Real-Time Recycling Sorting Using Deep Learning: A Step Toward Sustainable Waste Management

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In Ethiopia, a significant amount of waste is generated daily, with estimates ranging from 9,700 tons in 2015 to 12,200 tons in 2020. However, the recycling rate remains low, with only a small percentage of collected waste being recycled. Studies indicate that a large portion of waste ends up in landfills, open dumps, or the environment. For example, in Addis Ababa, only a small percentage of plastic waste is recycled, with the majority accumulating in uncontrolled disposal sites. *link*

Koshe sefer, Addis Ababa, Ethiopia

Only around 9% of plastic waste is recycled, with 79% of it accumulating in open dumping. According to Euro-map 2022, Ethiopia is the second-largest importer of plastic in East and Central Africa, spending 17m euros per year on plastic packaging imports.

But this is not a problem faced by Ethiopia only. It’s a global problem, but some countries are far behind compared to others.

Waste classification is crucial for effective recycling and reducing pollution because it enables the efficient separation and handling of different waste types, leading to better resource recovery and minimized environmental impact.

The Vision: Why Trash Classification Matters

Every year, millions of tons of waste are generated globally, with a significant portion ending up in landfills or being improperly disposed of. In Ethiopia, the average municipal solid waste generation is approximately 0.38 kg per capita per day, totaling around 43,700 tonnes daily (Municipal Solid Waste Management in Ethiopia). However, only about 5% of waste is recycled in urban areas like Addis Ababa, with much of it dumped illegally or burned, leading to environmental and health issues (Understanding Waste Management in Addis Ababa). Our project addresses this by automating waste classification, which can significantly improve recycling rates and reduce the environmental footprint.

This project aligns with the United Nations’ Sustainable Development Goals (SDGs):

- : Enhancing recycling efficiency promotes sustainable resource use.
- : Reducing landfill waste decreases methane emissions, a potent greenhouse gas.
- : Cleaner cities improve public health and quality of life.

Current Waste Management in Ethiopia

Ethiopia is making strides in waste management, notably with the Reppie Waste-to-Energy plant in Addis Ababa, which processes 1,400 tonnes of waste daily, converting it into electricity and handling about 80% of the city’s waste (Ethiopia Enhances Environmental Protections). Despite this progress, challenges persist: only 31.8% of municipal solid waste is collected legally, and recycling rates remain low at around 5% (Municipal Solid Waste Management in Ethiopia). The high organic content (73.13% biodegradable) offers opportunities for composting and biogas, but inadequate segregation at the source hinders these efforts. Our project complements initiatives like Reppie by providing a technological solution to improve sorting accuracy and efficiency.

