
Automated Garbage Classification Using ConvNeXt

A Machine Learning Approach to Improving Waste Sorting Efficiency

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Waste Management Challenge & Project Overview

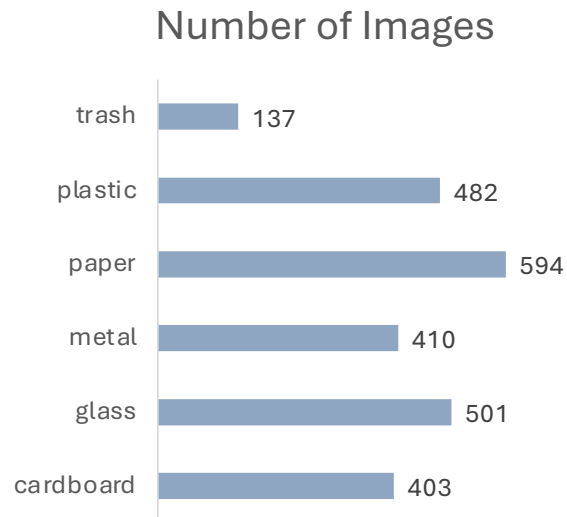
Global Challenge: Manual sorting of waste is often fraught with errors, requires significant labor, and incurs high costs, resulting in inefficiencies in recycling and greater reliance on landfills.

Project Goal: Create a deep learning model capable of categorizing images of waste into six distinct types – paper, plastic, metal, glass, cardboard, and general trash – to enhance sorting precision and minimize labor expenses.

Success Metrics:

- Achieve a classification accuracy of at least **90%**.
- Ensure precision and recall of at least **85%** for each waste category.
- Develop a system that can be deployed for real-time sorting with retraining capabilities.

Scope & Constraints



Scope:

Focus on classifying six categories (paper, plastic, metal, glass, cardboard, trash).

Aim for a solution that can be trained continuously with new data.

Constraints:

Data Limitations: The TrashNet dataset has only 2,527 images, leading to potential class imbalance (especially “trash” with only 137 images).

Computational Resources: Limited GPU/CPU capacity for large-scale deep learning.

The Data Science Problem & Dataset Overview

Data Science Problem Statement: Image classification for garbage types to increase sorting accuracy and reduce manual labor costs.

Dataset:

Name & Source: TrashNet dataset from Stanford, hosted on Kaggle.

Size & Composition: 2,527 images of six classes:

Paper (594), Glass (501), Cardboard (403), Plastic (482), Metal (410), Trash (137)

paper



metal



cardboard



trash



glass



plastic



Data Preprocessing Steps



Preprocessing:

- Resized all images to 242×242 ; normalized with ImageNet statistics.
- Handled a limited dataset size by using on-the-fly data augmentation – such as rotations, flips, zoom, translations, and brightness/contrast adjustments – to expand the training dataset.

Dataset Splits (randomly shuffled):

70% Train, 10% Validation, 20% Test.

Key Takeaway: Data augmentation is crucial to address imbalance and enhance model generalization, **and by performing it on-the-fly, it reduces memory usage while continuously introducing novel transformations in each training epoch.**

Approach & Methodology

Models Considered:

- **ConvNeXt:** Primary choice for image classification; pretrained on ImageNet for strong baseline.
- **YOLOv8 (Experimental):** Primarily an object detection model but can be adapted to classification.

Reasoning for ConvNeXt:

Solid performance, easier adaptation for custom tasks, robust with fewer data points.

Hyperparameter Tuning:

Custom grid search used to systematically explore learning rates, batch sizes, etc.

