Deep Learning in the Wild for Industrial Scale Plastic Waste Sorting

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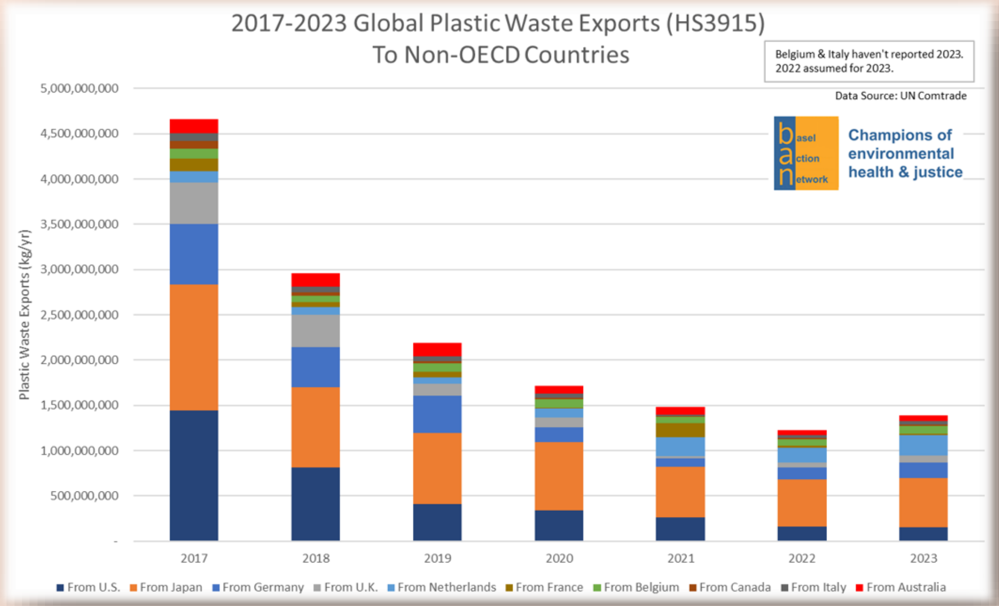
NEURAL INFORMATION PROCESSING SYSTEMS

Effects of Plastic Waste

- In 2015, out of 6300 Million metric tons (Mt) of plastic waste 79% was landfilled, 9% recycled, 12% burned, 1.7 Mt ended up in the Ocean which is 0.5% of the world's total plastic
- Microplastics affect growth, development of plants, compromise cardiovascular health in aquatic life, directly related to cardiovascular diseases humans and mice

What has been the solution?

- Until 2018 China's SWORD policy **75% of USA and 95% of EU** plastics has been exported
- Illegal shipment of plastics to developing countries persisted until the Basel Action Network implemented stricter regulations in 2022



Market Value

- Global plastic recycling market is increasing at 8.1% CAGR from **69.4 billion in 2023** to **$120 billion by 2030**
- The U.S. market was valued at **$2.19 billion in 2022** and is projected to increase at a CAGR of **7.9% by 2030**

Current Recycling Facilities

- Material Recycle Facilities (MRF) utilize manual, semi-automated, automated sorting
- Employ a range of methods, from manual labor to advanced technologies like NIR, XRF, and vision-based sorters.
- Labor-intensive, costly, and fraught with health risks, limited market value for other plastics than PET, HDPE

Existing datasets and approaches

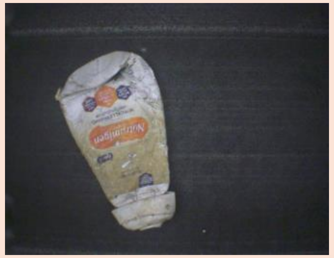
- Currently three public MSW datasets exist, offering limited samples
- Recent approaches to plastic sorting have evolved from traditional spectral-based methods to sophisticated ML solutions utilizing different types of network and vision data

