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AI-Based Waste Classification & Reporting System

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A B S T R A C T

Effective waste management is a pressing urban issue due to the rapid pace of industrialization and population growth. This paper presents an AI-powered application that facilitates the classification of waste and enables efficient complaint registration for uncollected or mismanaged garbage. The system employs a pre-trained Mask R-CNN object detection model, trained on the TACO dataset, to identify waste categories such as recyclable, non-recyclable, and hazardous materials. Through a user-friendly web interface, citizens can upload images of waste, which are then processed by the AI model to extract object data and register a complaint. This complaint, along with the image, detected objects, user details, and location, is stored in a MongoDB database. The goal is to empower municipalities with real-time data while promoting civic engagement in urban cleanliness. This system ensures accuracy in waste classification, timely reporting, and data-driven decision-making.

Keywords: Artificial Intelligence, Waste Detection, Object Classification, Complaint Management, Mask R-CNN, Urban Cleanliness, Civic Technology

1. Introduction

Effective waste management is a pressing concern in rapidly urbanizing regions, where increasing waste generation demands smarter solutions. Traditional systems often struggle with inefficiencies due to manual classification and delayed reporting. This paper presents an AI-based waste classification and reporting system that leverages computer vision and modern web technologies to detect, categorize, and report various types of waste in real time. By combining deep learning with a user-friendly complaint interface, the system aims to enhance urban cleanliness, support municipal efforts, and promote active citizen participation in sustainable waste management.

2. Literature Survey

The exponential increase in urban population has led to significant challenges in waste management across the globe. Traditional waste disposal mechanisms are no longer sufficient to ensure sustainable living in rapidly urbanizing environments [1]. Hence, smart waste management systems that integrate artificial intelligence (AI), Internet of Things (IoT), and automation technologies have gained increasing attention.

A. Smart Waste Management Systems

Modern waste management frameworks are moving towards automation using sensors and connected devices. Smart bins with real-time monitoring are being implemented in various cities to optimize waste collection and reduce operational costs [2][3]. These systems also improve hygiene levels by minimizing manual interaction with waste [4].

B. Role of AI in Waste Classification

AI techniques such as machine learning (ML) and deep learning (DL) are used to automate the waste classification process. These techniques analyze waste images and identify their types—such as biodegradable, recyclable, or hazardous—based on visual features [5][6]. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in classifying images of waste, especially when trained on datasets such as TACO (Trash Annotations in Context) [7].

C. Object Detection for Waste Recognition

Instead of single-label classification, recent advancements focus on object detection, which allows models to identify multiple waste objects within a single image. Techniques like YOLO (You Only Look Once) and Mask R-CNN have emerged as powerful tools for this task. Mask R-CNN, in particular, is effective in detecting object boundaries and assigning pixel-level masks, making it ideal for detecting overlapping or partially visible waste items [8][9][10].

D. Image-Based Complaint Systems

Several projects have attempted to integrate image analysis into civic complaint systems. For instance, some platforms allow citizens to upload images of waste or pollution, which are then manually verified and acted upon [11][12]. However, these systems lack automation and cannot scale effectively. By using AI to verify and categorize complaints, the reporting process becomes more efficient and accurate [13].

E. Technologies for Implementation

Flask, a lightweight Python framework, is commonly used to deploy AI models as REST APIs, making it easy to integrate machine learning models with web applications [14]. MongoDB offers flexibility in storing complaint data with varying formats such as images, user metadata, timestamps, and detection results [15]. Integrating such tools allows rapid prototyping and scalable deployment of AI-powered systems.

F. Gap Identification

Although many models have been built for classifying waste and several complaint management apps exist, few systems integrate real-time object detection with complaint reporting in a unified platform. Moreover, limited research focuses on using Mask R-CNN specifically for waste detection and combining it with a web-based user interface for end-to-end reporting [16][17]. Our proposed system (WM2025) aims to bridge this gap by developing a scalable, AI-based waste classification and complaint logging application.

3. Methodology

3.1 System Architecture

The WM2025 system architecture is composed of four essential components: Frontend, Backend, AI Model, and Database. The Frontend, developed with Next.js, delivers an intuitive and responsive interface that allows users to easily upload waste images, view classification results, and submit complaints. Its design ensures a smooth and seamless user experience, providing an efficient platform for interaction. The Backend, built using Flask, acts as the system’s backbone, hosting the AI Model and offering the necessary API endpoints to manage communication between the frontend and the server. The Mask R-CNN AI Model, integrated into the backend, plays a crucial role in detecting and classifying waste objects from uploaded images. It identifies various waste categories, such as recyclable, non-recyclable, and hazardous items, while providing bounding boxes to highlight the positions of these objects.

For Database management, MongoDB is employed to store detailed complaint data, including user information, detected objects, classifications, and timestamps. The flexibility of MongoDB, a NoSQL database, ensures that the system can easily scale and manage large volumes of complaint records while maintaining fast and efficient data retrieval. This architecture ensures that each component works cohesively, from the initial image upload and waste detection to the final complaint storage in the database. The entire flow is designed for reliability, scalability, and a smooth user experience. A system architecture diagram visually illustrates how these components interact, helping users and developers alike understand the data flow and functionality of the WM2025 system...