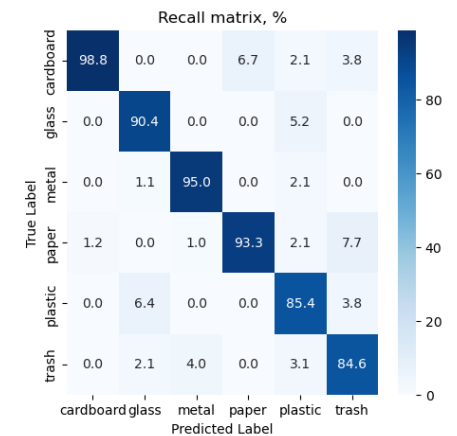
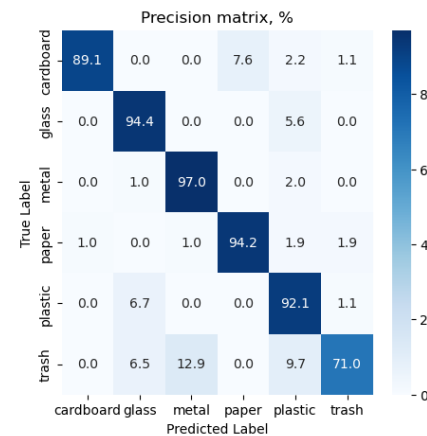
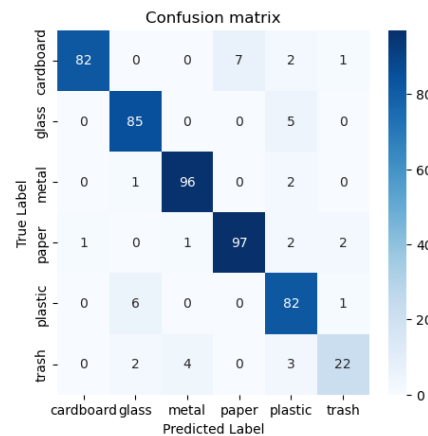
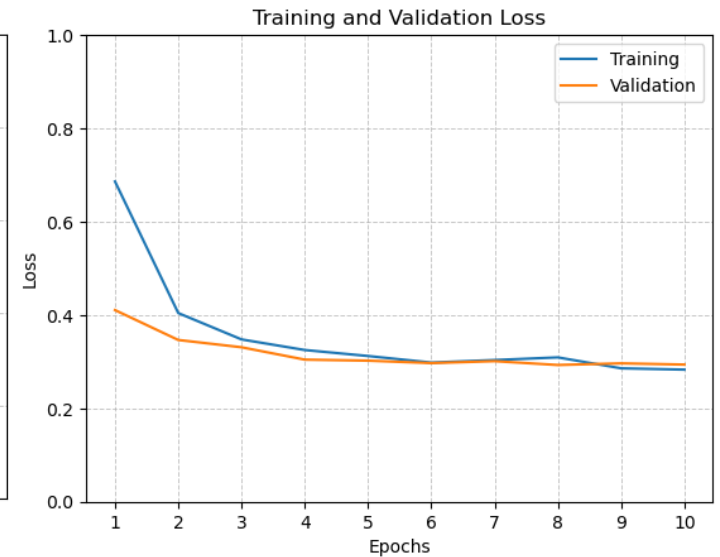
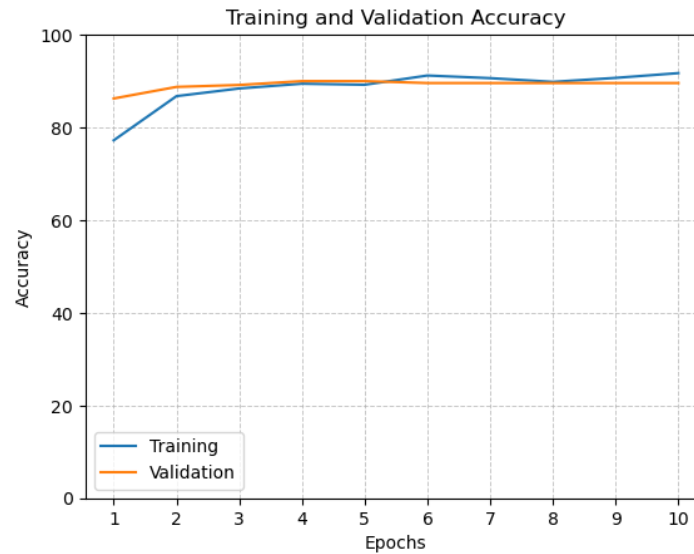
Hyper-parameter Tuning (the best results)

Parameters:

Initial Learning Rate: 0.00275
Learning Rate Decoy: 0.75
Batch size: 24

Results:

Loss: 0.2865
Accuracy: 92.06%
Worst Precision: 71.0%
Worst Recall: 84.6%



Hyper-parameter Tuning (other combinations)

Although the target of 85% recall and precision was not achieved, some variants still meet real business requirements.

| # | Initial Learning rate | Learning Rate decoy | Batch size | Test loss | Test accuracy | Worst precision, %(class) | Worst recall, %(class) |
|----|-----------------------|---------------------|------------|-----------|---------------|---------------------------|------------------------|
| 1 | 0.00400 | 0.85 | 24 | 0.2494 | 90.67% | 71.0% (trash) | 81.5% (trash) |
| 2 | 0.00300 | 0.85 | 24 | 0.2444 | 90.87% | 71.0% (trash) | 81.5% (trash) |
| 3 | 0.00275 | 0.85 | 24 | 0.2586 | 90.87% | 71.0% (trash) | 81.5% (trash) |
| 4 | 0.00250 | 0.85 | 24 | 0.2887 | 91.87% | 67.7% (trash) | 84.0% (trash) |
| 5 | 0.00225 | 0.85 | 24 | 0.2740 | 90.87% | 83.9% (trash) | 76.5% (trash) |
| 6 | 0.00200 | 0.85 | 24 | 0.2978 | 91.47% | 64.5% (trash) | 87.0% (trash) |
| 7 | 0.00100 | 0.85 | 24 | 0.2977 | 91.27% | 74.2% (trash) | 79.3% (trash) |
| 8 | 0.00400 | 0.80 | 24 | 0.2882 | 91.87% | 90.3% (trash) | 77.8% (trash) |
| 9 | 0.00300 | 0.80 | 24 | 0.2838 | 91.07% | 80.6% (trash) | 75.8% (trash) |
| 10 | 0.00275 | 0.80 | 24 | 0.2730 | 91.07% | 77.4% (trash) | 80.0% (trash) |
| 11 | 0.00250 | 0.80 | 24 | 0.2782 | 91.27% | 80.6% (trash) | 75.8% (trash) |
| 12 | 0.00225 | 0.80 | 24 | 0.2789 | 90.87% | 77.4% (trash) | 75.0% (trash) |
| 13 | 0.00200 | 0.80 | 24 | 0.2666 | 91.27% | 77.4% (trash) | 75.0% (trash) |
| 14 | 0.00100 | 0.80 | 24 | 0.3128 | 90.48% | 71.0% (trash) | 73.3% (trash) |
| 15 | 0.00400 | 0.75 | 24 | 0.2798 | 91.47% | 83.9% (trash) | 78.8% (trash) |
| 16 | 0.00300 | 0.75 | 24 | 0.2787 | 91.07% | 74.2% (trash) | 76.7% (trash) |
| 17 | 0.00275 | 0.75 | 24 | 0.2865 | 92.06% | 71.0% (trash) | 84.6% (trash) |
| 18 | 0.00250 | 0.75 | 24 | 0.2646 | 91.27% | 77.4% (trash) | 77.4% (trash) |
| 19 | 0.00225 | 0.75 | 24 | 0.2676 | 91.47% | 77.4% (trash) | 75.0% (trash) |
| 20 | 0.00200 | 0.75 | 24 | 0.2734 | 91.47% | 77.4% (trash) | 75.0% (trash) |
| 21 | 0.00100 | 0.75 | 24 | 0.3278 | 90.48% | 67.6% (trash) | 72.4% (trash) |