Datasets	Classes	Number of images	Details	Cons
Trashnet (2017)	6	2,527	Well-labeled, suitable for classification	No distinction between plastic types, doesn't represent MRF
TACO (2020)	60	1,500	Crowdsourced and annotated	No distinction between plastic types, doesn't represent MRF
ZeroWaste (2021)	7	10,715	Recreated MRF condition, well annotated	No distinction between plastic types

Approach/ Work	Data	Technology used
Discrimination Model with NIR (Yan Zheng et. al) 2018	Spectral (6 classes) 94 samples	NIR, PCA, Fisher Discrimination
Multispectral classification with deep CNN(Romans Maliks et. al) 2021	Spectral (PET, HDPE) 2118 samples	NIR, Data augmentation, 7 layers CNN, t-SNE, PCA, SVM
Classification with NIR and DL(Attilio Sbrana et al) 2023	Spectral (17 classes) 1491 samples	NIR, FAISS, N-BEATS, LightGBM
Integrating image sensors and DL(Choi et al.) 2023	Image (PET, PET-G) 2000 sam	Depth Camera,data augmentation, YOLOv8,

Dataset

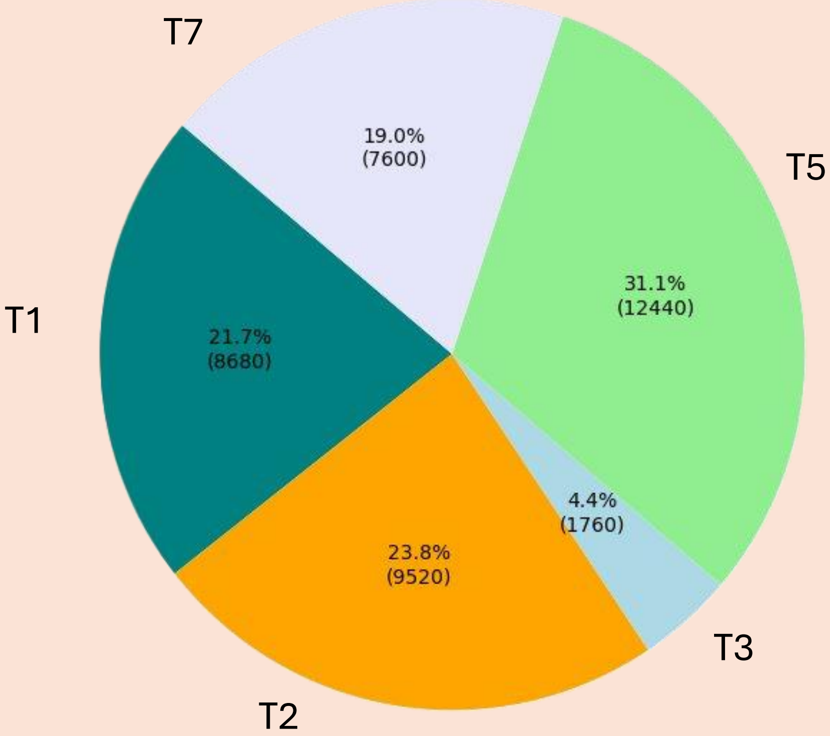
- Sourced from Solid Waste Authority of Palm Beach, Florida
- Data collection process is semi-automated, manually sorted first couple of bales, then utilized EcoSorter
- Although we found 10 types of materials in MSW, we focused on 5 types of plastics
- Ambiguous cases (Deformed/ scratched plastics) were evaluated by NIR facility in Idaho National Laboratories
- It comprises **40,000** high-resolution images (640x465 pixels)
- Three variants: a) normal (centered on uniform background), b) contextual (with 15-pixel margin), c) isolated(segmented object only