Objectives: Building a Smart Recycling System

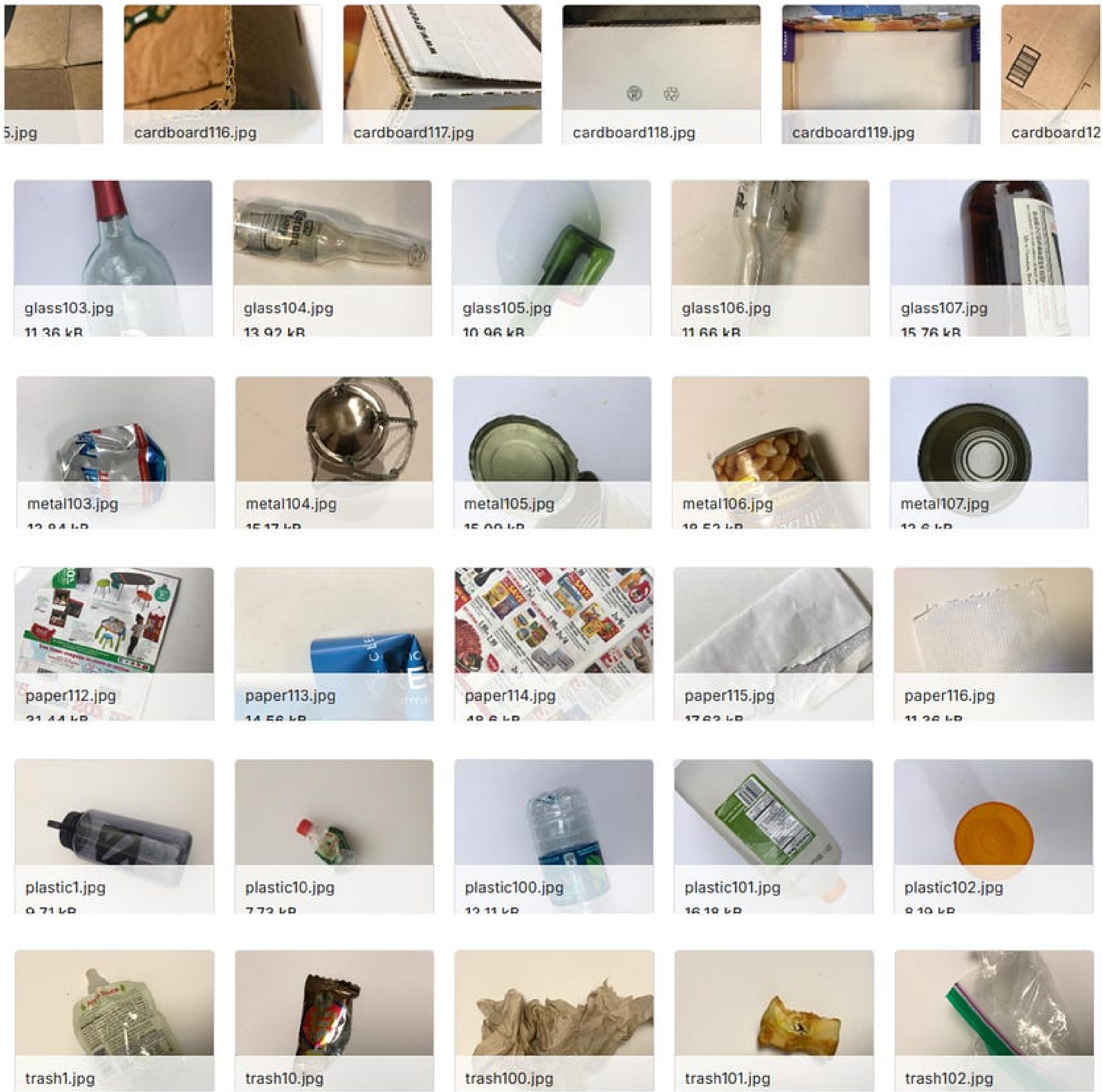
Our project had clear objectives:

- Develop a deep learning-based system to classify waste types (cardboard, glass, metal, paper, plastic, trash) in real-time.
- Preprocess and prepare the TrashNet dataset for training.
- Compare multiple deep learning models to select the best one based on accuracy and speed.
- Create a user-friendly web app for waste detection via uploaded or camera-captured images.
- Test the system to ensure reliable real-time performance.

The Data: TrashNet and Preprocessing

We used the Kaggle TrashNet dataset, which includes images of six waste categories: cardboard, glass, metal, paper, plastic, and trash, totaling around 2,527 images. The dataset was split into 80% training, 10% validation, and 10% testing sets. To enhance model performance, we applied preprocessing techniques:

- : Standardized pixel values to a range of [0, 1] for consistency.
- : Applied transformations like 90-degree rotations, horizontal and vertical flips, 20% zoom, and brightness adjustments (±10%) to increase dataset diversity and prevent overfitting.
- : Converted annotations to YOLO bounding box format for object detection, ensuring compatibility with our chosen model.



Trashnet Images

Model Selection and Training

We evaluated several deep learning models, including EfficientNet, ResNet50, Vision Transformer (ViT), and YOLOv8, focusing on accuracy, precision, recall, and inference speed. YOLOv8, known for its single-pass architecture that predicts bounding boxes and class probabilities simultaneously, emerged as the top performer, making it ideal for real-time applications like waste sorting on conveyor belts.

Why YOLOv8?

YOLOv8's lightweight design, particularly the YOLOv8-nano variant, balances speed and accuracy, achieving:

