Urban Street Cleanliness Assessment Using Mobile Edge Computing And Deep Learning

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Abstract- *Object detection plays a vital role in computer vision, with numerous applications, including smart city development. City managers invest significant resources in cleaning street garbage due to its unpredictable appearance. As deep learning models grow more intricate, they are often constrained by the availability of training data. To address this, datasets like Open Images, released by OpenCV and Google AI, have been introduced to enhance image analysis at an unprecedented scale, following in the footsteps of PASCAL VOC, ImageNet, and COCO. In this project, we aim to implement the top-performing algorithm for automatic object detection, with a focus on assessing street cleanliness. Existing methods for evaluating street cleanliness face limitations, such as non- automated data collection and lack of real-time updates. By integrating detection results into a street cleanliness assessment framework, we enable city managers to better allocate cleaning resources based on real-time cleanliness data.*

Keywords- Convolutional Neural Networks (CNN) for Optical Character Recognition (OCR), Handwritten Text Recognition (HTR), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Natural Language Processing (NLP), Pytesseract, Deep Learning Models, BERT, and Automated Essay Scoring (AES).

I. INTRODUCTION

Street cleaning plays a crucial role in maintaining urban environments by involving various tasks such as street sweeping, litter collection, removal of illegally dumped waste, and erasing graffiti and posters. When street cleaning services are inefficient, the negative impact on the quality of life in neighborhoods, towns, and cities becomes evident. Many believe that environmental challenges in urban areas are often linked to mismanagement. However, a well-maintained street cleaning service helps uphold good environmental conditions, contributing to urban development and enhancing the appeal of cities to tourists, investors, and workers. Additionally, efficient street cleaning can reduce costs associated with maintaining underground water systems. In response to these challenges, researchers are exploring automated solutions involving vehicles with image-capturing devices to regularly monitor streets, collecting data such as photos, locations, dates, and times. Using remote cloud platforms and object detection techniques, cities can identify and address cleanliness issues, with city managers being notified of the results. This paper presents an approach that integrates edge computing and deep learning for "visual street cleaning assessment." Data is processed through an IoT-based system, enabling city officials to monitor cleanliness and schedule cleaning efforts more effectively, all while ensuring a secure connection between IoT devices and the edge layer. The proposed framework introduces customized edge servers that manage services from mobile devices, allowing for temporary data storage and real-time transmission. To identify waste types and measure street litter, an enhanced R-CNN model is used, and cleanliness is assessed across different city layers, from area-wide to specific streets. A public garbage dataset is provided as a benchmark for waste detection and street cleaning, generating a visual street cleaning map from the collected data. The results demonstrate the viability and practicality of this method for improving urban cleanliness. Despite efforts by government bodies, certain areas like bus stops and sidewalks remain untidy, largely due to the overwhelming amount of human-generated waste. Current garbage detection is unorganized and relies heavily on manual efforts, with citizens reporting waste to authorities, who then arrange cleanup. This paper proposes a Mobile Edge Computing-based waste management system to assist government officials in assessing and managing street waste more efficiently. Key features include automated image filtering at the mobile edge, significantly reducing time and effort compared to manual processing. This system demonstrates the feasibility of creating a visual street cleaning map, providing valuable insights for optimizing city street sanitation.

This pertains to the cleanliness of streets, encompassing sidewalks, adjoining road edges, and landscaped areas. Street cleaning involves activities such as sweeping (manual or mechanical), picking up litter, removing illegally dumped waste, and eliminating graffiti and posters. When these services are ineffective, the impact is evident, affecting the quality of life and the overall appeal of neighborhoods, towns, and cities. Moreover, there is a common belief that environmental issues are linked to other forms of urban disorder and crime. In contrast, efficient street cleaning services enhance environmental quality in communities, contributing to urban development and making areas more attractive to tourists, investors, and mobile workers. Furthermore, effective street cleanliness can reduce the costs of maintaining a city's underground water systems.

