WasteWizard

Efficient Waste Sorting through Computer Vision

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MEET OUR TEAM

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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]

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]

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

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

PROBLEM → MVP → DATA PROCESSING → MODELING → RESULTS → CONCLUSION
Here is the architecture and technical components we used for our MVP:

1. User uploads files
2. Files saved to S3
3. Call model API to make waste prediction for each file
4. Model returns results
5. Add file information and prediction results to Waste Classification data table via AppSync
6. Return data from DynamoDB database
7. UI requests the output from the model run via AppSync, polls for new results every 3 seconds
8. Display data from DynamoDB table
9. AWS Amplify: Create UI, S3 bucket, RDS, and AppSync endpoints

AWS AppSync: Provide GraphQL API and AppSync endpoints

DynamoDB: Capture Model Output in Tablet Format
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

ML Task: Classification of Waste Disposal into 26 Categories

Recyclable
- Paper
- Metal
- Glass
- Plastic
  - Plastic Bottles
  - Plastic Containers
  - Plastic Cups

Non-Recyclable
- e-Waste Disposal
- Hazardous Waste
- General Trash
  - Trash
  - Medicine
  - Cigarette Butts
  - Plastic Bags

PROBLEM → MVP → DATA PROCESSING → MODELING → RESULTS → CONCLUSION
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

PROBLEM → MVP → DATA PROCESSING → MODELING → RESULTS → CONCLUSION
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

<table>
<thead>
<tr>
<th>Model</th>
<th>Train Accuracy</th>
<th>Train Macro F1</th>
<th>Test Accuracy</th>
<th>Test Macro F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority Baseline</td>
<td>0.120</td>
<td>0.010</td>
<td>0.120</td>
<td>0.010</td>
</tr>
<tr>
<td><strong>CNN – rembg, grayscale</strong></td>
<td>0.986</td>
<td>0.830</td>
<td>0.680</td>
<td>0.600</td>
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<tr>
<td><strong>ResNet50 – rembg, augmented</strong></td>
<td>0.890</td>
<td>0.930</td>
<td>0.810</td>
<td>0.770</td>
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<tr>
<td><strong>VGG16 – rembg, non-augmented</strong></td>
<td>0.986</td>
<td>0.701</td>
<td>0.750</td>
<td>0.680</td>
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<tr>
<td><strong>ViT – rembg, non-augmented</strong></td>
<td>0.916</td>
<td>0.897</td>
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<td>0.896</td>
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<tr>
<td><strong>Boosted 8 Transfer Learning Models</strong></td>
<td>0.724</td>
<td>0.657</td>
<td>0.609</td>
<td>0.515</td>
</tr>
</tbody>
</table>
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

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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

1. OPTIMIZING MODEL INFERENCE TIME

2. INTEGRATING CONTINUOUS MODEL LEARNING

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

Logo generated with Bing AI Designer

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