Raw


Normal


Contexual

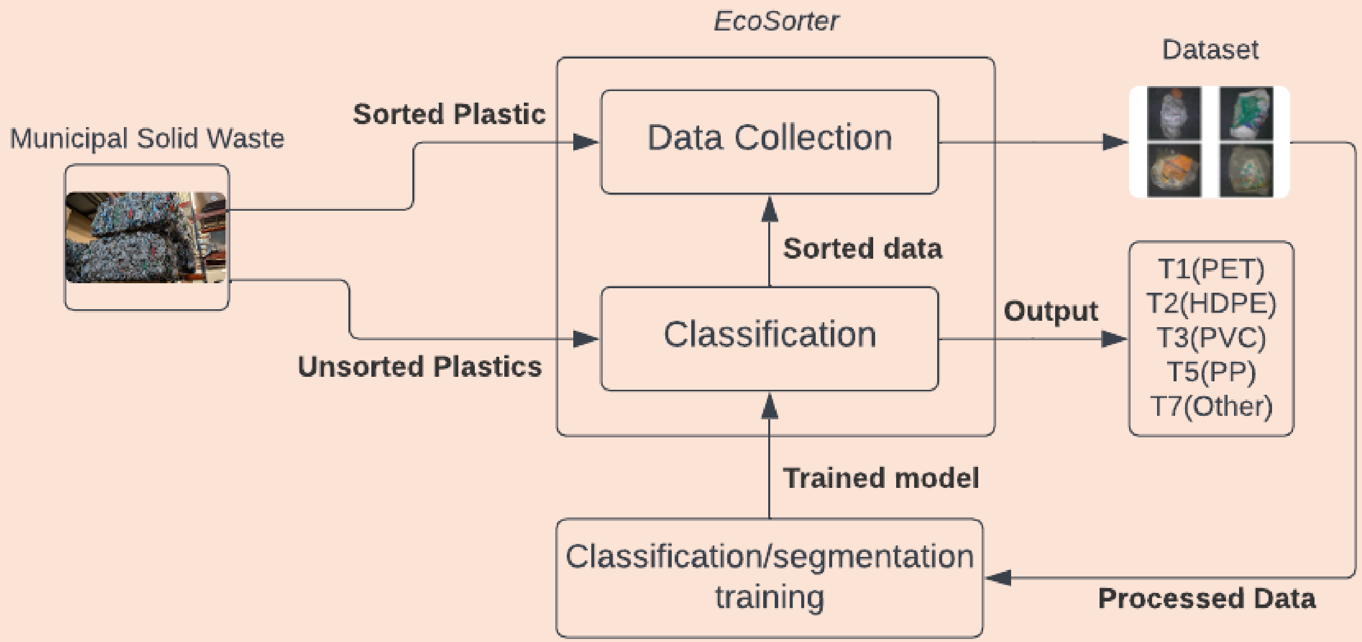
Isolated



Our Approach

- EcoSorter comprises of two integrated pipelines: Data collection and Classification and both are simultaneous
- All datasets, including raw images, were extensively trained, leading to the selection of Normal dataset
- Classifiers were trained with data augmentation (**rotation, flipping, brightness, color adjustment, and shearing**) and final layer modification for the current dataset
- ResNet-18, 34, 50, and EfficientNetV2M were tested, finally ResNet-50 was deployed in the current line
- YOLO-v5 was trained to **localize and extract** the objects from the conveyor belt, it mitigates the issue of capturing dark materials

Model	Accuracy	F1-Score	Parameters	Inference Time
ResNet-18	79.93%	0.80	4.8 M	0.104 ms
ResNet-34	82.93%	0.83	9.5 M	0.145 ms
ResNet-50	**87.19%**	**0.87**	**11.2 M**	**0.181 ms**
EfficientNet-v2m	80.02	0.66	0.66 M	0.88 ms



Experiments on Deformed Objects

- Plastic deformation- crushed, scratched, bending, distorted shapes, irregular surface textures
- Deformations impact the plastic's visual and spectral features
- Hypothesis- adding more variability, including deformed objects, will progressively improve the model's accuracy
- We train three models with 50%, 75%, and 100% of the dataset Type 7 objects as Arizona Tea jugs that contain both pristine and deformed objects and are around 98% of total Type 7

