WasteWizard

Efficient Waste Sorting through Computer Vision

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MEET OUR TEAM

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TABLE OF CONTENTS

PROBLEM OVERVIEW

We produce **2 billion metric tons** of solid waste globally per year[1]

75% of America's waste is recyclable, but we only recycle **32%**[2].

The US throws away **$11.4 billion** in recyclable packaging annually[3].

Material Recovery Facility (MRF) workers must sort through potentially hazardous waste[4].

The US is **#1** in waste-per-capita, producing **12%** of global waste production despite being 4% of global population[5].

At this rate, America's remaining 3000 active landfills have less than **60 years** until they reach capacity[6].

Image Source

OUR SOLUTION

Waste sorting is a crucial process in recycling to differentiate trash, recyclables, and toxic waste which end up in landfills, recycling centers, and trash incinerators.

WasteWizard makes waste sorting easier and more accessible, addressing these problems at the source.

Source

TARGET USERS

Households (Primary Users)

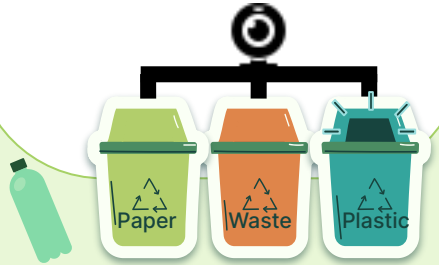
US households with internet access + camera

- Single-Family homes
- Multifamily residences
- HOA-managed complexes

Commercial Product

Integrated the AI to hardware system to be a smart trash bin:

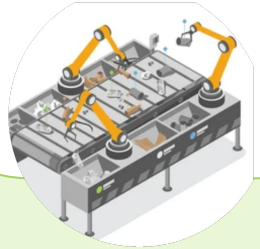
- Companies, Schools, Malls...



Waste Management Facility

Equip with AI-based computer vision for enhanced:

- Efficiency, accuracy, and safety in waste sorting at the facilities



PROJECT IMPACT

Individuals

→ Reduce difficulty

73% of US households have recycling access but only 43% recycle[4].

WasteWizard can help the remaining 30% (40 million households) get involved.

Recycling Industry

→ Improve safety (reduce manual sorting)

Over 300 waste management facilities in the US, with avg of 30 workers performing manual sorting.

Advanced waste sorting machines can relieve workers of unsafe working conditions.[3]

Environment

→ Save resources

Reduce landfill waste, prioritize material reuse for a better environment.

We can reduce landfill waste to 28 million tons annually.[4]

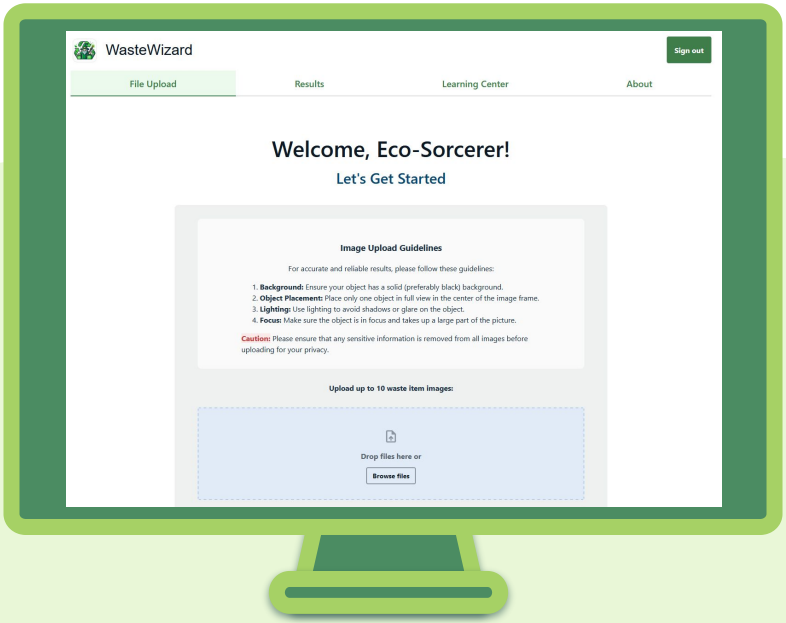
02 MVP

Minimum Viable Product (MVP)

