.

2. *Refinement and Enhancement*

YOLOv8 may utilize techniques like.

I. Spatial Attention ModuleSAM: This module is designed to focus the model’s attention on the most important areas of the extracted features, improving the detection of small or occluded objects.
II. Path Aggregation Network (PAN): This network merges features from different network layers, combining low-level details with high-level semantic information to create a more comprehensive understanding of the image.

3. *The Prediction Layers*

i. Grid Division: The image is divided into a grid of cells, like a 16×16 grid. Each cell acts as a zone for potential object detection.
ii. Per-Cell Predictions: Within each cell, the model predicts:
iii. Bounding Boxes: Predicts several bounding boxes of various sizes and aspect ratios, representing potential object locations within that cell.
iv. Confidence Scores: The model predicts a confidence score for each bounding box, indicating its belief that the box contains an object and the correct class.
v. Class Probabilities: Predicts the probability of each object class for each bounding box, allowing for object classification.

4. *Loss Functions*

During training, loss functions like Intersection over Union (IoU) loss and classification loss play a crucial role.

I. IoU Loss: Penalises incorrect box bounding predictions, ensuring a tight enclosure around the actual objects.
II. Classification Loss: Minimizes errors in predicting class probabilities, leading to more accurate object classifications.

5. *Output and Post-processing*

After processing the image, YOLOv8 generates a final output containing
Bounding boxes for detected objects, Confidence scores for each bounding box, Predicted class labels for each object. Additional techniques like Non-Maxima Suppression (NMS) might be applied to refine detections by removing redundant bounding boxes (Priyanto *et al.,* 2025).

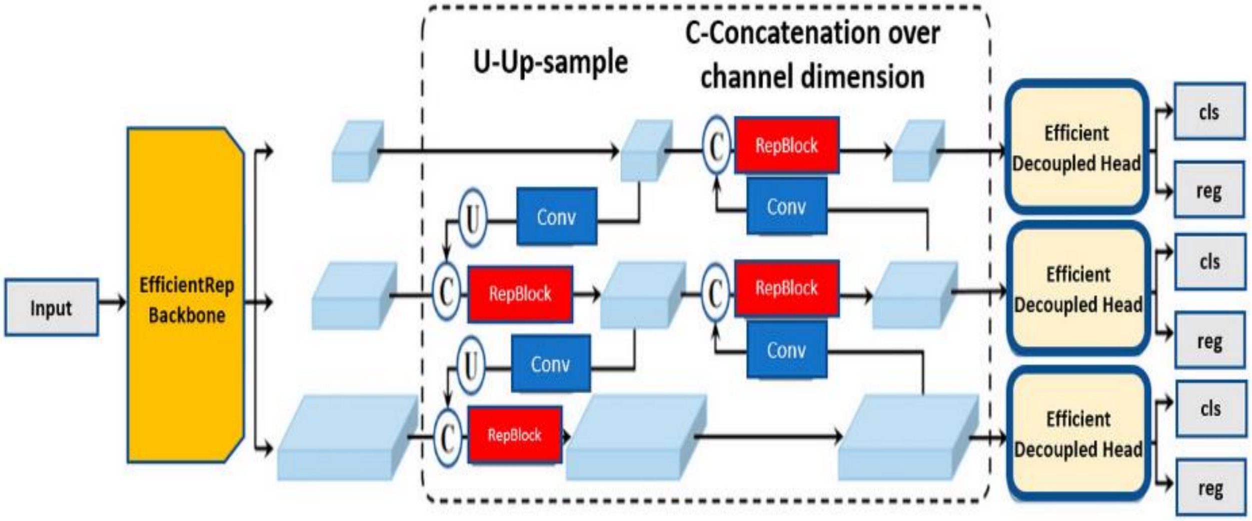


Figure 2: YOLOv8 Architecture (Priyanto *et al.,* 2025)