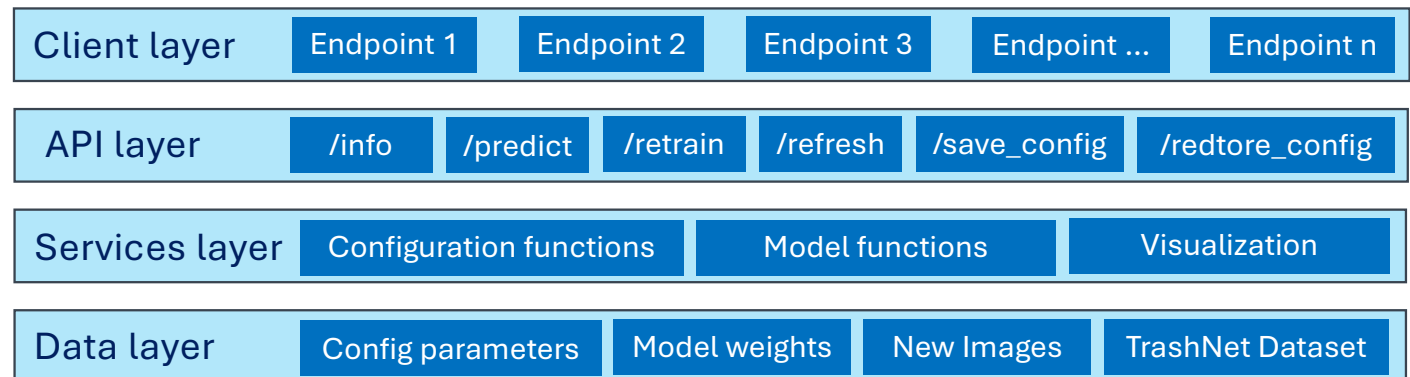
Solution Design & Production Deployment Readiness

Design Principles:

- **Flask Application** for easy model serving (prediction & retraining modes).
- **Cloud-Ready** with Docker containerization and AWS deployment strategies.

Rich API & Configurations:

- Modifiable hyperparameters (learning rate, batch size) via HTTP requests.
- Three retraining options: from scratch, fine-tune with new data, or retraining from scratch adding new data.



Deployment & Scalability

AWS Deployment Steps:

1. Containerize application modules using Docker and push image to Docker Hub.
2. Archive the dataset and the models and upload to AWS S3.
3. Launch AWS EC2 (g5.2xlarge with AWS Linux was used).
4. Install data and pre-trained model weights to EC2 volume.
5. Pull the image and run it on EC2 instance.

Scalability

- Multiple EC2 instances can be deployed behind a load balancer to handle increased traffic.
- A separate instance can be used for model retraining in one of three possible modes. The updated weights can then be applied to newly launched production nodes, replacing existing nodes without disruption.

Various Deployment Scenarios – *API Endpoints can respond in HTML ...*

API Documentation

/change - Change parameters of the configuration

Method: GET or POST
Arguments:
param - Name of the configuration parameter
value - New value for the parameter
Returns:
The updated configuration dictionary
or an error message if the parameter name is invalid
Note:
1. Changes are applied in memory only and will be reset after the app restarts.
2. Use `/save_config` to save the current parameters as default.

/info - Get current configuration settings

Method: GET
Arguments: None
Returns: The current configuration dictionary

/predict - Predict image classes

Method: GET or POST
Arguments:
folder - (optional) Folder containing images for prediction.
If not specified, sample images from `./data/processed/random_samples` will be used.
Returns:
A list of predicted image classes or an error message if the folder is not found

/refresh - Get more images from the original dataset for testing

Method: GET or POST
Arguments:
num - (optional) Number of images to fetch (default = 10)
Returns:
A list of filenames of the fetched images or an error message
Note:
1. For demonstration purposes only; images are taken from the training dataset.
2. All files that existed in the target folder before the request will be deleted

/save_config - Save the current configuration as the default

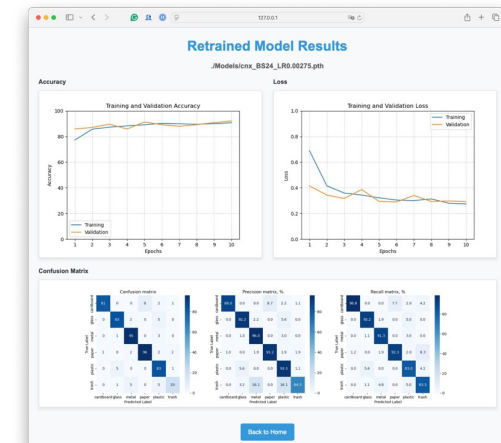
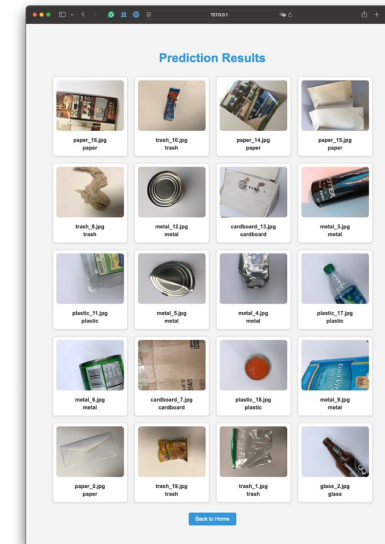
Method: GET or POST
Arguments:
confirm - Must be set to 'True' to save the configuration
Returns:
The saved configuration or an error message if confirmation is not provided