Model	Accuracy	Confidence under 50% on 288 items
50% dataset	51%	161
75% dataset	89.93%	34
100% dataset	93.75%	23

Pristine Type 7 object

Deformed Type 7 object

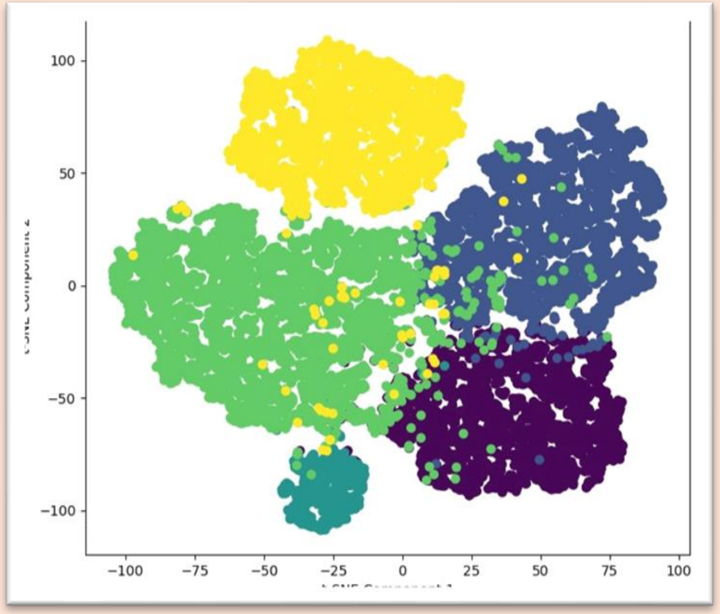
Model	Error Rate Reduction	Misclassification Improvement per Sample
50% to 75%	80%	11.4
75% to 100%	28%	0.99

Model Interpretability

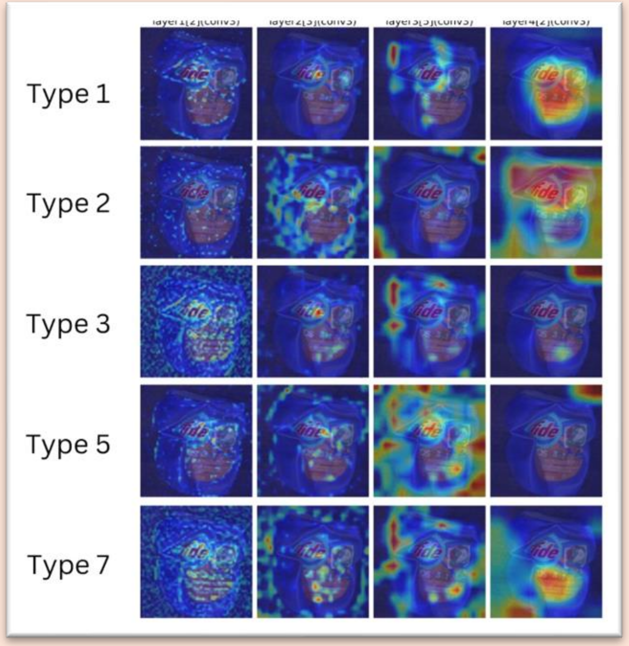
- We utilized t-SNE for class separation analysis and Grad-CAM to validate the model's focus on relevant features which is critical for industrial deployment transparency
- These visualization techniques help explain why the model misclassifies certain plastics

Economic Viability

- Processes 200 samples per hour across five plastic types, with a potential cost of $30 per ton



t-SNE features of ResNet-50 on training set, as indicated by the color: Dark Purple(Type 1), Blue(Type 2), Green(Type 3), Light Green(Type 5), Yellow(Type 7)



Grad-CAM heatmap of Type 2 plastic on ResNet-50. Columns represent layers ‘layer1[2](conv3)‘,‘layer2[3](conv3)‘, ‘layer3[5](conv3)‘, and ‘layer4[2](conv3)‘, with rows showing features extracted from each class