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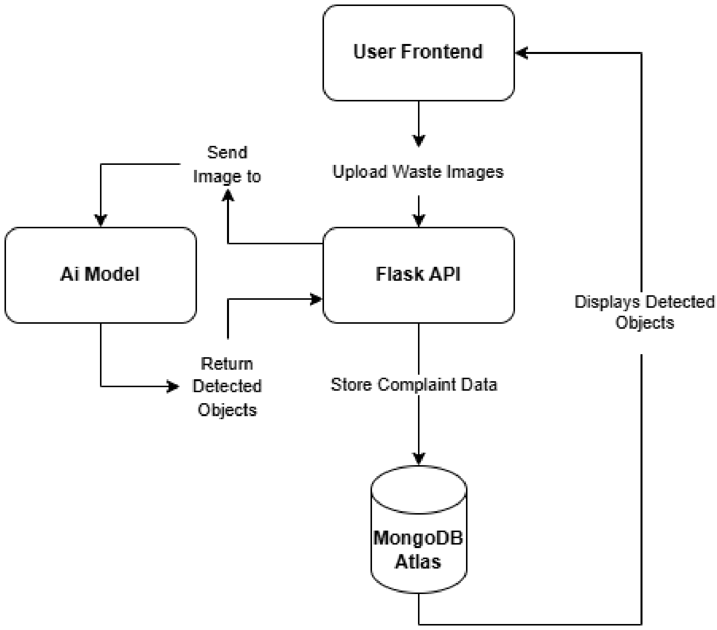

Fig 3.1 : System Architecture of the Waste complaint management system

3.2 Dataset Preparation

The TACO (Trash Annotations in Context) dataset is the foundation for the AI model used in WM2025. This dataset contains images annotated with bounding boxes and corresponding labels for various waste types. The preparation of the dataset involves several steps. Initially, images from the TACO dataset are merged, ensuring that the image paths and annotations align correctly. Preprocessing is then performed on the images, including resizing, normalization, and conversion to a format compatible with the Mask R-CNN model. Additionally, the annotations are adjusted as necessary to meet the input requirements for object detection. Labeling each image with specific waste categories, such as recyclable, non-recyclable, or hazardous, ensures that the model learns to classify objects accurately during training.

3.3 Model Training and Deployment

The Mask R-CNN model, which is used for waste object detection, is trained on the preprocessed TACO dataset. The training process focuses on teaching the model to detect multiple waste objects within images and classify them appropriately. Mask R-CNN not only predicts the class of each detected object but also provides the precise location of the objects through bounding boxes. Once trained, the model is saved as a .h5 file (for example, mask_rcnn_taco.h5) and deployed within the backend Flask API. The Flask server loads the model to process incoming images, performing real-time inference to detect waste objects and classify them accordingly.

3.4 Flask API Development

The Flask API plays a central role in WM2025 by handling interactions between the frontend and the AI model. Two main API endpoints are created: /predict and /submit_complaint. The /predict endpoint accepts image files from users, processes them using the Mask R-CNN model, and returns the detected waste objects along with their bounding boxes and classifications. This allows the frontend to display the results to the user. The /submit_complaint endpoint enables users to submit complaints, including information about the detected waste objects and their classifications. It also captures user details like location and stores all this data in the MongoDB database for future management.

The frontend of WM2025 is built using Next.js, a powerful React-based framework. It provides a responsive and intuitive interface for users to interact with the system. Users can easily upload images of waste, which are then sent to the backend for processing. Once the AI model processes the image, the frontend displays the detected objects, highlighting them with bounding boxes and showing their respective classifications (e.g., recyclable, non-recyclable). Additionally, users can submit complaints related to the detected waste, which include relevant details such as their location and the classification of the objects. The frontend design ensures that users can navigate through the system effortlessly, with clear instructions for each step.

3.5 Database Management

For efficient data storage and retrieval, MongoDB is used to manage the complaints generated by users. The MongoDB database is well-suited for handling the diverse and dynamic nature of the data involved in WM2025. Each complaint stored in the database includes essential information such as the complaint ID, user details, detected waste objects, and a timestamp. The database's flexible schema allows for the easy storage of images, object labels, and metadata. This structure ensures that administrators can query and manage the complaints efficiently. The use of MongoDB also ensures scalability, which is crucial as the system grows and more users submit complaints. The below image fig. 3.2 shows the complaitn stored in the databse.

Fig. 3.2 : The structure of the complaint data stored in the database (mongoDB)

3.6 Workflow Summary

The WM2025 system follows a straightforward workflow, ensuring seamless interaction between users, backend, and the database. First, a user uploads an image of waste through the frontend. This image is then processed by the Flask API, where the Mask R-CNN model detects and classifies the waste objects. The frontend displays the results, including bounding boxes and classifications. If the user is satisfied, they can proceed to submit a complaint, which includes their personal information, location, and the detected objects. The complaint is then stored in the MongoDB database, making it accessible for administrative review. This workflow ensures that the system functions efficiently, from image upload to complaint storage shown in fig. 3.3.

