Title: WasteWise Toronto - The Smart Waste Sorting Application

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Background to the Problem

The increasing volume of waste production in urban environments poses significant challenges for municipal waste management systems. With landfills nearing capacity and recycling rates lagging behind production, there is a critical need for innovative solutions to promote efficient waste sorting and recycling. While specific statistics may vary depending on the region and context, globally, urban areas generate substantial waste, with projections indicating a steady increase in waste production over the coming years. For instance, according to the World Bank, urban waste generation is expected to rise from 2.01 billion tonnes in 2016 to 3.40 billion tonnes by 2050 (World Health Organization, 2024). Toronto's economy produces around 2.1 million tons of solid waste annually, with projections increasing to 2.5 million tons by 2030 if current trends persist (Circle Economy, 2022).

The motivation behind WasteWise Toronto is to leverage advanced machine learning and data science techniques to improve sorting accuracy, thus enhancing recycling efforts and reducing the overall environmental footprint of urban waste management.

Existing Solutions

Two existing solutions, TOwaste and WasteWise Edmonton, were evaluated. While both apps provide primarily static features such as drop-off depots, waste sorting guides, and collection schedules, they also offer limited dynamic functionalities like search and notifications. Notably, WasteWise Edmonton achieved a higher user rating of 4.7 stars compared to TOwaste's rating of 3.8 stars on the Google PlayStore. Despite their positive reviews, neither application incorporates machine learning features to enhance user interactions. This presents a clear opportunity for us to distinguish our solution by filling this gap.

ML Canvas: Here is a link to our ML canvas.

Project Pipeline

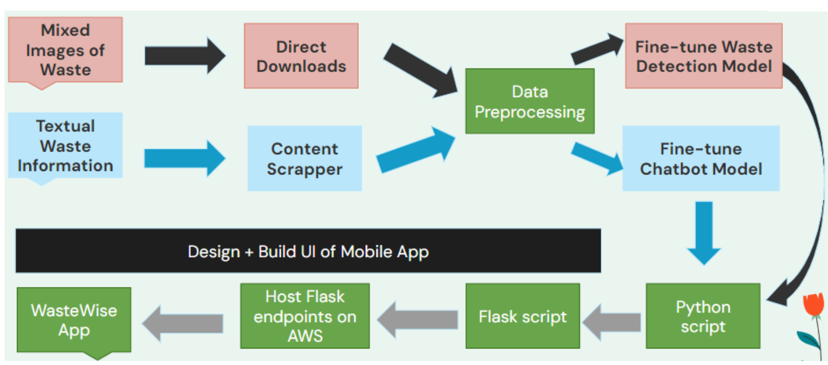

Figure 1. WasteWise Toronto Data and Development Pipeline

Experimental Conditions and Limitations

The experiment was conducted under environmental conditions utilizing Google Collab and Kaggle platforms with T4 GPUs, alongside Anaconda for setup. Additionally, the mobile app was developed using Ionic and hosted on AWS via Flask. However, limitations were observed, including the models being trained on a dataset with only 11 waste classes and 4800 images, and the mobile app's capability to handle only one waste item per image input. Furthermore, images were captured under fixed lighting conditions, posing challenges when used in poorly lit environments. As a solution, continuous monitoring of model performance in production and gathering feedback from end-users were prioritized for hypertuning parameters.

Data sources and Data Augmentation

At the core of WasteWise Toronto lies its data-driven intelligence, drawn from diverse datasets and reputable sources. Through meticulous curation, we've developed a comprehensive repository encompassing image-label pairs for object detection from Roboflow and Kaggle, covering 11 classes under the Creative Commons Attribution 4.0 International License. Additionally, textual information for the chatbot is sourced from the City of Toronto's website. The data exploration and augmentation process involved over 2100 images for each of the three bins (blue, green, and black), categorized into recyclables, organics, and general waste. Roboflow facilitated preprocessing tasks such as auto-orientation, resizing to 416x416, and applying transformations like flips, rotations, and shearing to enhance dataset diversity and model robustness.

About the Models

For the Object Detection Model, YOLOv8n was selected over YOLOv5 due to its potential for balancing speed and accuracy, supported by ample help, documentation, and community resources. The Chatbot Model, Gemini from Google, was preferred for its text understanding capabilities and free API access, further refined using LangChain with RAG over webpages sourced from the City of Toronto.

Presentation of Findings

YOLOv8n - The Yolov8n model was trained via supervised learning, with predictions based on class labels and bounding boxes indicating waste coordinates within the image dataset. Through experimentation with hyper-tuning parameters, the most optimal values (50 epochs, 64 batch size, 0.0001 learning rate, 0.15 dropout) were identified, resulting in a notable decrease in loss scores and an increase in precision values, indicative of improved detection accuracy. Despite training the model on a relatively small dataset of 4800 images and 50 epochs, the waste detection model achieved an overall precision of 72.6%, with 7 out of the 11 classes demonstrating very good precision scores ranging from 73% to 98%.

Google's Gemini - We scraped source documents from the City of Toronto website, utilized Google's GenAI embeddings to store them in a chromadb vectorstore, converted the vectorstore into a retriever, and incorporated a custom RAG prompt to provide additional context to the chatbot beyond the document content. To enhance the correctness of the fine-tuned Gemini model for the chatbot, we conducted multiple trials, with trial 4 achieving the highest correctness score of 0.86. To enhance the Gemini chatbot's consistency, addressing formatting inconsistencies by collecting data as PDFs instead of webpages, incorporating image information, and considering newer, higher-performing large language models (LLMs) are key future improvements.

Challenges, Conclusion and Future Work

Challenges included addressing data complexity by tackling issues of diversity and quality in ML model training, with image acquisition and preprocessing proving time-consuming. Another challenge involved ensuring the seamless integration of advanced technologies within a mobile app.

In conclusion, the project has potential impact awareness of proper waste disposal practices, while proving the efficacy of machine learning in enhancing waste sorting accuracy and user engagement. Future work entails expanding the dataset to improve model accuracy, scaling operations to new cities and regions, and enhancing features such as community-driven updates, drop-off depot scheduling, and personalized user interactions.

References

Circle Economy, 2022. *Lessons from North America: How Toronto is going Circular*. https://www.circle-economy.com/blogs/lessons-from-north-america-how-toronto-is-going-circular

World Health Organization, 2024. *What a Waste 2.0*. https://datatopics.worldbank.org/what-a-waste/#:~:text=As%20nations%20and%20cities%20urbanize,through%20open%20dumping%20or%20burning.