Step 1:
Users Upload Photo(s)

Step 2: Computer Vision
Real-time image classification

Step 3: Toss/Recycle
Inform user of appropriate disposal method

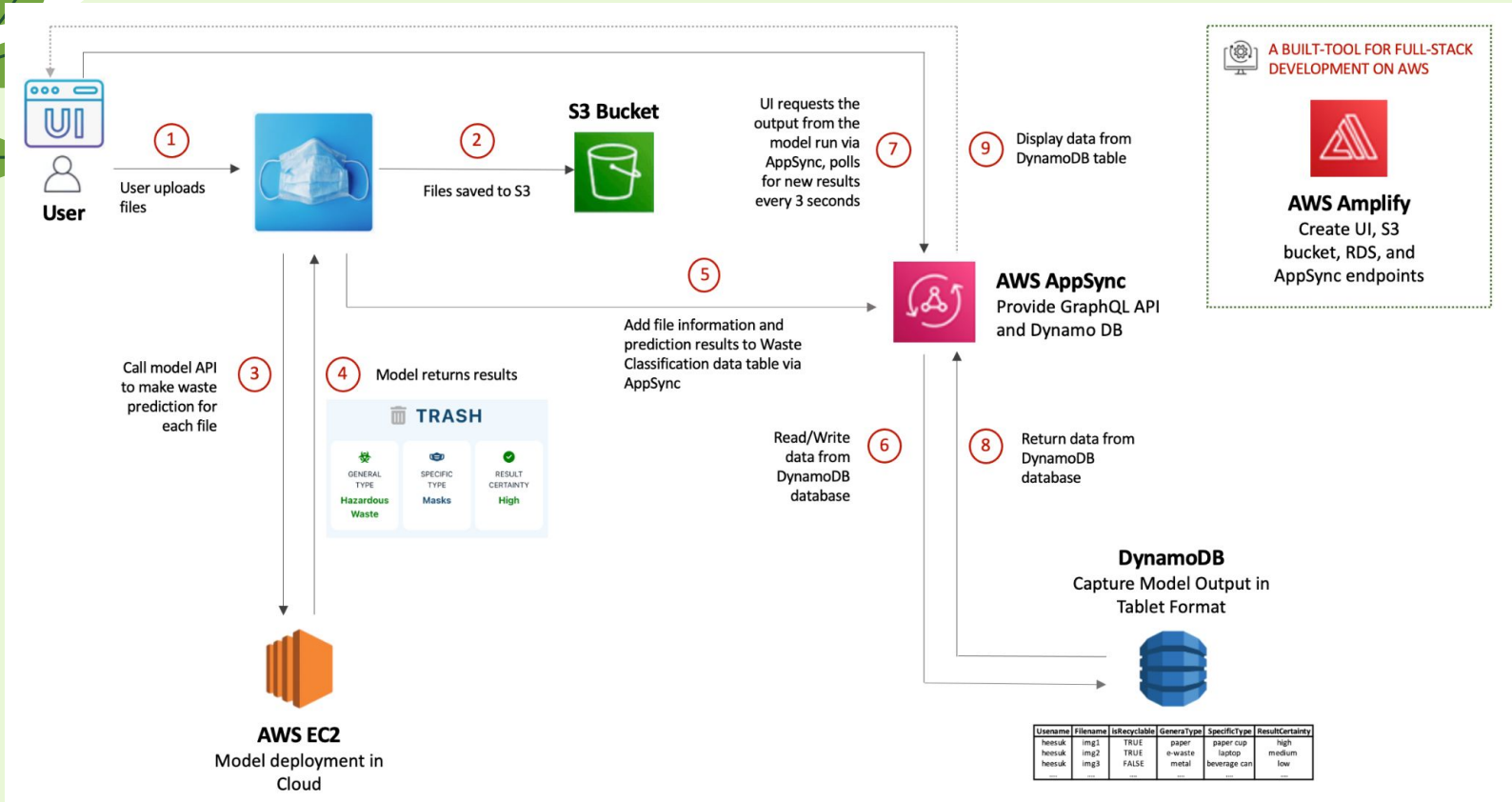


MVP Addresses Key Question:

How can I recycle this item?

