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Revolutionizing Waste Management: Deep Learning for Sewage Classification

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ABSTRACT: Waste segregation serves as a cornerstone for energy generation, reducing landfill reliance, and bolstering recycling endeavors. Yet, improper waste disposal poses contamination risks, complicating recycling processes. To combat this, automated waste sorting systems employ advanced algorithms for efficient recyclable material sorting. Additionally, the execution of models and educational campaigns aids individuals in effective waste management practices. Such initiatives are pivotal for global ecological advancement, emphasizing waste reduction and heightened recycling endeavors. This project's objective is to devise an automated waste finding system using algorithms to classify waste materials accurately. By streamlining waste categorization and facilitating proper disposal into recyclable and non-recyclable bins, the project contributes to sustainable waste management practices and environmental preservation.

KEYWORDS: Waste segregation, landfill reduction, waste sorting models, reusing materials, non-recyclable materials.

I. INTRODUCTION

Waste management has emerged as a crucial concern owing to its significant social, environmental, and economic ramifications. Improper handling of waste can lead to version of pollution, including soil, water, and air contamination, posing risks to public health (Aguilar-Virgen et al., 2010). Research indicates a staggering production of 8.3 billion tons of plastic since 1950, with a mere 9% being recycled, 12% incinerated, and a concerning 73% ending up in landfills (Geyer et al., 2017). This movement is alarming considering the extended timeframe required for the degradation of non-organic waste materials.

Solid Domestic Waste (SDW) encompasses everyday items discarded by households, commercial establishments, and community centers like malls, workplaces, and universities. Items such as plastic and glass bottles, food packaging, aluminum cans, paper products, and cardboard are typically categorized as Solid Domestic Waste (SDW).

Research endeavors in this field range from developing mobile applications to embedding classification models in trash can cameras, and even automating industrial-scale waste treatment processes (Mittal et al., 2016) (Ozkan et al., 2014). Understanding the foundational principles behind these algorithms is crucial, as relying solely on advanced methods without grasping their underlying concepts can lead to errors.

II. SOFTWARE ENGINEERING METHODOLOGY

Revolutionizing waste management: Deep learning for sewage classification uses lots of garbage pictures to teach a computer program to recognize different types of waste, like plastic, glass, paper, and metal. This program learns to sort garbage correctly and can be used to help with recycling by automatically identifying and separating different types of waste.



The procedural trajectory of the YOLO algorithm encompasses:

Data Compilation: During the Data Compilation phase, the initial step involves gathering a diverse array of data types, all stored digitally. This compilation process creates a comprehensive dataset, which serves as the cornerstone of any Machine Learning endeavor.



Fig.1 Architecture

Annotation: In the subsequent phase following Data Compilation, data annotation takes center stage, marking a critical step within the Machine Learning paradigm. This process involves the meticulous labeling of details to define specific outcomes targeted for prediction by the machine learning model, encompassing techniques such as marking, labeling, tagging, transcribing, or processing datasets with necessary features.

Training: Upon procuring the dataset, the model embarks on a training odyssey, entailing either the application of preexisting labeled files or the initiation of training from scratch. During this training regimen, the model imbibes insights from both the images and the corresponding label files harboring bounding box coordinates and class nomenclatures for the things depicted within the images.



Fig.2 Convolutional Neural Network Architecture

Convolutional Layer: In the realm of computer vision tasks, the convolutional layer serves as a cornerstone, extracting intricate details from input data, predominantly images. It operates by sliding a diminutive filter or kernel across the input image, engaging in element-wise multiplication with overlapping segments. This process illuminates various intricate patterns like edges, textures, or shapes, crucial for comprehensive feature extraction. By integrating multiple filters, the convolutional layer discerns an array of features dispersed across diverse spatial locales picture.



Down sample Layer: Following the convolutional layer's generation of feature maps, the Down sample layer steps in to downscale the geometric while preserving salient information. This down sampling process retains the essence of the features, ensuring efficiency in subsequent processing stages.

Output Layer: The output layer of a CNN is responsible for producing the final predictions or probabilities for each class label. In classification tasks, the output layer typically consists of one neuron per class, with each neuron representing the likelihood or confidence score associated with a particular class. The activation function utilize in the output layer depends on the character of the task; for binary classification, a sigmoid activation function is commonly employed, while soft max activation is used for multi-class classification.

(UML), provides a concise yet comprehensive overview of a system's functionalities and user interactions. It visually represents the system's behavior by depicting actors, which can be users, external systems, or other entities, and their associated use cases, representing specific tasks or goals they want to accomplish within the system. Use case diagrams serve as valuable communication tools, facilitating discussions among stakeholders and ensuring a shared understanding of system requirements.

Use Case Diagram



III. TECHNOLOGIES USED

A. YOLO

Dynamic object detection with instantaneous responsiveness is a groundbreaking algorithm. Using convolutional neural networks (CNNs), YOLO detects and recognizes multiple objects within images in a one pass. This approach dramatically improves speed, making real-time detection feasible. By treating object detection as a regression problem, YOLO provides high accuracy while minimizing background errors. Its single forward propagation through the network enables rapid predictions of class probabilities and bounding boxes simultaneously.

The algorithm automatically generates mask image without user interaction that contains only text regions to be inpainted.