Class probabilities (for each class)
Objectness score (confidence)
The box coordinates are predicted as:

$$b_x^\tau = 2\sigma(t_x) - 0.5 + c_x \quad (1)$$

$$b_y^\tau = 2\sigma(t_y) - 0.5 + c_y \quad (2)$$

$$b_w = (2\sigma(t_w))^2 \times w_{anchor} \quad (3)$$

$$b_h = -(20\,(t_w))^2 \times h_{anchor} \quad (4)$$

$t_x, t_y, t_w, t_h,$= network predictions (5)

1. Loss functions

(a) cloU Loss (Bounding Box Regression)

$$L_{CIOU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \quad (6)$$

where :

- IoU = intersection over union
- ρ = Euclidean distance between centers
- c= diagonal length of the smallest enclosing box
- v= consistency of aspect ratio

(b) BCE Loss (Classification)

$$l_{clg} = -\left(y\log(p) + (1-y)\log(1-p)\right) \quad (7)$$

$$Ld_g = -\left(y\log(p) + (1-y)\log(1-p)\right) \quad (8)$$

where p = predicted probability, y = ground truth label

(c) Optional: DFL (Distribution focal Loss)

If used, DFL helps in better localization by modelling box locations as a distribution:

$$L_{DFL} = L_{DFL} = \sum_{i=1}^{N}(y_1\,log(p_i) + (1-y_i)log(1-p_i) \quad (9)$$

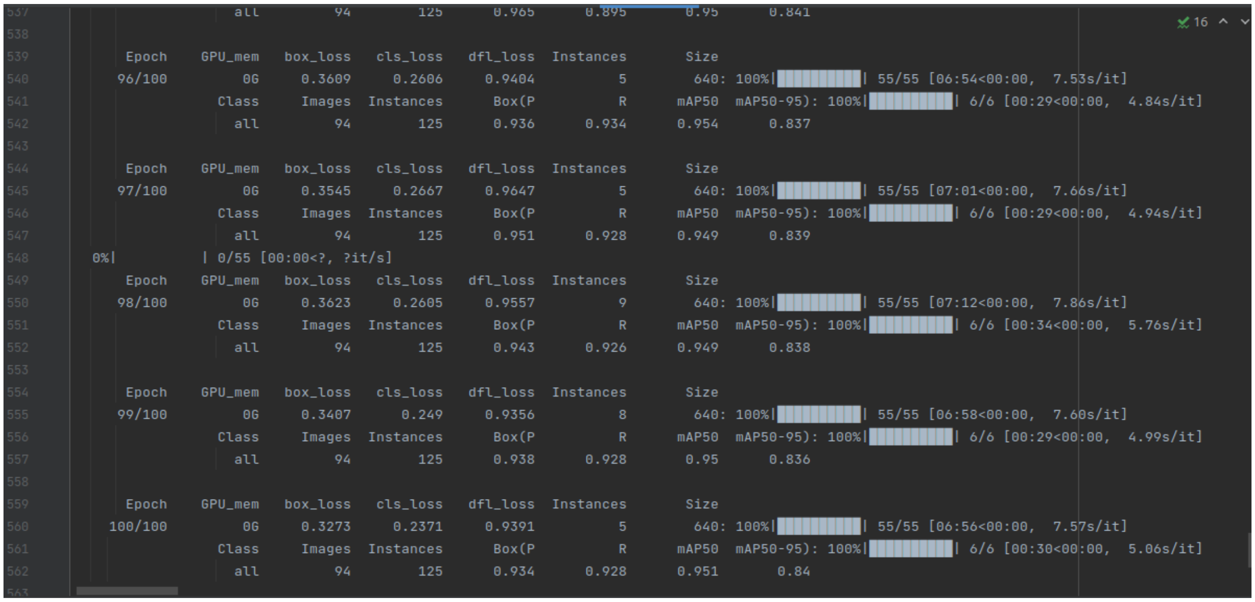
2. Overall loss

$$L_{total} = \gamma_{box}L_{cIoU} + \gamma_{clg}L_{BCE} + (optional) + \gamma_{DFL}L_{DFL} \quad (10)$$