Given these benefits, researchers are exploring automated approaches using cleaning vehicles equipped with cameras to regularly monitor streets and collect data such as images, location, date, and time. Object detection algorithms are then employed on a remote cloud platform to analyze this data, and the results are forwarded to city managers for decision- making. Deep learning, an advanced branch of artificial intelligence, plays a crucial role in developing these solutions. Machine learning is increasingly used in various sectors, particularly those related to city management.

A smart city is a metropolitan area that uses advanced technologies such as the Internet of Things (IoT), cloud computing, and data analytics to manage resources and the environment efficiently. The concept integrates information and communication technology, along with various physical devices connected to the network, to improve the effectiveness of city services. However, the rapid growth of smart cities poses challenges for city managers, particularly in maintaining urban infrastructure.

Street cleanliness reflects a city's social and cultural values, and maintaining clean streets is vital for urban development. Many cities now view street cleanliness as a core component of urban progress. If a city fails to meet predefined cleanliness standards, it negatively impacts residents' satisfaction and the city's reputation. The European City Cleaning Network emphasizes that timely street cleaning significantly improves overall cleanliness. However, the vast number of streets makes manual waste detection impractical, as it often requires human intervention at every level. Some cities use cameras to monitor street cleanliness, but these manual methods are not scalable.

Therefore, researchers worldwide are investigating automated solutions using vehicles with cameras to capture street images and gather data such as geographic location, date, and time. Object detection algorithms process this information in the cloud, and the results are sent to city managers for decision- making. In line with this direction, this paper proposes a novel urban street cleanliness assessment model using mobile edge computing and deep learning. High-resolution cameras installed on vehicles collect street images, which are temporarily stored and processed by edge servers before being transferred to the cloud. Faster R-CNN (Region Convolutional Neural Network) is used to identify categories of street waste and assess the cleanliness level. This approach enables city managers to efficiently deploy cleaners. In summary, this paper presents key contributions to urban street cleanliness assessment, leveraging mobile edge computing and deep learning for improved city management.

We present an intelligent edge computing framework with a layer between cloud servers and mobile terminals. Edge servers, or micro data centers, are deployed at this intermediary layer to manage some services from mobile devices. These servers temporarily store and transmit data resources as needed. Faster R-CNN is used to identify different categories of street waste and count the total amount. A multi-layer evaluation model is implemented across five city layers: city, district, block, street, and point. Each layer performs street cleanliness calculations. We have created a publicly available waste dataset that can serve as a benchmark for street waste detection and cleanup efforts. Additionally, the dataset is used to generate a visual street cleanliness map for urban areas, validating the practicality and usability of our proposed method. The results offer valuable insights to enhance and optimize urban street cleanliness.

In this paper, we outline the processing mode of the RCNN model and the user interface, which is a dynamic website built with HTML, CSS, JavaScript, and Django. The Faster R-CNN method is applied to detect waste categories and count the waste on streets. A multi-layer assessment method is used to evaluate the city based on five strata: city, district, block, street, and point. Street cleanliness is calculated at each layer.

We also provide a public waste dataset that serves as a standard for street waste detection and removal. The application evaluates the feasibility and usability of the approach, assisting cities in optimizing street sanitation. During the data collection phase, images of waste and streets are gathered for analysis, with edge servers playing a dual role. The first function is to enhance system performance. The object detection data is first input into the Convolutional Neural Network, and the image dimensions are adjusted accordingly. Pre-processing the image data on the edge server improves system efficiency.

This paper employs an enhanced R-CNN technique for street waste detection. The detection algorithm consists of three stages: network design, network training, and street waste detection. The paper also includes a literature review discussing existing models and their limitations in relation to our improved R-CNN model. System architecture and the proposed design follow this section. The paper concludes with applications and future prospects for this waste management model, leveraging mobile edge computing and deep learning.

