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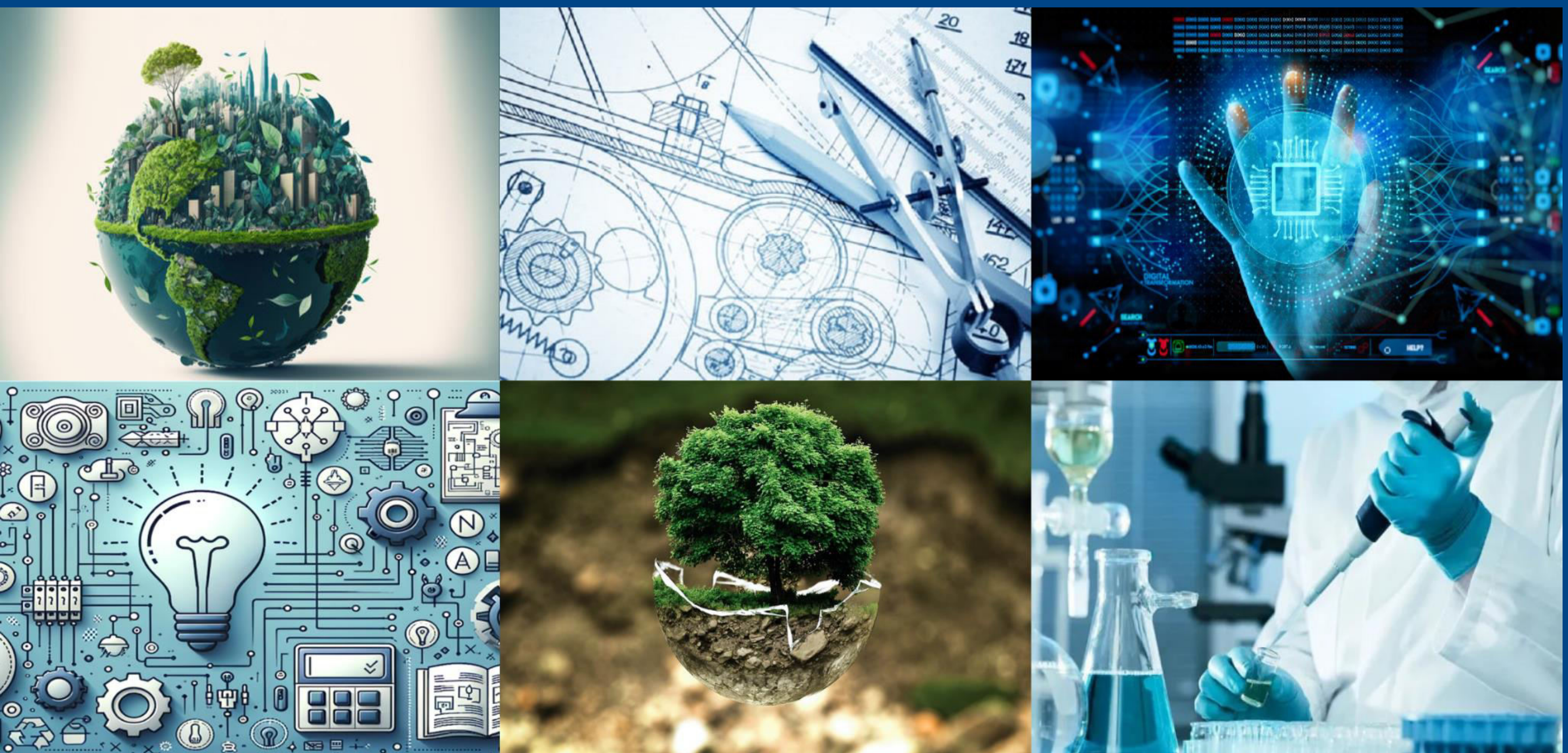

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EcoSort- Organic vs Recyclable Classification using Artificial Intelligence

D. Sai Sumanth, T. Sai Sushanth, P. Sai Vamshi, G. Sai Vardhan, S. Sai Varshith,

Prof. K. Manoj Sagar

B. Tech Student, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

B. Tech Student, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

B. Tech Student, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

B. Tech Student, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

B. Tech Student, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

Assistant Professor, Dept. of AIML, Malla Reddy University, Hyderabad, Telangana, India