Data Flow Diagram

Here is the architecture and technical components we used for our MVP:



Web App – Waste Wizard

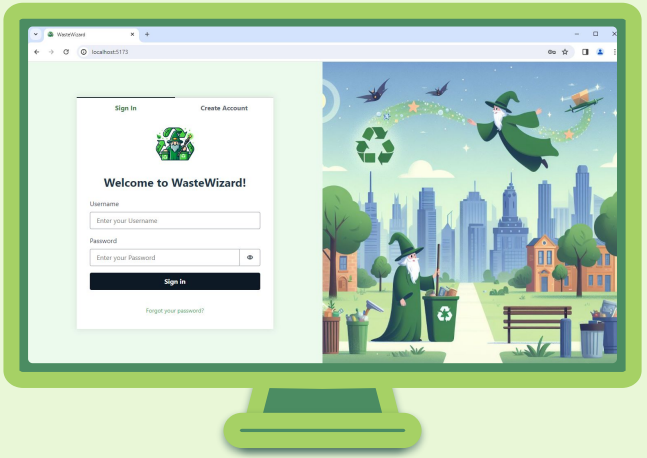
With React Router

Live Demo

USER FEEDBACK

User testing feedback helps us assess the response of our target audience.

"The UI is straightforward and easy to use! I found the specific tips for disposal really helpful." – Daisy



"This website has a lot of useful information, especially the Learning Center!" – David

"There were some waste items I didn't know were recyclable, so I would usually throw them in the trash. Now I know they are recyclable and the steps to take to throw them away. Thanks, WasteWizard!" – Beth

03

Data Exploration & Preprocessing

DATASETS

TrashBox

- 18,008 images (.jpg)
- Color (RGB) images
- 25 classes (cardboard, beverage cans, glass, plastic bags, etc.)