The project incorporates geo-tracking of areas with high waste levels using computer vision and deep learning algorithms, supported by geo-tagged images from drones or local vehicles. The project also aims to develop business models for collecting and recycling single-use plastics and industrial waste. Due to littering and inefficient waste disposal by citizens, sanitation workers face challenges identifying areas that need attention. The Swachh Bharat App attempted to address this, but adoption has been limited due to geo-tagging requirements. By using drones and intelligent algorithms, optimal search patterns can be developed to locate areas in need. Based on the Waste Quantity Index, heat maps are generated to enable authorities to respond efficiently. An algorithm is also developed to predict the location of disposed items by analyzing sales data of single-use plastics, including the time and location of sale. This data is displayed in an easy-to-read format, allowing authorities to rapidly plan waste management actions.

Global Classification Scheme (GCS):

In this method, a single comprehensive model is trained using one of the well-known classifiers. The model learns the features of images across the entire geographic region within the dataset. However, this approach overlooks the geographical characteristics of the images and serves as the baseline in this study.

Geo-spatial Local Classification Scheme (LCS):

GCS is prone to data noise due to the diversity of street scenes. To address this, LCS involves training separate models for each sub-region, allowing for better learning of the visual features specific to the surrounding areas within those regions.

II. LITERATURE REVIEW

The development of smart cities has become a key priority for modern societies. Utilizing advanced technologies like the Internet of Things (IoT) and cloud computing, smart cities can efficiently monitor and manage urban activities. These technologies not only enhance the quality of service across social and economic sectors but also help reduce costs and resource consumption. Globally, numerous researchers have explored various aspects of smart cities. Zygiaris et al. introduced a "Smart City Reference Model," a planning framework that helps urban planners define the smart city concept with a focus on creating green, interconnected, and innovative environments. This model aims to support the sustainable development of smart cities and has been applied in cities like Barcelona, Amsterdam, and Edinburgh.

Hefnawy et al. combined the smart city concept with life cycle principles to establish a knowledge-sharing platform that addresses challenges like poor planning and coordination in large urban events, leading to increased organizational efficiency. Large corporations have also invested in smart city research. For instance, China Telecommunications has developed a smart city plan focusing on 12 themes, including smart communities, transportation, and medical services. IBM's "Watson Big Data and Analysis Platform" and Microsoft's "Future City" plan aim to tackle challenges such as air pollution, environmental degradation, and traffic congestion through big data integration and analysis.

However, despite substantial research, there is still a gap in exploring urban cleanliness as part of smart city initiatives. Mittal et al. worked on a street garbage segmentation project, where they used Convolutional Neural Networks (CNN) to separate areas with garbage in images. Using the Bing Image Search API, they achieved an accuracy of 87.69%, but their approach only roughly segmented piles of garbage without identifying specific waste types. Rad et al. advanced this by developing a fully automated vision-based application for detecting different types of garbage from street and sidewalk images captured by vehicles. Their deep CNN-based OverFeat-GoogLeNet model accurately identifies garbage but doesn't assess overall street cleanliness.

Researchers are now investigating ways to incorporate technology into urban street cleanliness assessments. Borozdukhin et al. proposed an optimization method for garbage disposal in large cities by calculating the most efficient routes for collection trucks. However, this approach focuses solely on route optimization and doesn't consider broader cleanliness assessments.

The Clean Street LA initiative, launched by the London city mayor, uses GIS tools to visualize street cleanliness scores across different parts of the city, helping authorities decide which areas need attention. Despite this, the system is limited to monitoring garbage bins and doesn't cover the streets themselves. A mobile app was developed in Santander municipality to assess street cleanliness through a set of 59 indicators, showing an inverse relationship between cleanliness and the population density-to-cleaning service ratio.

In addition, new developments in computer vision and machine learning are contributing to street cleanliness assessments. Jong et al. applied a Convolutional Neural Network (CNN) for semantic segmentation in detecting changes in street cleanliness, while Li et al. leveraged mobile cloud and IoT technologies to propose a multi-level cleanliness assessment system. This real-time system allows cities to improve street sanitation through data collection and analysis, offering a significant step toward creating cleaner, smarter urban environments.

