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CITY CLEANLINESS USING GEO-TAGGED IMAGES

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***Abstract:** During the process of smart city construction, city planners and managers always spend a lot of energy and money for cleaning street garbage due to the random appearances of street garbage. Consequently, visual street cleanliness assessment is particularly important. However, the existing assessment approaches have some clear disadvantages, such as the collection of street garbage information is not automated and street cleanliness information is not real-time. To address these disadvantages, this paper proposes a novel urban street cleanliness assessment approach using mobile edge computing and deep learning. First, the high resolution cameras installed on vehicles collect the street images. Mobile edge servers are used to store and extract street image information temporarily. Second, these processed street data is transmitted to the cloud data centre for analysis through city networks. At the same time, Faster Region-Convolutional Neural Network (Faster R-CNN) is used to identify the street garbage categories and count the number of garbage. Finally, the results are incorporated into the street cleanliness calculation framework to ultimately visualize the street cleanliness levels, which provides convenience for city managers to arrange clean-up personnel effectively.*

Keywords: *Smart cities, street cleaning, garbage detection, deep learning, mobile edge computing.*

I INTRODUCTION

The project will include Geo Tracking of regions with high waste index detected using computer vision and Deep Learning image classification algorithms with help of geo tagged images captured by drones or mobile vehicles of the local areas coupled with development of business models for collection and utilization of single use plastics and various other industrial wastes. Due to littering and inefficient garbage disposal practices engaged in by citizens, it becomes a tough task for sanitation workers to determine which areas require attention and waste pickup. With the Swachh Bharat App, the government attempted to resolve this problem. Due to geo tagging requirements in this app, adoption is low. With the drone connectivity and intelligent algorithms, optimal search patterns for every area can be developed. Using this sweep-search technique, areas that require help can be located. Depending on the Waste Quantity Index of the area, appropriate heat maps are generated. These heat maps enable authorities to take necessary action efficiently. Furthermore, an algorithm is developed to use inputs such as single use plastic item sale, date of sale, time of sale and location of sale and provide output with a probable area in heat-map form that will show the most likely position of the disposed item. This data is displayed in a very simplified and readable form so as to enable authorities to plan further activities of waste management rapidly.

II.RELATED WORKS

A novel framework with multiple local trained models exploiting the similarity of local images so that the proposed models learn better street image classification for each geographical region. This paper also presents a case study of street cleanliness classification using a large real-world geo-tagged image dataset obtained from Los Angeles Sanitation Department.

A. This paper proposes a novel urban street cleanliness assessment approach using mobile edge computing and deep learning. First, the high-resolution cameras installed on vehicles collect the street images. Mobile edge servers are used to store and extract street image information temporarily. Second, these processed street data is transmitted to the cloud data center for analysis through city networks. At the same time, Faster Region-Convolutional Neural Network (Faster R-CNN) is used to identify the street garbage categories and count the number of garbage. Finally, the results are incorporated into the street cleanliness calculation framework to ultimately visualize the street cleanliness levels, which provides convenience for city managers to arrange clean-up personal effectively.

• The first step is data collection and scheduling feedback in the local management. The city administrators control the mobile station to collect the street garbage image data and respond to the level of street cleanliness presented by cloud center in real time. Then municipal cleaning personnel is arranged nearby.

• The second step is called data pre-processing. During this step, we use the edge server to store the image data captured by the mobile station temporarily and carry out road judgment of the images from the mobile station in advance. Then, the edge server filters out the images containing road areas. We use linear normalization to get the same size images and these images are sent to the cloud center for garbage detection.

• The third step is the model establishment and cleanliness calculation. During this step, the cloud server provides an object detection algorithm. Then a model is trained by selecting appropriate parameters and iterations to detect garbage on the street. In the garbage detection stage, we design a counting function to count the quantities of garbage detected.

• Finally, based on the results obtained by the use of the above detection, street cleanliness level is calculated with respect to different levels.

B. A novel framework with multiple local trained models exploiting the similarity of local images so that the proposed models learn better street image classification for each geographical region. In this paper a case study of street cleanliness classification using a large real-world geo-tagged image dataset obtained from Los Angeles Sanitation Department is presented.

• Global Classification Scheme (GCS) :

Among the classifiers discussed earlier, GCS approach constructs one single trained model using one of the well-known classifiers. The classifier learns the image features throughout the overall geographical region in a dataset. Thus, this approach does not consider the geo-properties of images and forms the baseline approach in this study.

• Geo-spatial Local Classification Scheme (LCS) :

GCS suffers from data noise caused by the variety of street scenes. Hence, the construction of a locally trained model per sub-region enhances learning the visual characteristics of the surrounding areas in a sub-region. In particular, each locally trained model focuses on learning the features of the categories without the distraction caused by the features of different street views. Hence, the probability of correct image classification increases.