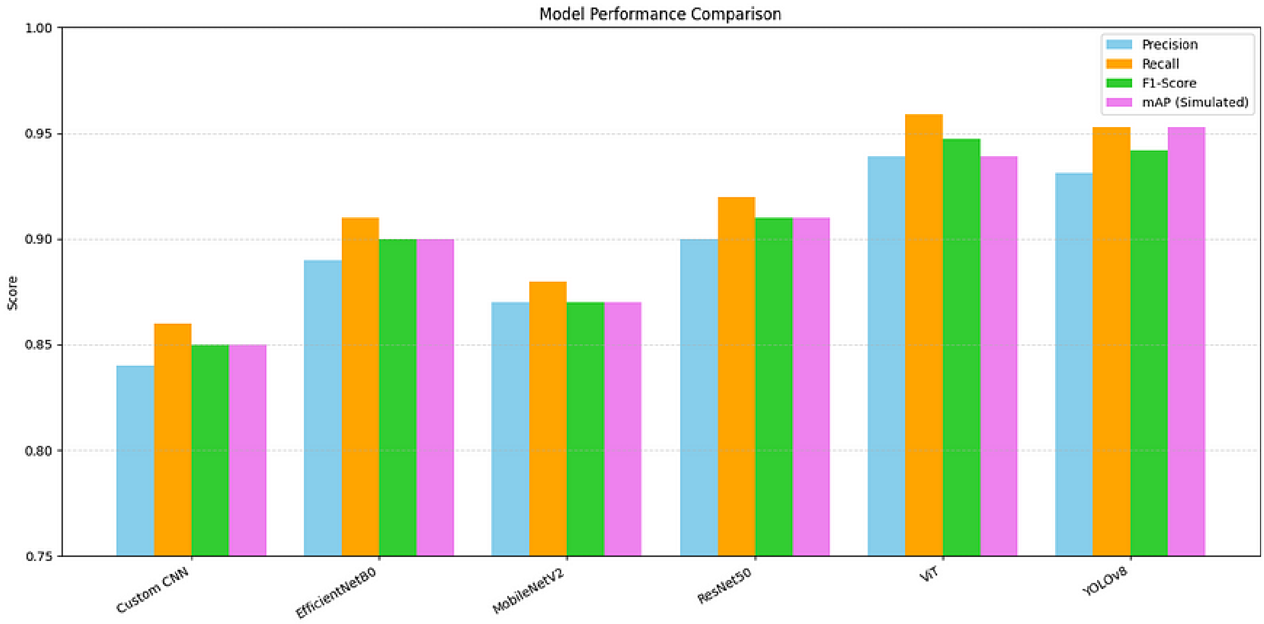
- 93.1%
- : 95.6%
- : 15.2 ms per image

We trained YOLOv8 on the preprocessed TrashNet dataset, fine-tuning hyperparameters like learning rate and batch size to optimize performance. The model was trained on a 640x640 input resolution to ensure fast inference without sacrificing accuracy.

Model Performance Comparison

Model	Precision	Recall	mAP@0.5
Custom CNN	0.820	0.800	0.840
EfficientNet	0.870	0.850	0.890
MobileNet	0.850	0.840	0.870
ResNet50	0.880	0.870	0.900
Vision Transformer (ViT)	0.830	0.820	0.860
YOLOv8	0.863	0.931	0.956