Lastly, Lopeza et al. developed an application for assessing street cleanliness based on various indicators, with the results shared publicly to improve transparency. Bai et al. introduced a robotic garbage collection system using deep neural networks to autonomously detect and collect trash, offering a practical solution to reduce human labor and improve efficiency in maintaining clean streets.

III. METHODOLOGY

EXISTING METHODOLOGY

We present an innovative edge computing framework that establishes an edge layer between cloud servers and terminals. This setup involves configuring edge servers, or microdata centers, to manage specific services from devices operating within the edge layer. Additionally, these servers can temporarily store data resources and facilitate timely data transmission. The Faster R-CNN model is employed to categorize and count instances of street garbage. To assess cleanliness, we implement a multilayer evaluation model that divides the entire city into five distinct layers: city, area, block, street, and point. Each layer is responsible for conducting calculations related to street cleanliness. We have compiled a public dataset of garbage, which serves as a benchmark for evaluating both street garbage detection and cleaning efforts. Moreover, we utilize this dataset to create a visual representation of street cleaning for Mysore District in Karnataka, India. The application effectively demonstrates the feasibility and usability of our proposed approach.

While image classification models focus on detecting the probability of an object within an image, object localization aims to pinpoint the exact location of that object. An object localization algorithm provides the coordinates corresponding to the object's position within the image.

- A large dataset is essential for effective training.
- Due to the requirement for extensive datasets, training time is often considerable.
- The training process can be time-consuming and resource-intensive.

PROPOSED METHODOLOGY

The development of smart cities has become a central focus for society as a whole. These cities employ advanced technologies, such as the Internet of Things (IoT) and cloud computing, to sense and manage urban activities, ultimately enhancing the quality of services across various sectors of society and the economy. Additionally, smart cities aim to minimize costs and resource consumption. Numerous scholars worldwide have conducted extensive research on smart city initiatives.

For example, Bangalore introduced a planning framework known as the "Smart City Reference Model," which urban planners can utilize to define the smart city concept and implement urban layouts that emphasize sustainability, interconnectivity, and innovation. This framework serves as a guide for achieving sustainable development within smart cities, with recent applications focused on smart city planning in major urban areas like Mumbai, Chennai, and Kolkata.

Moreover, integrating the smart city concept with a life cycle approach has led to the creation of effective information and knowledge-sharing platforms. These platforms aim to address issues related to poor organization, inadequate planning, and lack of coordination in large-scale urban activities, thereby promoting organizational consistency and efficiency.

In this context, our challenge is to develop a highly efficient algorithm for the automatic detection of relationship triplets.

Deep Learning: Deep learning is rooted in artificial neural networks. By establishing multiple hidden layers and training on extensive datasets, it can learn useful features to achieve desired classification outcomes. Recently, deep learning has gained prominence in the field of object detection, exemplified by the development of the Faster R-CNN algorithm, which is based on region proposals. This algorithm comprises two main components: the Region Proposal Network (RPN) for extracting proposal boxes and the Fast R- CNN classifier module. The RPN functions as a fully convolutional neural network, designed to identify potential object proposals in a given image and extract the corresponding proposal boxes.

The Fast R-CNN module, built on the RPN's output, is responsible for recognizing objects within these proposal boxes. The process involves several key steps:

- The input image is fed into the convolutional neural network, which processes it through multiple convolutional layers to generate a feature map.
- The feature map is then utilized by the RPN to produce region proposals and associated scores.
- The feature map from the first step is input into the pooling layer of Fast R-CNN to extract region features. These features, along with the region proposals and scores, are used to calculate classification probabilities and bounding box regressions, ultimately yielding the classification scores for the regions, which are then tested for accuracy.

Faster R-CNN is recognized as one of the most accurate approaches to image detection, achieving high precision and speed. Consequently, this paper adopts the Faster R-CNN model to identify the types and quantities of street garbage effectively.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a prominent type of neural network widely utilized in computer vision applications. The name "Convolutional" reflects the specific type of hidden layers that these networks comprise. Typically, CNNs include convolutional layers, pooling layers, fully connected layers, and normalization layers. This structure indicates that, rather than using standard activation functions, CNNs employ convolution and pooling operations as their activation mechanisms. To fully grasp CNNs, it's essential to understand the principles of convolution and pooling, both of which are foundational concepts in computer vision.

