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Final Project Proposal

Elevator Pitch: Train a neural network to classify and predict the recyclability of waste from images.

Context: We have noticed a large amount of furniture/items waste by students at the end of the spring semester during move out season. Although BU has a Goodwill system implemented to help decrease the massive amount of landfill waste, there are still a lot of waste being produced. We hope our model can help students detect what can be recyclable and the steps of how to recycle them properly. Our model will help students make informed decisions about their waste at the end of the semesters and beyond BU.

Methods: We are planning to use reinforcement learning to create an intelligent waste classification system that not only predicts recyclability but also learns the best disposal actions over time. We will start by training Convolutional Neural Networks for image classification to identify waste materials, which will serve as the foundational feature extractor for the RL model. help train our model. We will use ResNet. The layers we want to use are:

- **Convolutional Layers**: To extract key features from waste images.
- **Pooling Layers**: To reduce dimensionality and improve computational efficiency.
- **Fully Connected Layers**: To output a probability distribution over different material categories.
- **Augmentation Techniques**: Since waste objects appear in varying conditions, we will apply: Random rotations, Cropping, Brightness/contrast adjustments

Classification Labels

- Instead of binary classification (recyclable vs. non-recyclable), our model will predict categories such as: Plastic, Metal, Glass, Wood, Fabric etc…

Loss Function & Evaluation Metrics

- Categorical Cross-Entropy will be used as the loss function.

- Metrics to evaluate performance:
  - Accuracy: Overall classification performance.
  - Precision & Recall: To handle class imbalances (e.g., some materials like glass might be less common in datasets).
  - F1-Score: To assess misclassifications and optimize model balance.

Reinforcement Learning for Optimized Waste Disposal

Once the classifier provides waste material predictions, we will optimize disposal decisions using Deep Reinforcement Learning (DRL). The model will learn to select the best disposal action based on the waste image and its predicted material type, ensuring the most environmentally sustainable outcome.

Reward System: CO_2 Reduction-Based Learning

The reward system is designed to prioritize actions that reduce carbon emissions and penalize actions that contribute to environmental harm:

- Positive Rewards:
  - Recycling waste or composting organic materials earns rewards proportional to the CO_2 saved per kilogram.
  - Donating usable items instead of sending them to landfill results in bonus points, as it extends the product's lifespan and prevents additional resource consumption.
- Penalties:
  - Misclassifying recyclable or donatable items as landfill leads to a -5 point penalty.
  - Misclassifying high-impact waste, such as electronics, hazardous materials, or textiles, incurs a -10 to -20 point penalty, depending on its environmental impact.

Instead of relying on traditional classification accuracy, we measure performance based on CO_2 reduction efficiency, ensuring the model optimizes for real-world sustainability impact.

1. Total CO_2 Savings
   - Measures the total carbon emissions prevented by the model's correct disposal decisions.

    - A higher total CO_2 savings value indicates better performance.
2. CO_2 Accuracy (Sustainability Accuracy)
    - This metric assesses how much CO_2 is saved per classification, ensuring the model focuses on environmentally impactful decisions.
    - It is calculated by dividing the total CO_2 saved by the total number of predictions made.
3. Precision and Recall Adjusted for Environmental Impact
    - CO_2 Precision measures how many items predicted as CO_2-saving were correctly classified.
    - CO_2 Recall evaluates how many total opportunities to reduce CO_2 were acted on correctly.
    - These metrics ensure the model prioritizes the correct classification of high-impact waste, such as electronics, over lower-impact materials.

Data Sources: Our data set will be drawn from kaggle. We currently have two data sets to help train our model. We want our model to perform well with the validation set, thus we want to provide it with a well-diversified and balanced dataset.
https://www.kaggle.com/datasets/feyzazkefe/trashnet
https://www.kaggle.com/datasets/mostafaabla/garbage-classification/data
https://www.kaggle.com/datasets/akshat103/e-waste-image-dataset/data

Code resources: For our project, we will use a combination of public resources and our own custom implementation. We will reference GitHub repositories, Stack Overflow, and we will also use Generative AI tools such as ChatGPT.

What's new: Our model will employ a multi-class waste classification approach, extending beyond the conventional recyclable vs. non-recyclable distinction. By integrating Reinforcement Learning (RL), we aim to reduce CO_2 emissions by optimizing disposal decisions based on environmental impact rather than just classification accuracy. The model will prioritize actions that lead to greater CO_2 reductions, allowing us to quantify the total environmental impact of correct classifications and continuously improve sustainability outcomes.

Plan:

Week 1(March 18-28):

- Find dataset that contains different labeled waste categories such as Recyclable, Non-Recyclable, Donatable, E-waste, Label each item with its CO2 impact value for reward calculation(research)
- Implement resnet based feature extraction, train CNN classifier to predict waste categories. Evaluate classification performance with accuracy, precision, recall

Week 2:

- Build the reinforcement learning environment(state, action space and reward system)
- Implement CO2 based rewards and misclassification penalties
- Train our model with CNN-based classifier outputs

Proposed demonstration or evaluation:

Create a Streamlit app to allow users to upload images, and this system will return predicted waste type + disposal recommendations, additionally we plan to display CO2 impact estimates for user awareness

Experiments:

Data Augmentation Strategies for Feature Extraction:

Baseline no augmentation: train raw images only to establish a reference

We will use geometric augmentation specifically random rotations and color augmentations specifically grayscale conversion. With this we can check how accurately the ResNet50 model classifies waste types under different augmentations.

For the reward structure we will have a fixed CO2 based rewards. Every correct disposal action is assigned a fixed CO_2 savings value (e.g., plastic = +2, electronics = +50).

Confidence-Weighted CO_2 Rewards

- The reward scales based on the classifier's confidence in its decision.
- If the model is 80% confident, it only gets 80% of the possible CO_2 savings.