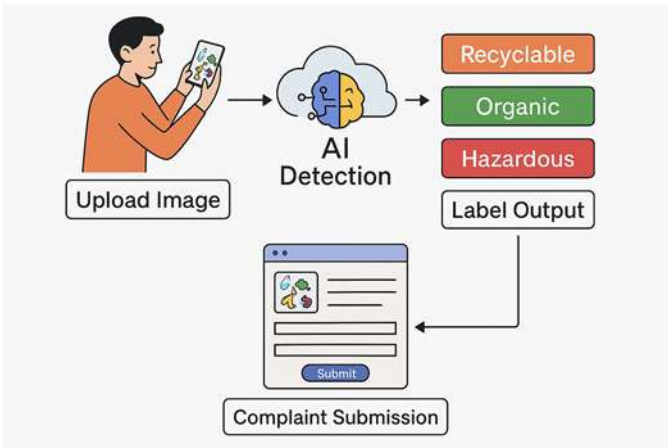

Fig. 3.3 : The Work Flow of the Complaint management System

3.7 Tools and Technologies Used

Several powerful tools and technologies are employed to build and run the WM2025 system. Python is the primary language used for backend development and AI model training. TensorFlow is utilized to build and train the Mask R-CNN model for waste object detection. The Flask framework is used to develop the API, which serves as the interface between the frontend and the model. The frontend is developed using Next.js, providing a modern and responsive user interface. For database management, MongoDB is used, offering a flexible and scalable solution for storing complaint data. The entire system leverages these tools to create a robust, efficient, and scalable waste classification and reporting platform.

4. Implementation

The implementation of the WM2025 system involves several key stages, starting from dataset preparation to final deployment. The process begins with the collection and preprocessing of the TACO dataset, which includes waste image data and corresponding annotations. This dataset is cleaned and structured to ensure that the images and their labels are in the correct format. The images are resized and normalized to fit the input requirements of the Mask R-CNN model. Additionally, any necessary data augmentations are applied to enhance the model’s ability to generalize across various types of waste.

Once the dataset is ready, the next step is the training of the Mask R-CNN model. This model is a popular deep learning architecture for object detection, and it is particularly suited for tasks involving multiple objects within an image. The model is trained on the processed TACO dataset to detect waste objects and classify them into categories like recyclable, non-recyclable, and hazardous. During training, the model learns to predict both the class of each object and the corresponding bounding box around the object. The trained model is saved and integrated into the backend of the system.

The backend, built using Flask, is responsible for managing requests from the frontend and interacting with the trained AI model. Flask serves as the interface for users to upload images for classification. When an image is uploaded, the Flask API loads the trained Mask R-CNN model, performs object detection, and returns the classification results along with the bounding boxes for each detected object. The results are then sent back to the frontend for display. To ensure efficient communication, the backend exposes various API endpoints, including /predict for image classification and /submit_complaint for storing user complaints.

The frontend of the system is developed using Next.js, which provides a responsive and interactive user interface. Users can easily upload waste images, which are then processed by the backend. The classification results, including the detected objects and their classifications, are displayed on the interface with bounding boxes highlighting each object. Additionally, users can fill out a form to submit complaints, which includes their personal details, location, and the classification results. Once submitted, the complaint data is stored in MongoDB, which handles the persistence of complaint information.

Finally, the MongoDB database stores all the complaint records, including user data, waste object classifications, and timestamps. The system is designed to scale, allowing for efficient querying and management of large volumes of complaints. The use of MongoDB's flexible schema ensures that different types of complaint data can be easily handled and expanded as necessary.

In summary, the WM2025 system integrates advanced AI models with a robust backend and frontend, ensuring smooth functionality from waste image upload to final complaint storage. The system is designed for scalability, providing a user-friendly interface while maintaining efficient data management through the use of Flask and MongoDB.

5. Results

The WM2025 system effectively detects and classifies waste objects from user-uploaded images using the trained Mask R-CNN model. Upon image upload, the model processes the image, identifies various objects, and classifies them into categories such as recyclable, non-recyclable, or hazardous. The results, including the bounding boxes around detected objects, are displayed on the frontend for users to review. Users can then submit complaints along with the detected waste objects, which are stored in MongoDB. The system ensures accurate and efficient classification, providing a scalable solution for waste management and reporting.

6. Conclusion

In conclusion, the WM2025 system demonstrates the powerful integration of AI and web technologies to address waste classification and reporting. By utilizing the Mask R-CNN model for object detection and classification, the system accurately identifies waste objects and categorizes them into relevant classes. The seamless interaction between the frontend, backend, and database ensures an efficient and user-friendly experience, enabling users to easily upload images, view results, and submit complaints. The use of MongoDB ensures scalable and reliable storage of complaint data, making the system a robust solution for modern waste management.

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