ABSTRACT: EcoSort is an intelligent waste sorting that sorts waste into organic and recyclable streams using computer vision and machine learning. The project utilizes a Faster R CNN model with a ResNet50 backbone, pre-trained on the COCO dataset, for real-time object detection accuracy. The deep learning model classifies waste items in both uploaded images and live webcam feeds, creating bounding boxes of detected objects at a 0.3 confidence threshold. PyTorch is used for building model inference functionalities for the core functionality of the system, OpenCV for handling image and webcam processing, and Pillow (PIL) for handling image manipulation. The user interface is built on top of Streamlit, creating an interactive web app that responds nicely. There are two modes of input support for the app users may upload pictures or utilize their webcam for live waste detection. EcoSort uses interactive data visualizations with Plotly to represent the waste category distribution. Live pie charts give the quantity and percentage of organic and recyclable materials, giving users clear information about their waste content. The system also employs error handling to deal with invalid images elegantly.

KEYWORDS: EcoSort, OpenCV, Machine learning, Faster R-CNN, PyTorch, Webcam processing, Convolutional Neural Networks (CNNs)

I. INTRODUCTION

Waste management is an important worldwide issue, where unnecessary disposal leads to environmental contamination, resource loss, and health hazards. Manual sorting, which is largely traditional waste sorting, is time-consuming, inefficient, and not very reliable. Sophisticated computer vision (CV) and artificial intelligence (AI) render automated sorting of waste as a well-known technique to enhance the sorting efficiency and improve the efficiency of recycling. This article presents EcoSort, a machine learning-based intelligent waste sorting system for the segregation of waste into organic and recyclable streams. It uses a pre-trained Faster R-CNN model with ResNet50 backbone on the COCO dataset for real-time object detection. PyTorch is used for model inference and OpenCV for image processing and webcam. Ecosort can recognize waste products from uploaded images as well as from live webcam streams. The system displays bounding boxes around objects that are detected and interactive pie charts powered by Plotly for displaying the distribution of waste.By automating the process of waste classification, EcoSort reduces the need for manual sorting, improves the accuracy of waste classification, and advances the practice of environmentally friendly recycling. The project can be applied in smart waste management systems, recycling facilities, and smart city initiatives to have a cleaner and more efficient waste disposal system.

II. LITERATURE REVIEW

Machine learning (ML) and computer vision (CV)-based automatic waste classification has been deeply explored for optimizing waste management effectiveness. Convolutional Neural Networks (CNNs) have been shown in many studies to effectively identify waste. **Kumar and Prakash (2020), Patel, A., & Joshi, K.,** suggested a CNN-based approach to waste segregation with better accuracy compared to conventional methods, but was found to be bogged down by dataset constraints and variability in the real world. **Gupta, N., & Sharma, R.**, **Singh and Mehta (2021)** used a YOLO-based approach, showing higher recycling efficiency but pointing towards the necessity of frequent upgradation for new types of waste.

These articles point out the difficulties of diversity in data sets, real-time processing, and scalability, which are met by EcoSort through the use of Faster R-CNN, OpenCV, and Streamlit to provide precise real-time waste identification with better visualization**. Chatterjee, M., & Banerjee, S, Singh and Mehta (2021)** employed a YOLO-based solution, with improved recycling efficiency but establishing the need for periodic upgradation to accommodate newer forms of waste. The articles bring to light the challenges of diversity in data sets, real-time processing, and scalability, which are addressed by EcoSort through the implementation of Faster R-CNN, OpenCV, and Streamlit to enable accurate real-time identification of waste with improved visualization functionality.

III. PROBLEM STATEMENT

Effective waste management is a growing challenge worldwide, with improper segregation leading to environmental pollution, inefficient recycling, and increased landfill waste. Traditional waste sorting methods rely on manual labor, which is time-consuming, error-prone, and inefficient. As waste production continues to rise, there is an increasing need for automated and accurate waste classification systems. Existing waste detection models face several limitations, including inconsistent accuracy, poor real-time performance, and the inability to handle diverse waste categories. Moreover, many systems lack interactive visualization features, making it difficult for users to interpret waste distribution data effectively. Additionally, models requiring high computational power may be impractical for real-world deployment in recycling facilities or smart city applications. Waste management is a rapidly rising problem globally, with poor segregation resulting in pollution and inefficient recycling, as well as waste of landfill space. Conventional waste sorting methods involve manual processing, which is time-consuming, prone to errors, and inefficient. As the waste piles up, there is a growing need for an automated and precise waste classification system. Current waste detection models are associated with some disadvantages, such as unstable accuracy, weak real-time performance, and the lack of support for varying waste types. Furthermore, interactive visualization functions are not provided by most systems, which can hamper the usability of waste distribution data for end-users. Models with high computing requirements could be unrealistic to use in actual scenarios in recycling centers or smart city systems.