Kaggle: waste_pictures

Supplemental images (.jpg) for trash and battery class

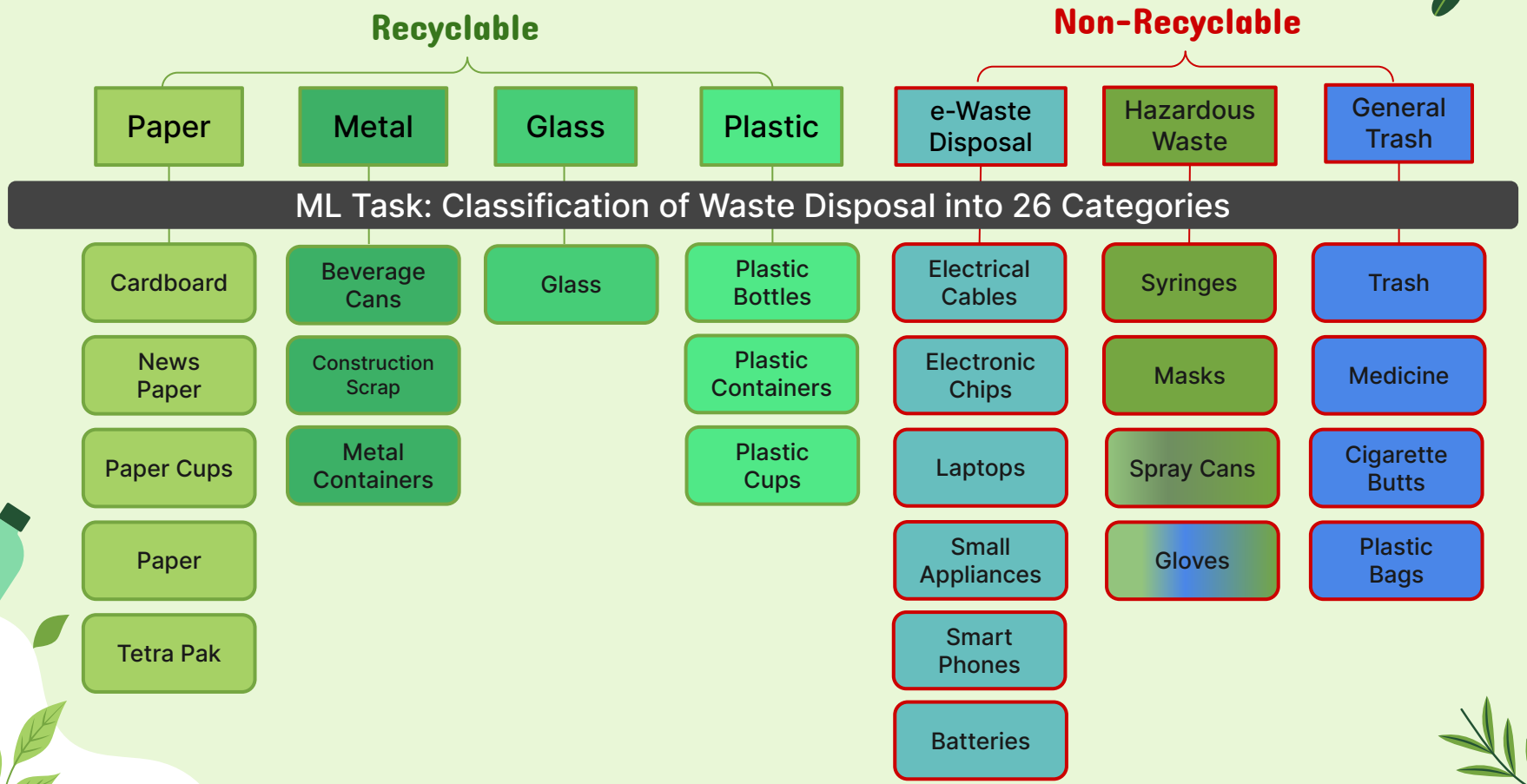
- Color (RGB) images
- 839 Battery Images
- 930 Trash Images

Kaggle: Garbage Classification

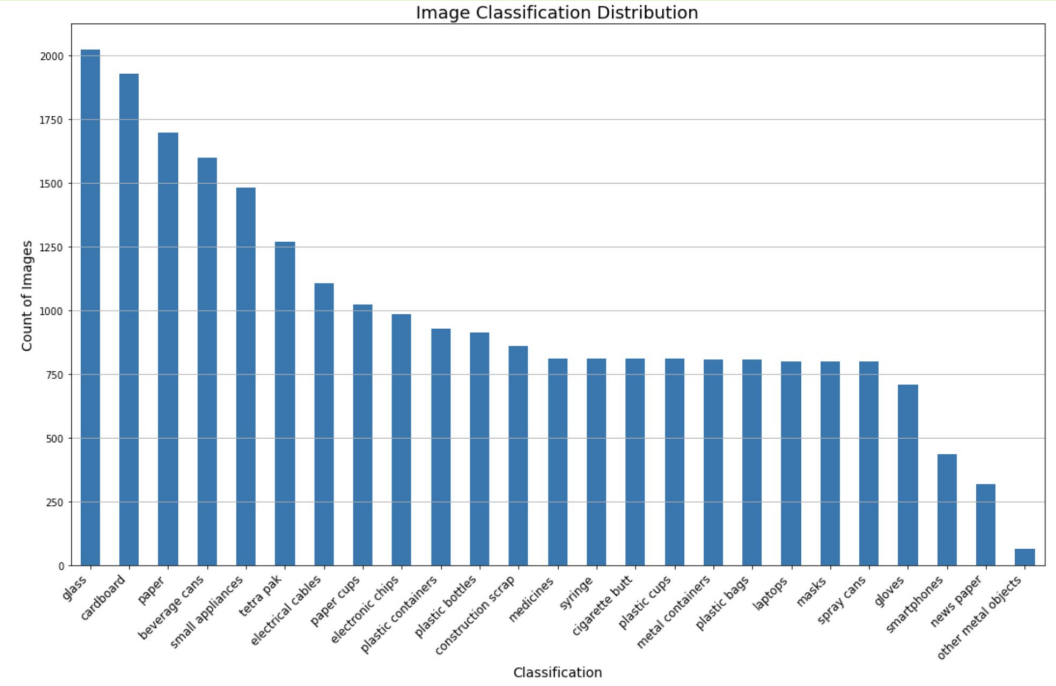
Supplemental images (.jpg) for trash and battery class