where γ are weighing hyperparameters

2.4 Training Progression of the Proposed Model

The training process of the proposed e-waste identification model was conducted over 100 epochs, and the progression of key training metrics is summarized and in the training log provided, as presented in Figure 3.



```
                 all         94        125      0.965      0.895       0.95      0.841

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
     96/100         0G     0.3609     0.2606     0.9404          5        640: 100%|██████████| 55/55 [06:54<00:00,  7.53s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:29<00:00,  4.84s/it]
                   all         94        125      0.936      0.934      0.954      0.837

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
     97/100         0G     0.3545     0.2667     0.9647          5        640: 100%|██████████| 55/55 [07:01<00:00,  7.66s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:29<00:00,  4.94s/it]
                   all         94        125      0.951      0.928      0.949      0.839
  0%|          | 0/55 [00:00<?, ?it/s]
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
     98/100         0G     0.3623     0.2605     0.9557          9        640: 100%|██████████| 55/55 [07:12<00:00,  7.86s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:34<00:00,  5.76s/it]
                   all         94        125      0.943      0.926      0.949      0.838

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
     99/100         0G     0.3407      0.249     0.9356          8        640: 100%|██████████| 55/55 [06:58<00:00,  7.60s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:29<00:00,  4.99s/it]
                   all         94        125      0.938      0.928       0.95      0.836

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
    100/100         0G     0.3273     0.2371     0.9391          5        640: 100%|██████████| 55/55 [06:56<00:00,  7.57s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:30<00:00,  5.06s/it]
                   all         94        125      0.934      0.928      0.951       0.84
```

Figure 3: Training Report of the Model

As training progressed, several key metrics demonstrated the model's learning and improvement over the epochs. Initially, the loss values, including box_loss, cls_loss, and dfl_loss, were relatively higher in the early epochs (Epoch 1: box_loss = 0.8989, cls_loss = 1.815, dfl_loss = 1.322). These loss values represent the error between the model's predictions and the ground truth, and a decreasing trend indicates that the model is effectively learning to minimize these errors. Throughout the training epochs, a general trend of decreasing loss values can be observed. By Epoch 90, the loss values significantly reduced (box_loss = 0.459, cls_wsloss = 0.3365, dfl_loss = 1.008), indicating substantial improvement in the model's ability to accurately predict bounding boxes and classify e-waste objects. This reduction in loss signifies that the model is becoming more proficient at learning the underlying patterns in the training data. Concurrently with the decreasing loss, the evaluation metrics on the validation dataset, specifically Precision (P), Recall (R), mAP@50, and mAP@50-95, showed a generally increasing trend. In the initial epochs, for example, at Epoch 1, the mAP@50 was 0.786 and mAP@50-95 was 0.592. As the training advanced, these metrics improved, reflecting the model's enhanced accuracy and robustness in e-waste object detection and classification. In the later epochs of training (Epochs 90-100), the evaluation metrics reached notably high values. For instance, at Epoch 90, the mAP@50 reached 0.957 and mAP@50-95 was 0.837. The final epoch (Epoch 100) demonstrated comparable performance with mAP@50 at 0.951 and mAP@50-95 at 0.84. These high mAP values, sustained in the later epochs, indicate that the proposed model achieved excellent object detection performance on the validation dataset. The consistently high precision and recall values in the later epochs (Epoch 100: Precision = 0.934, Recall = 0.928) further reinforce the model's ability to accurately identify e-waste objects with minimal false positives and false negatives. The training progression, as evidenced by the decreasing loss values and increasing evaluation metrics, demonstrates the effectiveness of the proposed model and the training process in learning to accurately identify and classify electronic waste. The high mAP scores achieved in the later epochs suggest that the model is well-suited for deployment in automated e-waste recycling systems.

2.5 Confusion Matrix of the Model

The performance of the proposed e-waste identification model was further analyzed using a confusion matrix. Visually represents the confusion matrix, providing a detailed breakdown of the model's classification performance by comparing the predicted classifications against the actual ground truth labels.