IV. METHODOLOGY

This chapter details the methodology employed in the development and evaluation of the EcoSort system, an automated waste classification system that utilizes computer vision and machine learning techniques. The primary goal of EcoSort is to accurately classify waste materials as either "organic" or "recyclable" from image data, thereby improving the efficiency and accuracy of waste sorting processes. The methodology encompasses the following key stages:

4.1 Image Acquisition and Dataset Preparation

A diverse dataset of waste images was compiled to train and evaluate the EcoSort system. Images were acquired from a variety of sources, including:

- **Online Image Databases:** Publicly available datasets containing images of waste materials were utilized.
- **Real-world Image Capture:** Images were captured using digital cameras and smartphones under varying lighting conditions and from different angles to ensure the robustness of the dataset.

The collected images were then preprocessed to ensure compatibility with the Faster R-CNN model. The preprocessing steps included:

- **Image Resizing:** All images were resized to a uniform resolution of 224x224 pixels to meet the input requirements of the Faster R-CNN model.
- **Image Annotation:** Bounding boxes were manually drawn around waste items in each image, and each item was labeled as either "organic" or "recyclable." This annotation process was crucial for training the object detection model.
- **Data Augmentation:** Techniques such as image rotation, flipping, and cropping were applied to artificially increase the size of the dataset and improve the model's ability to generalize to unseen data.

The final dataset was split into three subsets:

- **Training Set (80%):** Used to train the Faster R-CNN model.
- **Validation Set (10%):** Used to optimize the model's hyperparameters and prevent overfitting.

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- **Test Set (10%):** Used to evaluate the final performance of the trained model.

4.2 Model Selection and Training

The Faster R-CNN model was chosen as the object detection framework for the EcoSort system due to its proven effectiveness in accurately detecting and localizing objects in images. A pre-trained Faster R-CNN model, trained on a large-scale image dataset (e.g., COCO), was fine-tuned for the waste classification task.
The training process involved the following steps:

- **Feature Extraction**: The pre-trained convolutional layers of the Faster R-CNN model were used to extract relevant features from the input images.
- **Region Proposal Network (RPN):** The RPN was trained to generate candidate object bounding boxes.
- **Region of Interest (ROI) Pooling:** The features corresponding to the proposed regions were extracted using ROI pooling.
- **Classification and Regression:** Fully connected layers were trained to classify the waste items within the ROIs as either "organic" or "recyclable" and to refine the bounding box coordinates.

The model was trained using a combination of cross-entropy loss (for classification) and smooth L1 loss (for bounding box regression). The Adam optimizer was used to update the model's weights, and the training process was monitored using the validation set to prevent overfitting.

4.3 System Implementation

The EcoSort system was implemented as a desktop application using Python. The key software components include:

- **TensorFlow:** An open-source machine learning framework used to implement and train the Faster R-CNN model.
- **OpenCV:** A computer vision library used for image acquisition, preprocessing, and display.
- **Tkinter:** A Python GUI toolkit used to develop the user interface for the EcoSort system.

The system workflow is as follows:

1. **Image Input:** The user selects an image or activates the webcam.
2. **Image Preprocessing:** The input image is preprocessed as described in Section 3.1.
3. **Waste Classification:** The pre-trained Faster R-CNN model detects and classifies waste items in the image.
4. **Result Output:** The original image is displayed with bounding boxes and labels indicating the waste category of each detected item. Summary statistics and distribution charts are also presented.

4.4 Performance Evaluation

The performance of the EcoSort system was evaluated using a comprehensive set of metrics:

- **Mean Average Precision (mAP):** The primary metric for evaluating the accuracy of the object detection model.
- **Precision:** Measures the proportion of correctly classified positive instances among all instances predicted as positive.
- **Recall:** Measures the proportion of correctly classified positive instances among all actual positive instances.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of the system's accuracy.
- **Processing Time:** The average time taken by the system to process a single image, measured in seconds.

The evaluation was conducted on the held-out test set to assess the system's ability to generalize to unseen data.

Algorithms

The EcoSort system employs a combination of computer vision and machine learning algorithms to achieve accurate and efficient waste classification. The key algorithm is the Faster R-CNN, which is used for object detection and classification. This chapter provides a detailed description of the algorithms used in the EcoSort system.