• Failed to estimate an aggregated cleanliness level of a region that contains images of various cleanliness levels.

• Failed to generalize the solution.

C. The paper presents a conceptually simple, flexible, and general framework for object instance segmentation. The approach efficiently detects objects in an image and also simultaneously generating a high-quality segmentation mask for each instance. This is about the automation of street cleanliness assessment in near real-time. The question of how can we assess the status of streets more efficiently and effectively is answered.

The method of Mask R-CNN extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition. Mask R-CNN simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps.

This paper proposes a multiple-level assessment on how the cleanliness status of streets is collected using mobile stations, connected via city network, analysed in the cloud, and presented to city administrators online or on mobile. The usability and feasibility of our system are evident from the real applications.

Since we only compute masks on the top 100 detection boxes, Mask R-CNN adds∼ a small overhead to its Faster R-CNN counterpart (e.g., 20% on typical models).

Does not give us a solid plan for collection and disposal of waste.

III. PRELIMINARIES

1. MOBILE EDGE COMPUTING:

With the rapid construction of smart cities, the Internet gen erates a large amount of data. Traditional cloud computing requires that data must be transmitted to the cloud center for centralized processing. Remote cloud is a smart brain for processing big data . Since the cloud center is usually far away from end users, it is largely unable to provide low latency. In order to solve this problem, mobile edge com puting has been proposed to deploy computing resources to devices close to the terminal. The European Telecommuting cations Standards Institute (ETSI) defines mobile edge computing (MEC) as a distributed mobile cloud computing (MCC) system. The computing resources are close to mobile devices, and functions such as computing, storage, and processing are added to the wireless network side. In fact, mobile edge computing is based on cloud computing. It only calculates a small part of service. It is especially important for big data analysis. For example, when a user uploads a video or makes a comment, he/she can send it to a remote server through an edge virtual server. The edge virtual server can extract the video content and estimate the possibility that other people want to watch the video. If the probability is high, the edge server will cache this video locally so that anyone interested in this video can get the video directly from its cache instead of receiving it from a remote server, which saves transmission resources and reduces latency. In this paper, we use mobile edge computing to process street images in advance and filter out pictures that meet our needs, which has a good effect on recognition efficiency.

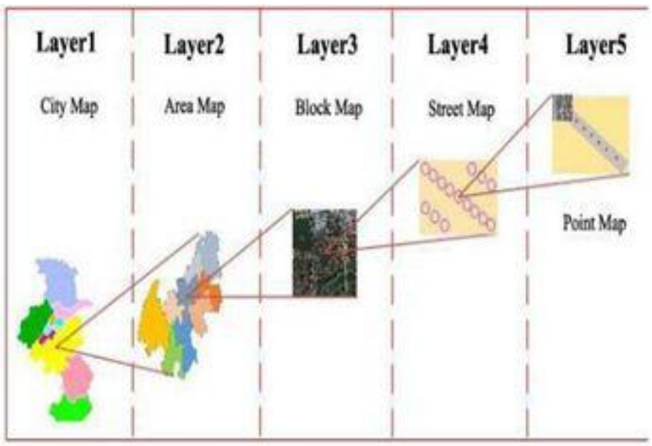

FIGURE 1. Multi-Level Assesment Model

2.DEEP NETWORK :

Deep learning originates in artificial neural networks. By establishing multiple hidden layers and training large amounts of data, useful features can be learned to achieve the expected classification effect.

3.R-CNN :

The method, called Mask R-CNN, extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition. Mask R-CNN simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps. To unify RPNs with Fast R-CNN object detection networks, we propose a training scheme that alternates between fine-tuning for the region proposal task and then fine-tuning for object detection, while keeping the proposals fixed. This scheme converges quickly and produces a unified network with convolutional features that are shared between both tasks.

IV. URBAN STREET GARBAGE DETECTION AND CLEANLINESS ASSESSMENT APPROACH

A. APPROACH OVERVIEW :

Each city/state/region is divided into smaller localities and smaller subregions are formed and for each subregion different CNN models are trained with tuning then according to the specific region. Locally trained models are generated and then these models are used to create a structure in which each geotagged image is redirected to a specific geotagged model. Optimally, we can create locally trained models for each locality using Grid or Quadtree. Each Locally trained model is made using CNN GoogleNet which has Least error rate of 43% compared to AlexNet and BerkleyNet. Edge computing can reduce latency and resources. Compared with traditional cloud computing, the main difference is that some services are processed on the edge in advance when a large amount of data is generated. R-CNN is also widely used in image recognition. Based on the above work, we design a novel urban street garbage detection and cleanliness assess ment approach. The approach combines mobile edge comput ing and R-CNN to detect urban street garbage. Based on the above detection results, we use the street cleaning standard to calculate street cleanliness.