- Color (RGB) images
- 946 Battery Images
- 986 Trash Images

Waste Sorting Categories



Exploratory Data Analysis



EDA FINDINGS:

Image Shape

Computer Vision model expects inputs of a fixed shape (num sample, height, width, 3)

Image Size

224 x 224 image size allow models to process the data more efficiently

Color Palette

RGB, many pretrained models were trained using color images

Data Pipeline: Preprocessing

Original images

Resize with padding

Remove transparency

Remove duplicates

Remove background

Normalize pixel values

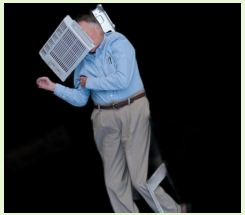
RGB images

80/20 split

Ex. Metal container

Ex. Plastic bottle

Cardboard



Battery

Laptops

HOW WE OVERCAME UNUSABLE IMAGES

We manually removed mislabeled images, improving model performance:

- Single object or multiple objects of the same material
- Remove mixed materials
- Remove people

04 Modeling Approach

Modeling Techniques that we explored...

- Class weight adjustments
- Regularization Techniques
- Hyperparameter Tuning
- Transfer Learning
- Ensemble Modeling
- Model Checkpointing

Primary Evaluation Metric: Macro F1 Score

PRIMARY METRIC

We used Macro F1 score for model selection and evaluation.

HOW DOES IT WORK?

Macro F1 takes the F1 scores of each class and averages them, treating all classes equally.

WHY MACRO F1?

Our dataset class distribution doesn't mirror real-world usage.

We ensure equal weight for each class with Macro F1 Score.

Model Experiments

	Train Accuracy	Train Macro F1	Test Accuracy	Test Macro F1
Majority Baseline	0.120	0.010	0.120	**0.010**
CNN – rembg, grayscale	0.986	0.830	0.680	**0.600**
ResNet50 – rembg, augmented	0.890	0.930	0.810	**0.770**
VGG16 – rembg, non-augmented	0.986	0.701	0.750	**0.680**
ViT – rembg, non-augmented	0.916	0.897	0.918	**0.896**
Boosted 8 Transfer Learning Models	0.724	0.657	0.609	**0.515**

Our final model (ViT) balanced performance and efficiency

Accurate

The ViT model yielded the highest validation macro f1 score of 90%

Efficient

Total training and evaluation time was ~2 hours, an indicator of speed of prediction for unseen data