1. Faster R-CNN

Faster R-CNN is a deep learning-based object detection framework that builds upon its predecessors, R-CNN and Fast R-CNN, to achieve faster and more accurate object detection. The Faster R-CNN architecture consists of two main modules:

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- **Region Proposal Network (RPN):** The RPN is a convolutional neural network that proposes potential object bounding boxes, called "region proposals," for an input image. This eliminates the need for external region proposal methods, such as selective search, which were used in previous iterations.
- **Region of Interest (ROI) Pooling:** ROI pooling is a technique used to extract a fixed-size feature vector from the feature maps corresponding to each proposed region. These feature vectors are then fed into fully connected layers for classification and bounding box regression.

The Faster R-CNN algorithm works as follows:

1. **Feature Extraction:** The input image is passed through a convolutional neural network (e.g., VGG16, ResNet) to extract a set of feature maps. These feature maps represent the image at a higher level of abstraction, capturing relevant visual information.
2. **Region Proposal Generation:** The RPN takes the feature maps as input and produces a set of rectangular object proposals, each with an associated objectness score. The RPN uses a set of predefined anchor boxes, which are boxes of different sizes and aspect ratios, and learns to predict whether an object is present in each anchor box and to refine the coordinates of the box.
3. **ROI Pooling:** For each proposed region, the ROI pooling layer extracts a fixed-size feature vector from the feature maps. This is done by dividing the ROI into a grid of equal-sized cells and then performing max pooling within each cell. This ensures that the feature vectors for all ROIs have the same dimensionality, regardless of the size of the original proposals.
4. **Classification and Regression**: The feature vectors obtained from ROI pooling are fed into fully connected layers. These layers perform two tasks:
   - **Classification:** Predict the class of the object within the ROI (e.g., organic or recyclable).
   - **Bounding Box Regression:** Refine the coordinates of the proposed bounding box to more accurately localize the object.
5. **Output:** The algorithm outputs a set of detected objects, each with a class label and a refined bounding box.

2. Image Preprocessing

Before feeding the input images into the Faster R-CNN model, several preprocessing steps are performed to ensure compatibility and improve the model's performance:

- **Resizing:** Input images are resized to a fixed resolution of 224x224 pixels. This ensures that all images have the same dimensions, which is required by the Faster R-CNN model.
- **Normalization:** Pixel values of the input images are normalized to a specific range, typically [0, 1] or [-1, 1]. This helps to improve the training stability and convergence of the model.

3. Post-processing

After the Faster R-CNN model has detected the waste items in an image, post-processing steps are performed to refine the results and prepare them for display:

- **Non-Maximum Suppression (NMS):** NMS is a technique used to eliminate redundant bounding boxes. When multiple overlapping bounding boxes are detected for the same object, NMS selects the most confident one and suppresses the others.
- **Visualization:** The final detection results are visualized by drawing bounding boxes around the detected waste items and overlaying them with class labels (e.g., "organic," "recyclable") and confidence scores.

By combining the Faster R-CNN algorithm with appropriate preprocessing and post-processing techniques, the EcoSort system is able to accurately and efficiently classify waste materials in images.