DATA COLLECTION AND MOBILE EDGE PROCESSING :

1) DATA COLLECTION :

During the data collection stage, the main task is to col lect garbage and street images needed by the assessment approach. When a vehicle equipped with a high-resolution camera is in a city street environment, the information col lected includes mainly two parts: street image information and local management information. For street image infor mation, the cleaning vehicle equipped with a high-resolution camera is shot on each street according to the administra tor's assignment. The distance between adjacent shooting points is set by the administrator, and the cleaning vehicle takes pictures at each shooting point according to the four directions including left, front, right and back. The shooting range is 150 − 300m2. For mobile stations, the following rules are set: 1) fixed image resolution; 2) vehicle speed is approximately 25 kilometers per hour; 3) shooting points are a fixed distance; 4) there are 4 pictures in each shooting points. For local management information, the mobile station needs to report the location to the city manager regularly. The administrator responds in time and arranges cleaning staff to clean. carry out road judgment of the images from the mobile station in advance. Then, the edge server filters out the images containing road areas. We use linear normalization to get the same size images and these images are sent to the cloud center for garbage detection. The third step is the model establishment and cleanliness calculation. The second task is to filter out valuable data in advance through edge servers. Sometimes, the data collected by a mobile station may be useless. For example, there are some problematic pictures that include house, car or camera shoot ing angle causes the street blocked in 4 pictures collected at a certain shooting site. For the whole garbage detection system, pictures without full street images are obviously useless. In order to reduce the consumption of resource and time, we design the edge data processing layer. When the layer receives street images from mobile stations, street image information is temporarily saved for road detection. Image data that contains city roads is filtered and passed to the cloud center for street cleanliness assessment.

2) MOBILE EDGE PROCESSING :

Mobile station : There is a specific garbage collection vehi cle in the city. We install cameras with high resolution, high pixel and network transmission capabilities on the top of the garbage collection vehicle. The camera faces the ground and covers the front 50 meters. The garbage collection vehicle takes photos regularly in city streets every day according to a specific line and these data is transmitted into edge servers in time. At the same time, urban citizens can also act as garbage collection vehicles. They can collect street garbage data with their own mobile devices and transmit the collected data to edge servers.

Edge server : Edge server is at the edge of the network. It directly connects to nearby mobile devices through a wire less data link to handle a portion of service requested from mobile devices. It also has the ability to temporarily. Cloud : This layer is used to create training models and perform street garbage detection tasks. Meanwhile, the cloud server presents urban street cleanliness level in time and feedback relevant information to city managers.

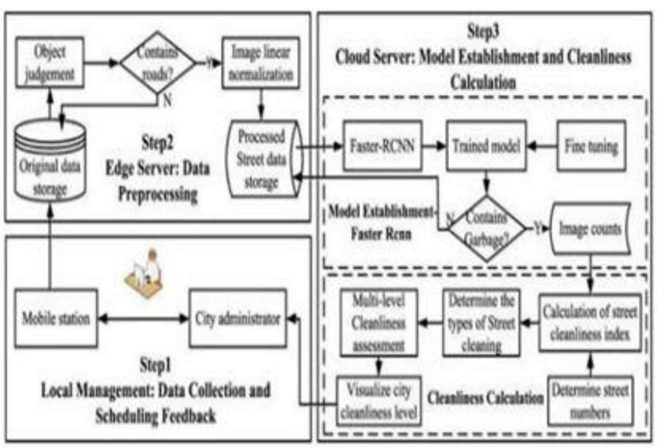

Figure 2. Urban Street Garbage Detection And Cleanliness Assessment.

C) IMAGE DETECTION USING NEURAL NETWORK (R-CNN) :

1) NETWORK STRUCTURE :

The main task of this part is to select and design the network structure. We first input any size pictures to the CNN network to prepare for getting feature map. The CNN network we choose is the ZF-Net proposed by Zeiler and Fergus. The input layer is a 224×224 3-channel RGB image, and the first layer contains 96 convolution kernels. In order to avoid the first layer convolution kernels mixing high-frequency, lowfrequency information and there is no intermediate frequency information. The filter size is set to 7 × 7 in the first layer.Then the maximum pooling operation is performed, the stride is set to 2. The normalized operations are compared, and 96 different feature templates produced are 55 × 55 size.Layer 2, 3, 4 and 5 have similar operations. The layer outputs 256 feature maps of size 6 × 6. Layer 6 and layer 7 are fully connection layers. Finally, the layer 5's result sample is input to the classifier and the bounding box regression.The classifier gives the category of the region proposal, and the bounding box regression gives the position information of the region proposal.