Test Evaluation Metrics

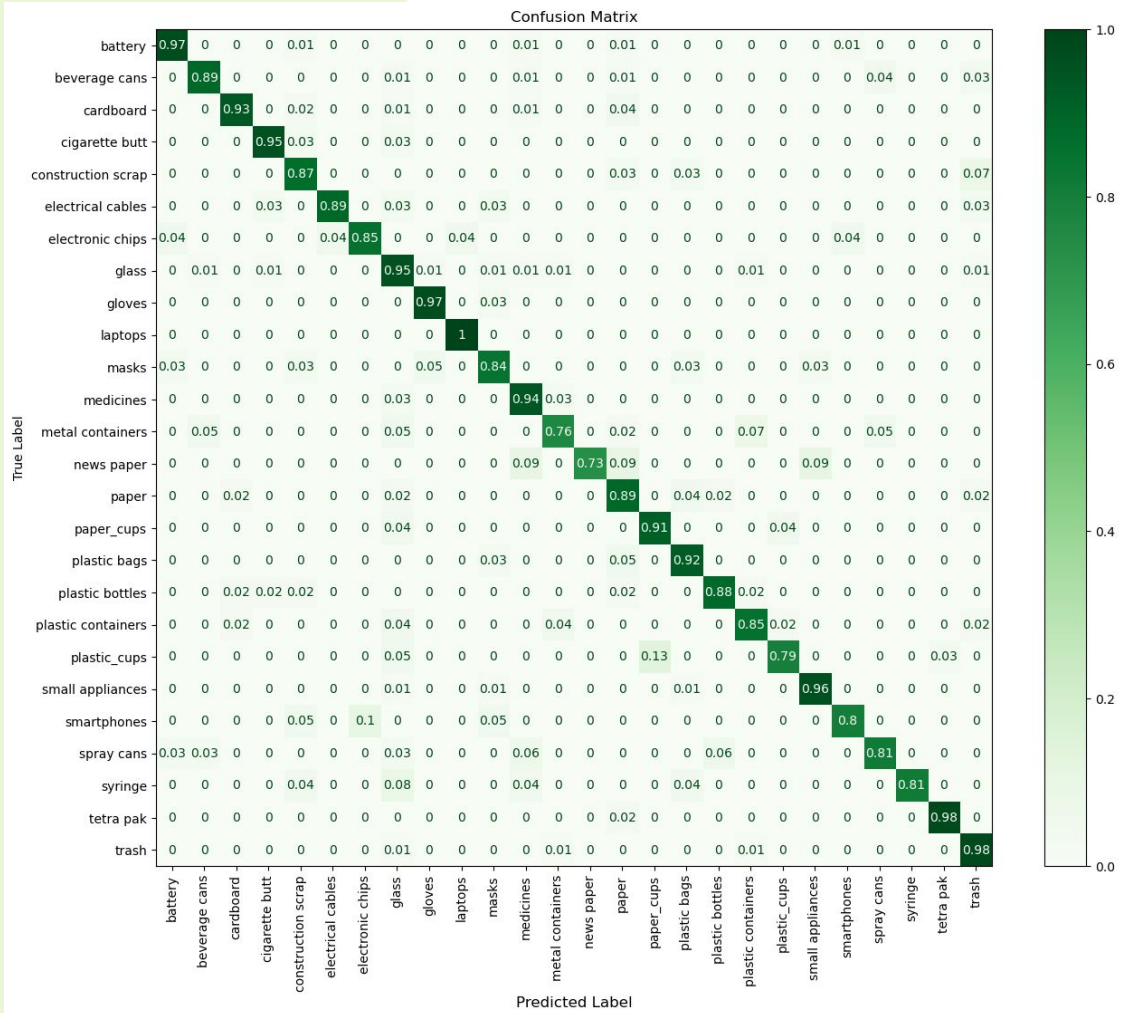
- **Accuracy:** 92%
- **Macro F1:** 90%
- **Precision:** 91%
- **Recall:** 89%

Best Hyperparameters:

- **learning_rate:** 2.003e-05
- **num_train_epochs:** 12
- **per_device_train_batch_size:** 9
- **weight_decay:** 0.00027797

Our model was successful in many cases:

- Classes with >=97% correct
  - **Laptops**: 100%
  - **Tetra Pak**: 98%
  - **Trash**: 98%
  - **Battery**: 97%
  - **Gloves**: 97%



But there is room for improvement...