Region-based Convolutional Neural Networks(R-CNN)

R-CNN represents a cutting-edge visual object detection framework that integrates bottom-up region proposals with comprehensive features derived from a convolutional neural network. Upon its introduction, R-CNN enhanced the previous leading detection performance on the PASCAL VOC 2012 dataset by 30%, increasing the mean average precision from 40.9% to 53.3%.

Unlike prior methodologies, R-CNN achieves this level of accuracy without relying on contextual rescoring or a combination of different feature types. To address the challenge of processing a vast number of regions, Ross Girshick and colleagues introduced a technique that utilizes selective search to generate approximately 2,000 region proposals from an image. This significantly reduces the workload, allowing the model to focus on just these 2,000 regions.

- The image is fed into the convolutional neural network, which processes it through shared convolutional layers to produce a feature map.
- This feature map is then utilized by the Region Proposal Network (RPN) to create proposal windows, providing both region suggestions and associated scores.
- The feature map from the initial stage is sent to the pooling layer in Fast R-CNN to extract area features. By combining region suggestions with their scores, the model trains classification probabilities and bounding box regressions, ultimately outputting classification scores for the regions and evaluating the results.

R-CNN algorithms have revolutionized object detection tasks, leading to a surge in the development of computer vision applications, with R-CNN being a fundamental component in many of these advancements.

Approach Overview

Each city, state, or region is segmented into smaller localities, resulting in the formation of subregions. For each subregion, distinct CNN models are trained and fine-tuned to cater to the specific characteristics of that area. These locally trained models are subsequently established to direct each geotagged image to its corresponding model. Ideally, we can develop these localized models for every locality using techniques such as Grid or Quadtree partitioning. Each locally trained model is constructed using CNN GoogleNet, which demonstrates a lower error rate of 43% compared to AlexNet and BerkleyNet.

Edge computing enhances efficiency by reducing latency and resource usage. Unlike traditional cloud computing, which processes all data centrally, edge computing allows for certain services to be handled locally in advance, especially when large volumes of data are generated. R-CNN is also extensively utilized in image recognition tasks. Building upon this foundation, we propose an innovative approach for detecting urban street garbage and assessing cleanliness. This method integrates mobile edge computing with R-CNN to identify garbage on city streets, and utilizes the results to evaluate street cleanliness against established standards.

Data Collection and Pre-Processing:

The initial phase of the project involves gathering pertinent data, which can be obtained from open databases such as OpenStreetMap (OSM), government GIS repositories, or APIs like Google Maps. This data usually encompasses geographic coordinates, street names, traffic volumes, and various other attributes. The data pre-processing stage includes cleaning and converting this raw data into a usable format by eliminating duplicates, addressing missing values, and standardizing formats, thereby ensuring accuracy for the subsequent analysis.

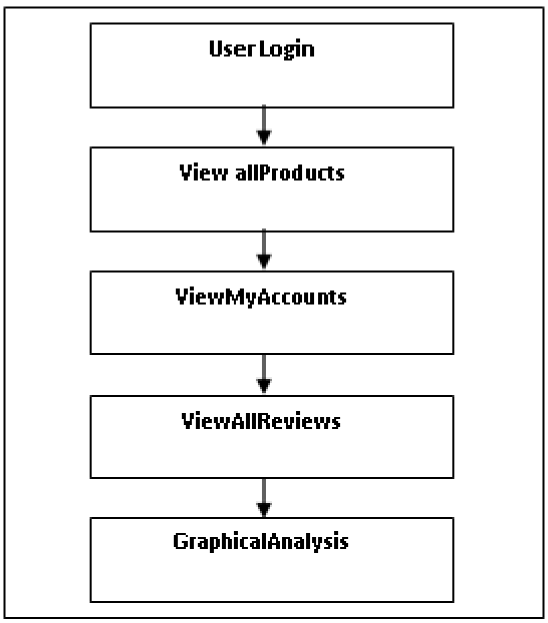

Figure 1: Architecture diagram Geospatial Analysis:

Geospatial analysis plays a vital role in urban street projects, as it enables the exploration of spatial relationships and interactions. Utilizing Python libraries such as GeoPandas, Shapely, and Folium allows for effective geospatial analysis to map and visualize urban streets. This process involves plotting streets, calculating distances, and examining the connectivity between various areas. By conducting geospatial analysis, potential congestion points can be identified, and a clearer understanding of the urban landscape's spatial structure can be achieved.