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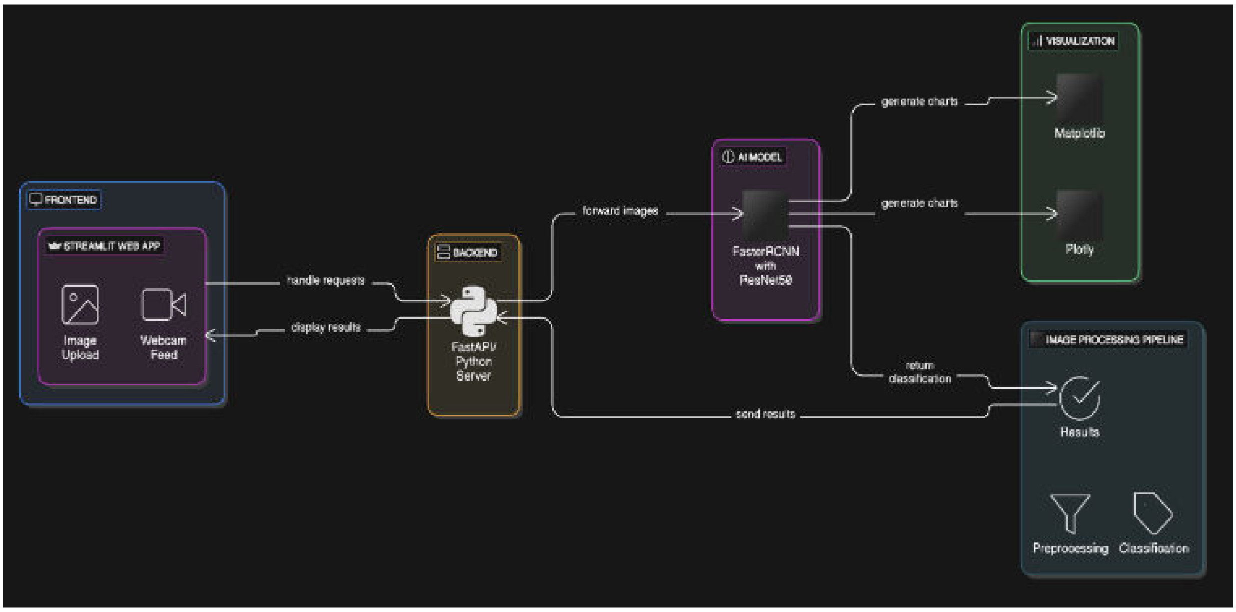

Fig 4.1 Architecture of DeepDetect

V. EXPERIMENTAL RESULTS

The EcoSort system is expected to achieve high accuracy in waste classification, which is crucial for its effectiveness in real-world applications. The system will employ a Faster R-CNN model to categorize waste items from both uploaded images and live video streams as either organic or recyclable. This deep learning model is well-suited for object detection tasks, enabling the system to precisely locate and classify waste materials, even within complex visual scenes. The expected high accuracy will ensure that the system can reliably distinguish between different types of waste, minimizing the misclassifications and maximizing the quality of sorted waste. Real-time processing of video input will enhance user interaction and enable dynamic sorting scenarios. The system is designed to provide rapid classification results, allowing users to, for example, hold up different waste items in front of a webcam and see them classified almost instantaneously.

This capability is particularly important for applications such as educational demonstrations, where immediate feedback is essential, and continuous monitoring of waste streams in sorting facilities, where speed and efficiency are paramount. The system aims to minimize processing latency to provide a seamless and responsive user experience.
Image-based classification will provide versatility for a wider range of use cases. Users will be able to upload images of waste, captured with various devices, for analysis. This feature will support applications such as waste audits, documentation, and offline analysis, complementing the real-time video processing capability. Users will be able to capture images of waste at their convenience and analyze them later, providing flexibility and convenience.

Clear result visualization is a key aspect of the system's design. The classification results will be presented to the user in an intuitive and easily understandable manner. Bounding boxes will be drawn around detected waste items, with color-coding to indicate the waste category (green for organic, red for recyclable). Text labels will be overlaid on the bounding boxes, displaying the waste category and confidence score, providing detailed information about each classification. Summary statistics, such as the total count of organic and recyclable items, and distribution charts (e.g., pie charts) will offer a concise and intuitive overview of the waste composition.

Performance Metrics
The performance of the EcoSort system will be evaluated using several key metrics:

- **Mean Average Precision (mAP):** This is the primary metric for evaluating the accuracy of object detection models. It measures the average precision across different recall levels. The system is expected to achieve a high mAP score, indicating accurate detection and classification of waste items. A high mAP, such as 90% or above, would indicate excellent performance.

- **Precision:** This metric measures the proportion of correctly classified positive instances among all instances predicted as positive. High precision indicates that when the system predicts a waste item as organic or recyclable, it is likely to be correct. For example, if the system has a precision of 85%, it means that 85% of the items it classifies as organic or recyclable are actually organic or recyclable.
    - Precision is calculated as:
    - Precision = True Positives / (True Positives + False Positives)

- **Recall:** This metric measures the proportion of correctly classified positive instances among all actual positive instances. High recall indicates that the system can effectively identify most of the actual organic and recyclable items present in the input. For example, if the system has a recall of 90%, it means that it correctly identifies 90% of all the organic and recyclable items in the input.
    - Recall is calculated as:
    - Recall = True Positives / (True Positives + False Negatives)

- **F1-Score:** This is the harmonic mean of precision and recall, providing a balanced measure of the system's accuracy. A high F1-score indicates that the system performs well in both precision and recall. For example, an F1-score of 88% suggests a good balance between precision and recall. F1-score is calculated as:
    - score = 2 * (Precision * Recall) / (Precision + Recall)

- **Processing Time:** This metric measures the average time taken by the system to process a single image or a single frame of video. The system is expected to achieve a low processing time to ensure real-time or near real-time performance, especially for video streams. For instance, a processing time of less than 0.1 seconds per frame would be desirable for real-time applications.