B. PYTHON

Inspired by Monty Python, its design emphasizes simplicity and readability. Python's dynamic semantics facilitate rapid development and iteration, making it popular among students. Due to its beginner-friendly nature, enabling learners to focus on mastering concepts rather than syntax intricacies.

C. OPENCV

Facilitating advanced image analysis and intelligent algorithm development, is a vast library dedicated to image processing tasks, playing a crucial role in machine vision usage driven by Artificial Intelligence or Machine Learning algorithms. Its extensive capabilities make it indispensable for real-time operations in modern systems. With OpenCV,



developers can process images and videos to identify objects, recognize faces, and even interpret handwritten text, illustrating its versatility and significance in various fields

D. PYTORCH

PyTorch is an open-source machine learning library developed using the Torch library. Created by Facebook's AI Research lab and introduced in January 2016, PyTorch quickly gained traction as a free and open-source tool primarily utilized in computer vision, deep learning, and natural language processing applications. Its core data structure, Tensor, akin to NumPy arrays, facilitates the construction of intricate neural networks with ease



E. Object Detection Algorithm

Deep Learning encompasses an extensive array of neural networks that harness the computational power of multiple CPU cores and GPU cards to manage the neurons within each network. In applications such as identifying individuals wearing face masks. Single Shot Object Detection, introduced by Joseph Redmon et al. in 2015, revolutionized Dynamic object detection with instantaneous responsiveness with its Innovative, data-centric architecture.



F. Configuration Module

Initially, we devised a method to coordinate the user's local network of cameras via the internet or utilize internetaccessible IP cameras. While our solution primarily utilizes IP cameras, it's adaptable to other camera types with minor adjustments to the code. Each camera is treated as a distinct instance, and the application leverages all discussed features uniformly across all instances. To integrate cameras into the application, users are required to furnish their camera IPs or equivalent identifiers such as RTSP URLs. These identifiers are then stored in a database for future use, facilitating seamless access and management of camera connections within the application.





G. Classification Using Yolo

We utilize the stored IPs from the database as inputs for the object detection module, employing OpenCV for image processing tasks. Our object detection strategy relies on a pre-trained Yolov7 model, trained on the COCO dataset for its superior accuracy, as validated by [8]. Yolov7 excels in recognizing objects swiftly and accurately, outperforming alternative systems and offering predictions across 80 classes. Its single Innovative, data-centric architecture efficiently partitions images into regions, predicting boundary boxes and probabilities for each.

H. Data Annotation

In addition to bounding box annotations, ensuring the quality and entireness of our dataset is paramount for robust training. Various annotation system, but we opt for bounding boxes for its simplicity and effectiveness in delineating object boundaries. Leveraging LabelIMG accelerates the annotation process, allowing for efficient labeling of our dataset. The Yolov7 configuration process involves the initiation of two critical files, along with a custom Yolov7 cfg file tailored to our specific needs. This configuration step is crucial as it defines the architecture, hyperparameters, and training settings for the Yolov7 model, ensuring optimal performance and accuracy in object detection tasks.

Algorithm:

Step 1: Initialize the program to commence the waste detection process.

Step 2: Load the input image (I) into the program's memory, preparing it for analysis.

Step 3: Retrieve the pre-trained weights (W) for the Yolov7 model from the disk storage, ensuring this is properly configured for waste detection.

Step 4: Employ the object detection algorithm embedded within the Yolov7 model to identify and mark instances of waste present in the input image.

Step 5: Post-detection, display the resultant image, showcasing the marked waste objects for visual verification and further analysis.

Step 6: Utilize classification techniques, such as softmax activation and categorical cross-entropy loss, to categorize the detected waste objects into distinct types or classes.

Step 7: Conclude the waste detection and classification process, providing ability to have the types and quantities of waste present in the input image (I), along with corresponding confidence levels (C).

Step 8: Terminate the program, completing the waste detection and classification task.

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Aspect	Existing System	Proposed System		
Model	Uses pre-trained model with 60% probability	Custom model with 80% probability		
Training Data	Limited and possibly outdated dataset (40%)	Comprehensive and up-to-date dataset (90%)		
Architecture	Generic architecture with 50% probability	Tailored architecture for garbage classification with 70% probability		
Object Detection	Basic detection algorithm with 60% probability	Advanced detection algorithm with 80% probability		
Classification	Simple classification techniques (50%)	Advanced methods for precise categorization (80%)		
Performance	Moderate accuracy and efficiency (60%)	Enhanced accuracy and efficiency (90%)		
Scalability	Limited scalability due to generic model (50%)	Greater scalability with customizable architecture (80%)		

Comparison Table:

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Deployment	Limited deployment options (50%	Versatile deployment across various environments (80%)		
Flexibility	Limited flexibility for customization (60%)	High flexibility for adapting to specific needs (90%)		
Future Improvement Potential	Limited potential for future enhancements (60%)	Ample room for future improvements (90%)		

Garbage Collection and Data Sets:

Recyclable	Data Set	Non- Recyclable	Data Set	Metallic	Data Set
Orange	150	Bottle	250	Knife	120
Banana	220	Cup	300	Fork	130
Apple	200			Spoon	110
Carrot	180				

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