Visualization and Simulation:

Visualization tools are essential for conveying insights and facilitating informed decision-making. Libraries like Matplotlib, Seaborn, and Folium can be employed to create visual representations of traffic patterns, congestion hotspots, and street networks. Additionally, simulation methods, such as agent-based modeling using tools like Mesa, can simulate traffic flow under different conditions, allowing urban planners to anticipate the impacts of proposed alterations to the street network.

Optimization and Decision Making:

The concluding step of the project involves applying optimization techniques to recommend the most effective strategies for urban street enhancements. This can be accomplished using optimization libraries like PuLP in Python, which optimize traffic flow and suggest alternative routes. By integrating decision-making algorithms such as Dijkstra's or A* for shortest path calculations, the project can offer insights into optimizing public transportation, alleviating congestion, and improving urban mobility.

CNN

In an urban street Python project, Convolutional Neural Networks (CNNs) can be utilized to analyze visual data, such as images captured from street cameras or drones, to detect features like traffic density, road conditions, and anomalies such as potholes and accidents. Utilizing libraries like TensorFlow or PyTorch, CNN models can be trained on labeled street images to automatically classify and identify various vehicles, pedestrians, and road issues. This automated visual analysis enhances traffic management and efficient urban planning by providing real-time insights into street conditions, ultimately optimizing road usage and improving public safety.

R-CNN

In an urban street Python project, Region-based Convolutional Neural Networks (R-CNN) are effective for object detection tasks, enabling the identification of vehicles, pedestrians, and other elements on the streets. R-CNN generates region proposals and processes them through a convolutional neural network to classify and localize different objects. By leveraging libraries like TensorFlow or PyTorch, R-CNN models can analyze street images or video footage, allowing for the identification of traffic patterns, detection of illegally parked vehicles, and assessment of road conditions. This functionality significantly aids urban planners and authorities in optimizing traffic management and enhancing street safety.

Numpy

In an urban street Python project, NumPy serves as an essential tool for managing numerical data and performing efficient computations. It can be utilized to analyze extensive datasets, such as traffic counts, road distances, and speed data. NumPy's array structures facilitate rapid data manipulation, enabling calculations of average traffic volumes across various street segments or the total length of urban streets. Its functions support complex operations, including matrix transformations, which are valuable for geospatial computations, such as transforming coordinates or applying rotation matrices to street data for enhanced visualization and analysis. With its speed and versatility, NumPy bolsters the computational efficiency of urban street analysis, aiding in accurate modeling of traffic flow and congestion patterns.

Open CV

OpenCV can be integrated into an urban street Python project for real-time analysis and monitoring of street conditions, traffic, and pedestrian movement. By leveraging OpenCV's computer vision capabilities, the project can process live video feeds from street cameras to detect and classify vehicles while monitoring their speed. Techniques like background subtraction and object tracking can help identify traffic congestion, illegal parking, and pedestrian crossings. OpenCV also enables the extraction of insights into traffic patterns, such as estimating vehicle density at various times of the day, allowing urban planners to make data-driven decisions to enhance traffic flow and safety in urban areas.