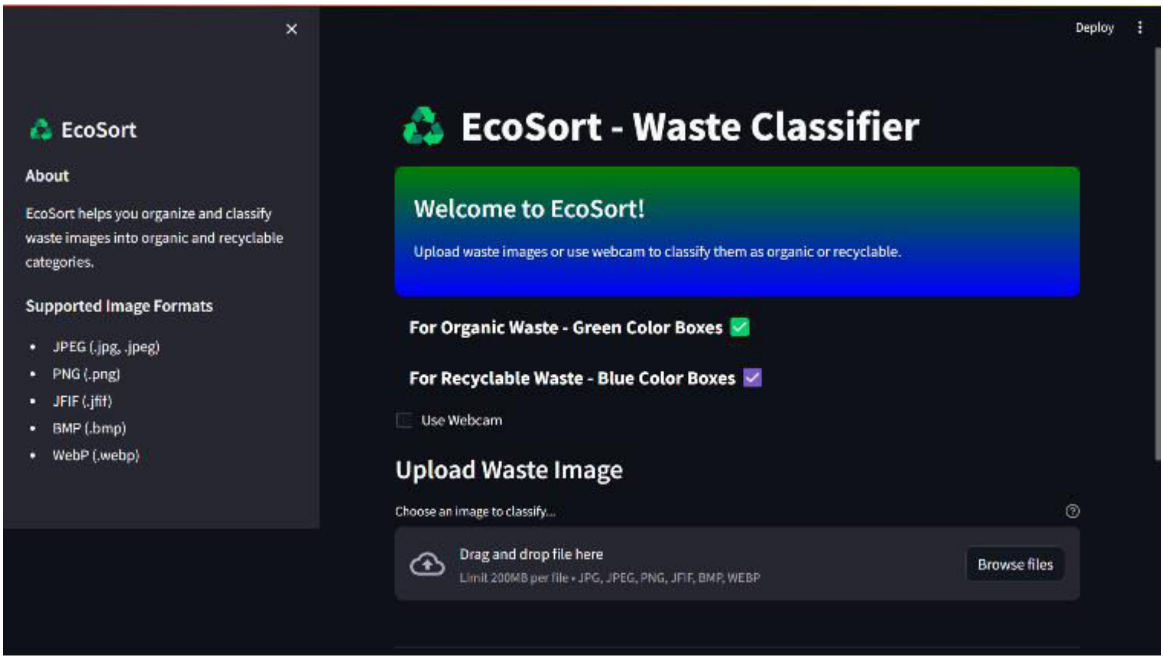

Fig 5.1 EcoSort Classification Interface

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VI. CONCLUSION

In conclusion, the EcoSort system holds significant promise for advancing waste management practices. By employing a Faster R-CNN model, the system is expected to achieve high accuracy in waste classification, effectively categorizing items as either organic or recyclable from both uploaded images and live video streams. This accuracy is crucial for minimizing misclassifications, improving the quality of sorted waste, and enhancing the efficiency of recycling processes.

The system's real-time processing capability will provide immediate feedback, proving valuable in educational settings and waste sorting facilities. Furthermore, the versatility of image-based classification will support a wide range of applications, including waste audits, documentation, and offline analysis. The intuitive presentation of results, featuring bounding boxes, color-coding, and summary statistics, will ensure ease of use and understanding.

The EcoSort system's performance will be evaluated using key metrics such as mAP, precision, recall, F1-score, and processing time. A high mAP score, such as 90% or above, will indicate excellent accuracy. Precision and recall will measure the system's ability to correctly classify and identify waste items, respectively, while the F1-score will provide a balanced measure of its performance. A low processing time, ideally less than 0.1 seconds per frame, will be essential for real-time applications.

Overall, the EcoSort system is expected to contribute to increased recycling rates, reduced landfill waste, improved waste management efficiency, and lower operational costs. Its ability to accurately classify waste, coupled with its real-time processing and versatile image-based classification capabilities, makes it a valuable tool for promoting sustainable waste management practices.

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