/restore_config - Restore configuration from a saved file

Method: GET or POST
Arguments:
confirm - Must be set to 'True' to restore the configuration
path - (optional) Path to the configuration file (default: `DEFAULT_CONFIG_PATH`)
Returns:
The restored configuration or an error message
Note:
1. If the specified configuration file does not exist or is inaccessible, the default values will be set (these values may differ from those saved in `app_config.json`).

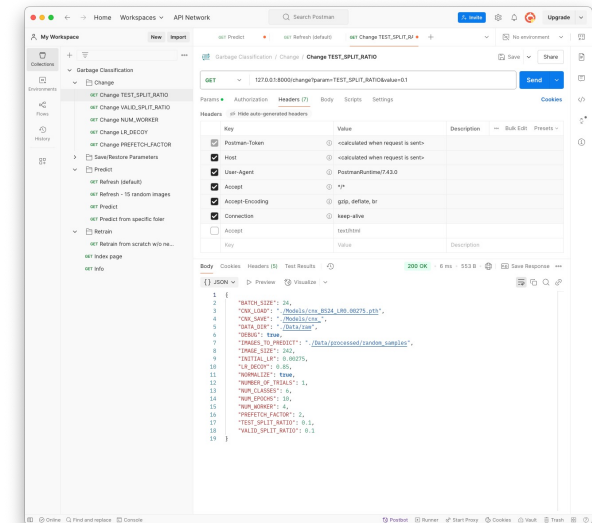
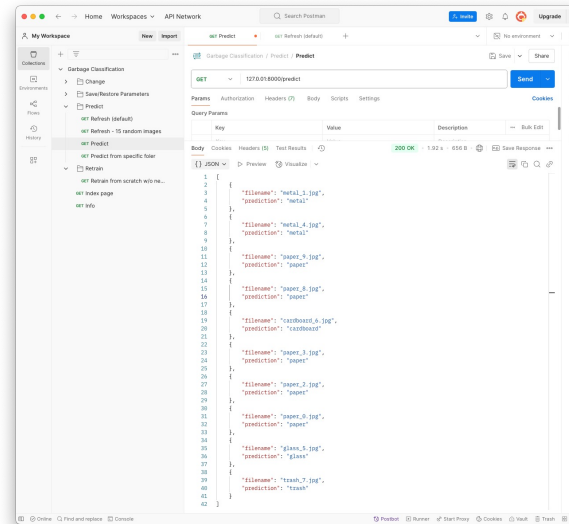
/retrain - Retrain the model

Method: GET or POST
Arguments:
folder - (optional) Folder with new data for training
from_scratch - (optional) 'True' to retrain from scratch (default: 'False')
verbose - (optional) 'True' for detailed training logs (default: 'False')
Returns:
A message indicating successful deployment of the new model or an error message



Various Deployment Scenarios –

... *or JSON*



Roadmap & Practical Considerations

1. **Comprehensive Cross-Validation:** Use K-fold cross-validation to strengthen model stability and hyperparameter robustness.
2. **Misclassification Analysis:** Investigate misclassified images to uncover hidden patterns and refine performance.
3. **Active Learning:** Highlight uncertain predictions for manual labeling, continually enhancing the model.
4. **YOLOv8 Evaluation:** Test YOLOv8 under identical conditions to compare results directly with ConvNeXt.
5. **Edge Deployment:** Evaluate lightweight variants (e.g., ConvNeXt-Tiny, YOLOv8) for real-time inference on embedded devices.
6. **Class Balancing:** Explore oversampling or SMOTE-like approaches to better handle underrepresented classes.



Thank you!