- Classes with < 80% correct:
  - Plastic Cups: 79%
    - 13% misclassified as paper cups
  - Metal Containers: 76%
    - Misclassified as plastic containers, beverage cans, glass, and spray cans
  - Newspaper: 73%
    - Misclassified as medicines, paper, small appliances
    - Items on newspaper

Interpretable Insights

Target users can use model outputs to address the problem:

Model Classification Output

Informs users about the waste item's material composition

Result Certainty

Shows users our certainty in the item's classification, (low, medium, high), derived from the prediction's softmax score

Waste Disposal Suggestion

Nudges users towards correct waste disposal actions for specific waste items

TOP 3 TECHNICAL CHALLENGES

Addressing Data Quality

Manual image cleanup and label correction

Balancing Resource Constraints

AWS credits, training runtimes, development bandwidth

Adapting to New Technologies

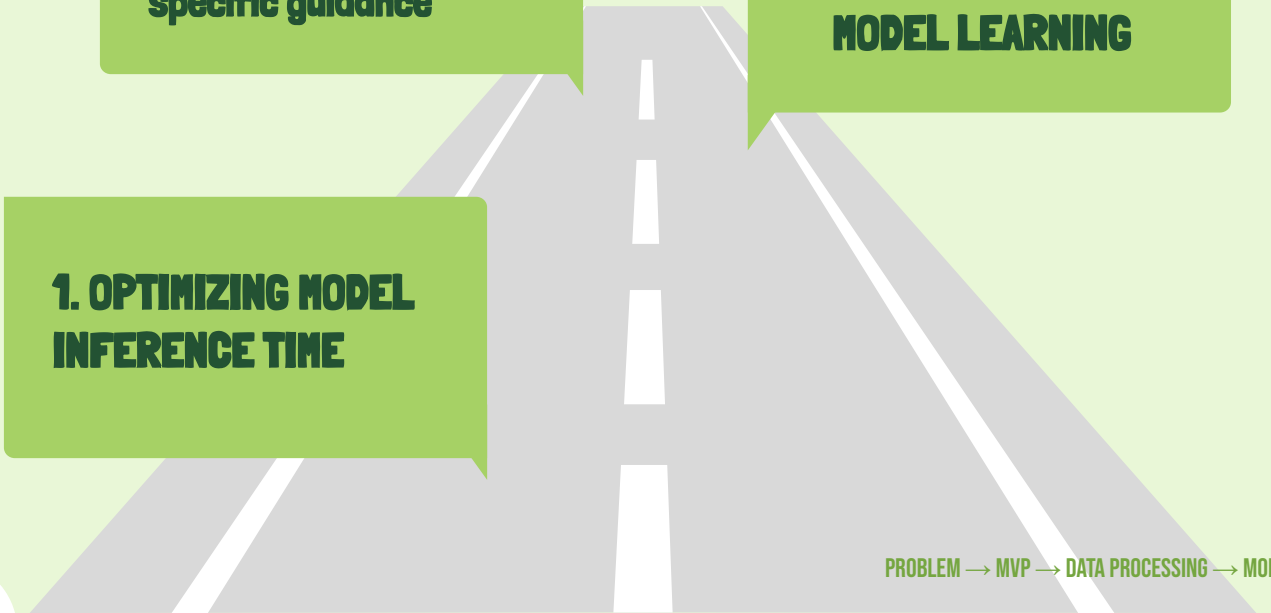
Learned many new libraries: React for full-stack app and AWS for model deployment

FUTURE ROADMAP ITEMS

3. OTHER FEATURES: mobile app, location-specific guidance

2. INTEGRATING CONTINUOUS MODEL LEARNING

1. OPTIMIZING MODEL INFERENCE TIME



Our Mission

Revolutionize waste management through AI-driven solutions, promoting a culture of sustainability and empowering eco-conscious communities for a healthier planet.

APPENDIX

For more info:
https://wastewizard-mids.webflow.io/

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