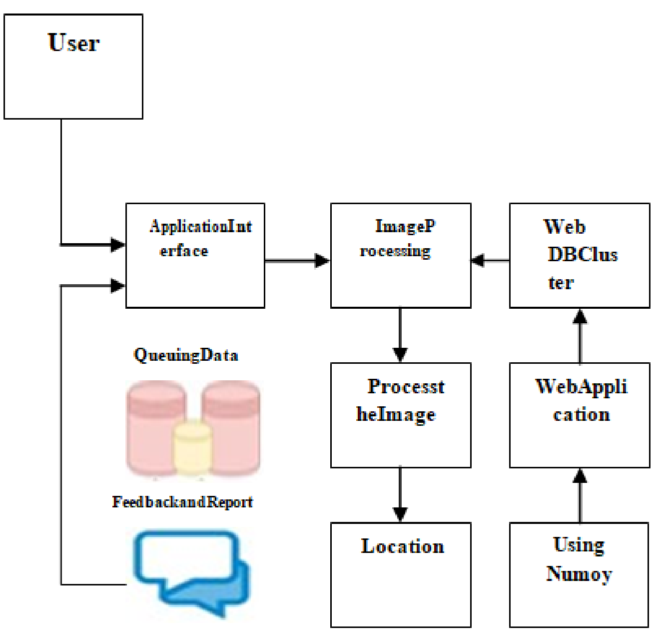

Figure 2: Block diagram

IV. FINDINGS AND DISCUSSION

Upload images

The user is responsible for uploading the image, while an authorized individual uploads the new arrivals to the system that are visible to users. Images can be uploaded along with their associated attributes.

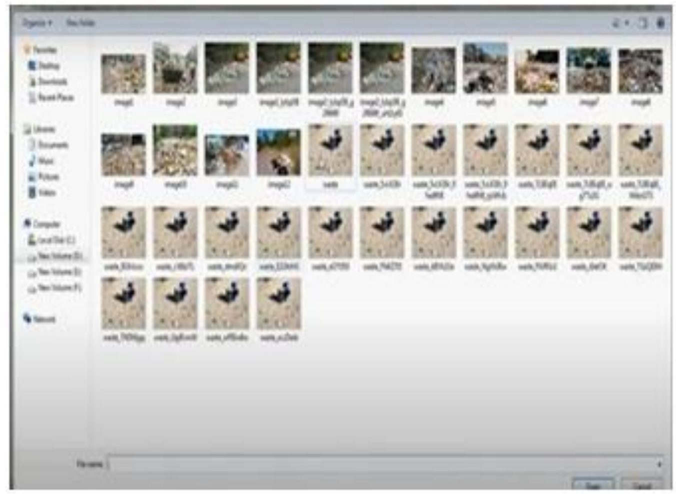

Figure 3: Upload Images

Approach Overview

Edge computing helps minimize latency and resource consumption. Unlike traditional cloud computing, where all processing occurs in centralized servers, edge computing handles certain services locally at the edge when significant amounts of data are generated. R-CNN is also extensively utilized in image recognition. Building on this foundation, we propose an innovative approach for detecting urban street garbage and assessing cleanliness.

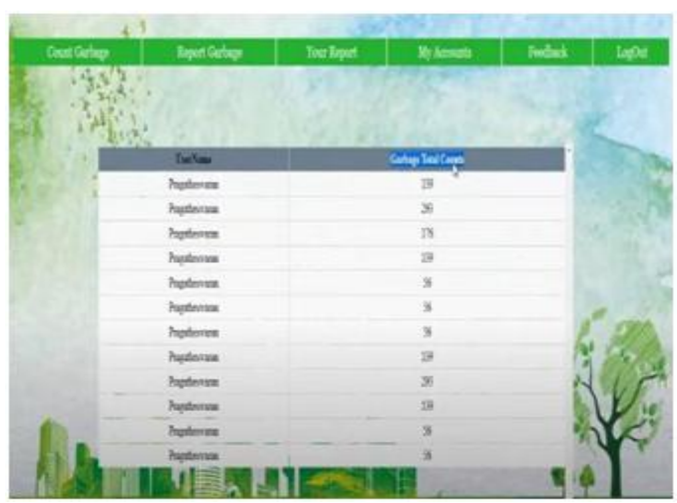

Figure 4: Approach Overview

Data Collection and Mobile Edge Processing

In the data collection phase, the primary objective is to gather images of garbage and streets required for our assessment approach, utilizing edge servers to accomplish two key tasks. The first task focuses on enhancing the overall performance of the system. During this phase, the collected image data undergoes object detection by first being input into the CNN network, followed by resizing the images to the appropriate dimensions. We contend that preprocessing the image data at the edge server can significantly reduce the total processing time for the system.