Evaluation Results

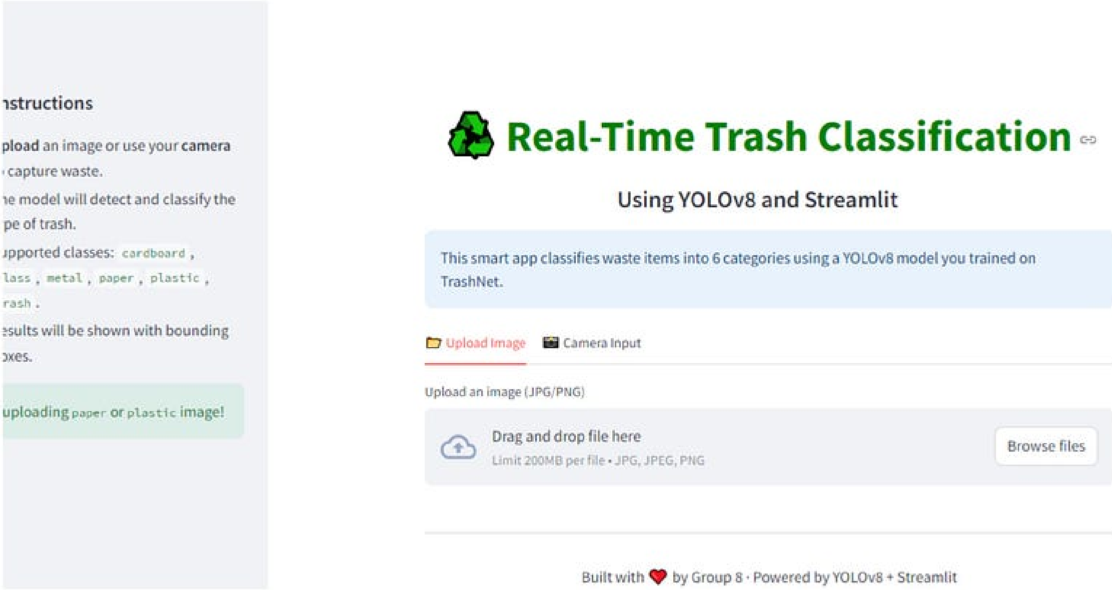


Deployment: Bringing the Model to Life

We developed a Streamlit web app for user interaction, enabling users to:

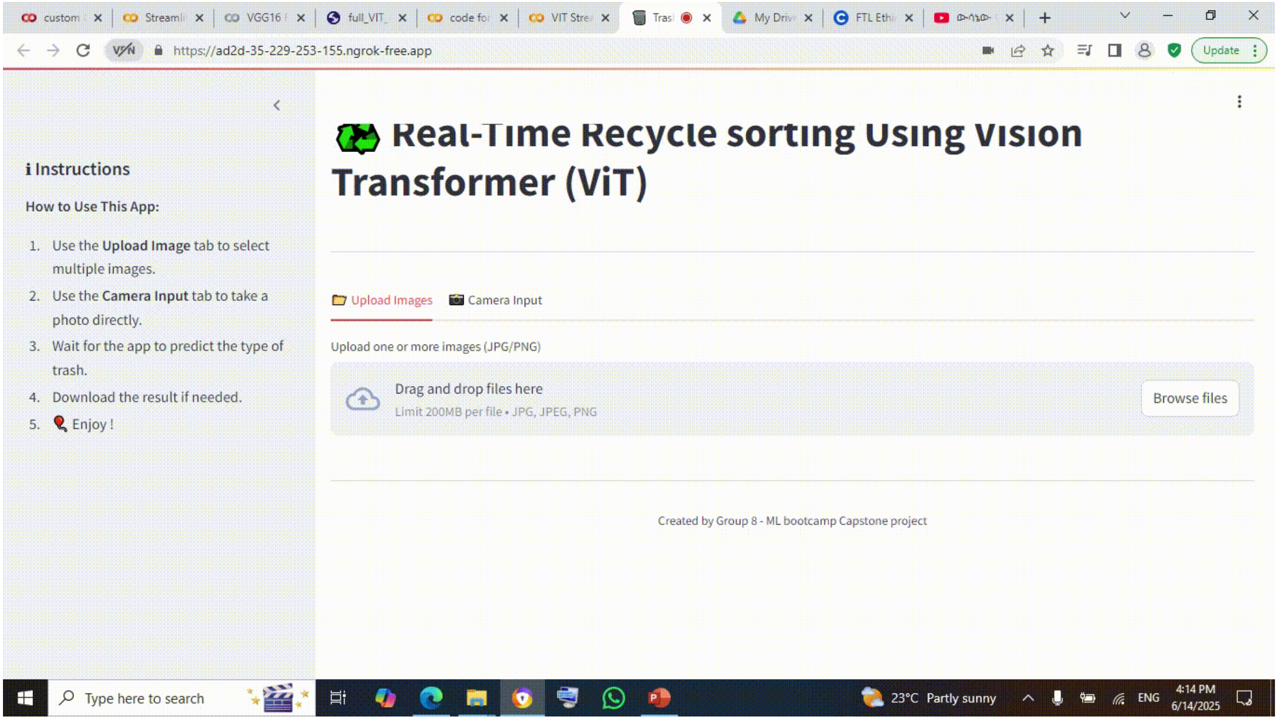
- Upload images or capture photos via webcam.
- View real-time waste classification with bounding boxes around detected objects.
- Access results for the six supported waste categories.

We used ngrok for public deployment, ensuring accessibility for testing. To optimize real-time performance, we employed YOLOv8-nano and handled various image formats to ensure compatibility across devices.



Conclusion

Our real-time trash classification system showcases the power of deep learning in addressing environmental challenges. By automating waste sorting, we aim to boost recycling rates, reduce landfill waste, and support Ethiopia’s journey toward sustainable waste management. We hope this project inspires further innovation, encouraging others to leverage AI for a greener planet.



Trash image classification demo

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