2) NETWORK TRAINING :

After we design the garbage detection network, it is obviously necessary to train the network to learn the characteristics of the street garbage. The specific network training process for our application is divided into four steps:

• RPN pre-training is performed. The RPN is initialized by using ImageNet [18] to train network parameters.The Gaussian distribution with a standard deviation of 0.01 and a mean of 0 are used to initialize the additional layers. Then the end-to-end fine-tuning task is used for the region proposal.

•Fast R-CNN pre-training is performed and using the proposals obtained by the step 1 to perform end-to-end fine-tune training of Fast R-CNN, and the ImageNet model is used to initialize network parameters.

• Re-initialize the RPN training with the network finetuned by Fast R-CNN in step 2 and fix the shared convolutional layers. That is, the learning rate is set to 0.

• The shared convolutional layer is fixed in step 3, and using the region proposal obtained in step 3 to fine-tune the fully connection layer of Fast R-CNN.

3) STREET GARBAGE DETECTION:

In this stage, we use the trained model to detect garbage on the street. These street images are input to the CNN, and then the CNN reflects the features of images to the feature map by calculating. Each proposal region network can calculate a proposal region corresponding to each other. The input images generate 300 region proposal boxes. Then the classification layer and the regression layer display the region proposal box where the garbage is located. Here, we set a counting function. As shown in formulae 2, every time, a region proposal box is generated, and the bounding box is automatically counted once. That is, the value of the count function is incremented by one and finally, we count the categories and quantities that are detected in the region proposal box.

D. MULTI-LEVEL CLEANLINESS ASSESSMENT MODEL:

Based on the layered model, the cleanliness values of the city streets are evaluated in five levels below.

Definition 1: City ={City, Area, Block, Street, Point} where

•City is the geographical area of a city.A city corresponds to one map.

• Area is an internal part of a city. Usually, a city map is divided into many areas.

• Block is a part of an area. Usually, an area is divided into many blocks.

• Street is composed of roads divided into several blocks in the city. Each street belongs to one corresponding block, and each street has a number of grid points.

Every area has a corresponding number and these numbers represent how many areas divided there are. For example, there are 13 administrative regions in Nanjing. Consequently, this city has 13 numbers. Jiangning District is numbered 1 and Qinhuai District is

numbered 13. Similarly, every area is divided into different blocks. The number of sub administrative regions determines the number of blocks. For example, there are 10 sub-administrative regions in Jiangning District. Consequently, this area has 10 corresponding num bers. Following this way, other layers are also numbered similarly. Color represents the cleanliness level of every layer. Area Value (AV) below is indicated with an average of results from each block within the area.

V. CALLENGES IN EXISTING SYSTEM AND PURPOSE OF

• The current system has not been automated and thus lacks efficiency

• This is evident from the growing waste on the streets and other public areas.

• There is no authority to keep an eye on the officials in charge of cleanliness.

• The proposed system will increase efficiency exponentially as well as serve as a checkpoint to ensures the officials are actually working.

• The current system is manual and displays lethargy. Automating it will ensure cleanliness and also promote a sense of accountability.

VI. METHODS

Geo-Spatial Local Classification Schme (LCS)

1. REGION DIVISION

Ideal for Indian localities

Each city/ state/region/ is divided into smaller localities and smaller subregion are formed and for each subregion different CNN models are trained with tuning then according to the specific region.

2. TRAINING MODELS

Locally trained models are generated and then these models are used to create a structure in which each geotagged models. Optimally we can create locally trained models for each locality using grid or Quadtree. Each locally trained model is using CNN GoogleNet which has least error rate of 43% compared to AlexNet and BerkleNet.

3. VISUALIZATION

Once the system is trained and tested with maximum accuracy the detected levels of cleanliness can then be used further to map the hotspots of cleanliness on the map by using basicvisualization techniques. These hotspots can be used to trigger the authorities about localities with high waste index. So once the user uploads a geotagged street image, with help of that image the locality will get classified into cleanliness levels.

VII. CONCLUSION

The new result is estimation of several approaches in image recognition and classification and their application to empty containers recognition and sorting in Reverse Vending Machine. Different existing Networks of CNN or self designed and trained networks can be used and accuracies can be tested to get best results and used in the final system.

Hence, Street Cleanliness using geotagged images is a helpful solution to the problems faced by authorities in day to day life. Hence, a system will help authorities to collect, sort, identify various waste types(PET, can).

LeNet training can be more efficient if we use 56x56 and higher resizing of training images. Use of double LeNet models each of 2 classes gives a more efficient output than single model of 3-6 classes.

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