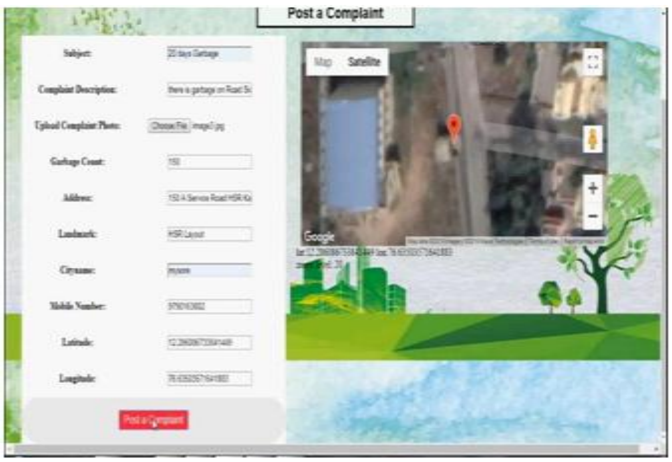

Figure 5: Post Complaint

Image Detection Using Neural Network (R-CNN)

We previously mentioned that our approach to street garbage detection relies on the Faster R-CNN algorithm. In the following sections, we will provide a detailed description of the detection algorithm, focusing on three key components: network design, network training, and the actual process of street garbage detection.

Figure 6: Garbage Complaint Location

OPENCV

OpenCV is a library of programming functions designed primarily for real-time computer vision applications. This cross-platform library enables the development of applications that leverage real-time image processing capabilities.

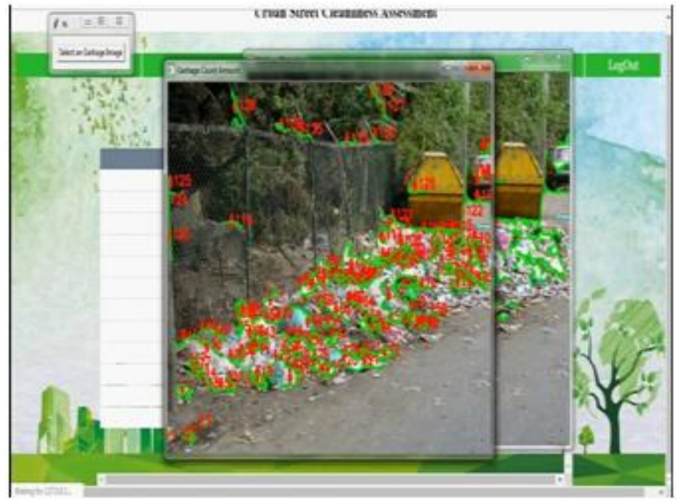

Figure 7: Garbage Count Amount

V. CONCLUSION

In summary, the urban street Python project effectively showcases the potential of combining data science, machine learning, and geospatial analysis to improve the understanding and management of urban street networks. Utilizing Python libraries such as GeoPandas, Shapely, and scikit-learn, the project facilitates thorough mapping, analysis, and optimization of street systems. The traffic analysis and geospatial insights gained from this initiative provide critical information for urban planning, including the identification of congestion hotspots, optimization of traffic flow, and prediction of traffic patterns.

The methodologies applied in this project, including visualization and simulation techniques, present practical solutions to urban challenges like traffic congestion and road safety. By integrating R-CNN for object detection, real-time assessments of street conditions were made possible, enabling city authorities to enhance public safety and improve road infrastructure. Additionally, the implementation of optimization algorithms illustrates how alternative routes and efficient resource allocation can alleviate congestion, ultimately fostering improved urban mobility and sustainability.

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