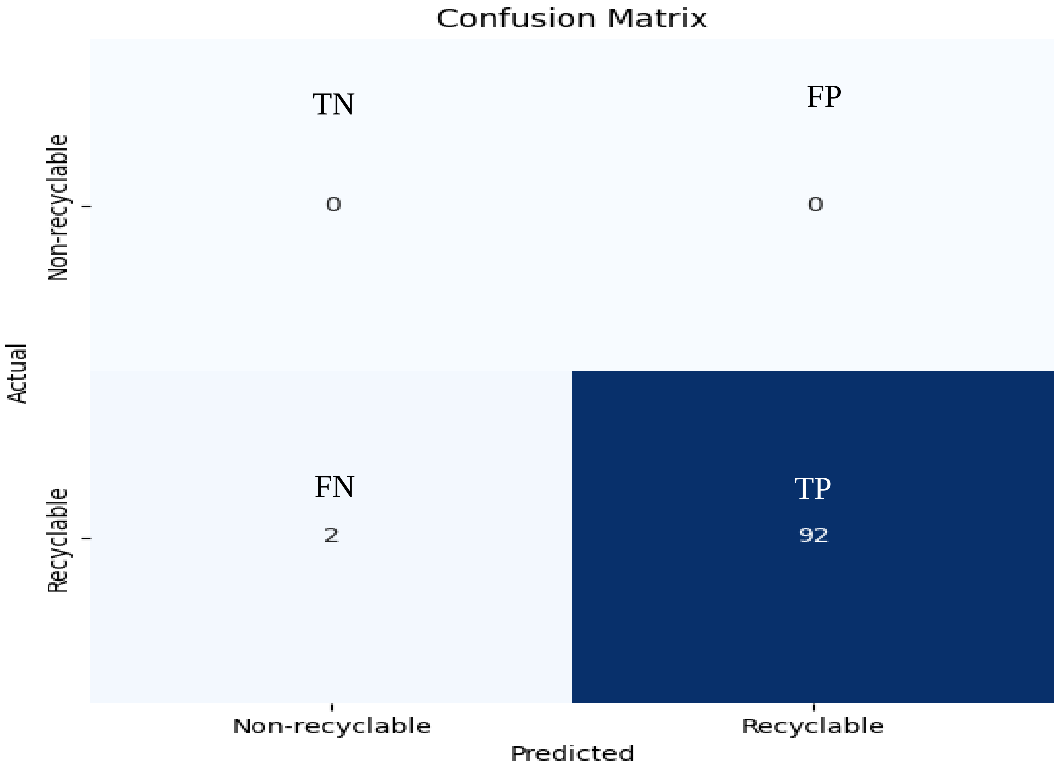


Figure 4: Confusion Matrix of the Model

3. Results and Discussion

The training analysis of the YOLOv8-based model showed consistent improvement across 100 epochs, with steadily decreasing loss and rising performance metrics. By the later epochs, the model achieved excellent object detection results, demonstrating high mAP values and a well-balanced trade-off between precision and recall. These outcomes confirm the effectiveness of transfer learning and highlight the robustness of YOLOv8 for this task. The model's ability to generalize well indicates its suitability for handling complex e-waste images, where variations in shape, size, and texture often pose challenges. The strong detection performance underscores YOLOv8's architectural advantage in real-time object recognition, making it particularly effective for fast and accurate classification. Overall, the results validate YOLOv8 as a reliable backbone for building scalable, automated e-waste identification systems.

4. Conclusion and Future Research

The research developed an automated e-waste identification model using deep learning and computer vision to enhance recycling efficiency. A YOLOv8-based CNN model with transfer learning was trained on a Kaustubh2402 ewaste-dataset, achieving high accuracy (mAP@0.5 = 0.950, F1-score > 0.93) in detecting and classifying e-waste. A user-friendly Streamlit web application was also created for real-time identification. The results demonstrated the model's effectiveness and practical applicability in improving e-waste sorting and management.

Future research should focus on refining and extending the automated e-waste identification system to enhance its efficiency, accuracy, and real-world applicability. One key area of improvement is the integration of more advanced deep learning techniques, such as attention mechanisms and transformer-based models, to improve feature extraction and classification performance. Additionally, optimizing the model for deployment on edge devices and Internet of Things (IoT) systems would enable real-time processing and scalability in waste management applications.

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