Urban Street Cleanliness Assessment Using Mobile Edge Computing And Deep Learning

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Abstract- *During the process of smart city construction, city 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 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 personnel effectively.*

Keywords- Smart cities, street cleaning, garbage detection, deep learning, mobile edge computing

I. INTRODUCTION

A smart city is an urban area that uses state-of-the art technologies such as the Internet of Things (IoT), Cloud computing and other information technologies to manage and assess there sources and environment of a city in an efficient way. The smart city concept integrates information and communication technology, and various physical devices connected to the network to optimize the efficiency of city operations and services. However, due to the rapid development of a smart city, city managers are facing huge challenges in how to develop and maintain urban infrastructure. Street cleanliness represents the spiritual outlook and humanistic atmosphere of a city. Keeping the streets clean is good for the development of modern cities. Currently, many major cities regard urban street cleanliness as one of the primary tasks of urban civilization. If the urban street cleanliness level does not pass the pre-defined standard, it will have a serious effect on citizen's satisfaction and also affect At present, the large number of streets makes the amount of garbage on streets uncontrollable. Meanwhile, the process of garbage detection on streets is not automated and always requires human intervention at almost every level. Citizens check the location of garbage manually and submit reports to city administrators, then city administrators arrange nearby city personnel to sweep garbage. Some cities even set up cameras at the crossroads of the streets to see if there is any garbage in the area. However, these manual solutions cannot grasp garbage cleanliness of all the streets of the city in time. For this reason, researchers around the world are studying automated approaches, using a cleaning vehicle with cameras to capture the streets regularly and collect street information, such as street pictures, geographical location, date and time. Besides, existing object detection algorithms are used to detect images in the remote cloud platform. Finally, the detection results are sent to the city managers for decision making.

II. LITERATURE REVIEW

[1] S. Zygiaris., "Smart city reference model: Assisting planners to conceptualize the building of smart city innovation ecosystems", The objective of this paper is to address the smart innovation ecosystem characteristics that elucidate the assembly of all smart city notions into green, interconnected, instrumented, open, integrated, intelligent, and innovating layers composing a planning framework called, Smart City Reference Model. Since cities come in different shapes and sizes, the model could be adopted and utilized in a range of smart policy paradigms that embrace the green, broadband, and urban economies. These paradigms address global sustainability challenges at a local context. Smart city planners could use the reference model to define the conceptual layout of a smart city and describe the smart innovation characteristics in each one of the six layers. Disadvantage is There is no information about cleanliness assessment.

[2] U. Aguilera, O. Peña, O. Belmonte, and D. López-de-Ipiña., "Citizen centric data services for smarter cities", Smart Cities use Information and Communication Technologies (ICT) to manage more efficiently the resources and services

offered by a city and to make them more approachable to all its stakeholders (citizens, companies and public administration). In contrast to the view of big corporations promoting holistic "smart city in a box" solutions, this work proposes that smarter cities can be achieved by combining already available infrastructure, i.e., Open Government Data and sensor networks deployed in cities, with the citizens' active contributions towards city knowledge by means of their smart phones and the apps executed in them. In addition, this work introduces the main characteristics of the IES Cities platform, whose goal is to ease the generation of citizen-centric apps that exploit urban data in different domains. The proposed vision is achieved by providing a common access mechanism to the heterogeneous data sources offered by the city, which reduces the complexity of accessing the city's data whilst bringing citizens closely to a prosumer (double consumer and producer) role and allowing to integrate legacy data into the cities' data ecosystem. Disadvantage is It is suitable for the text based data collection. to various spots in the city and manually verifying if the street needs cleaning and taking action if required. However, this method is not optimized and demands a huge investment in terms of time and money. This paper introduces an automated framework which addresses street cleaning problem in a better way by making use of modern equipment with cameras and computational techniques to analyze, find and efficiently schedule clean-up crews for the areas requiring more attention. Deep learning-based neural network techniques can be used to achieve better accuracy and performance for object detection and classification than conventional machine learning algorithms for large volume of images. The proposed framework for street cleaning leverages the deep learning algorithm pipeline to analyze the street photographs and determines if the streets are dirty by detecting litter objects. The pipeline further determines the degree to which the streets are littered by classifying the litter objects detected in earlier stages. The framework also provides information on the cleanliness status of the streets on a dashboard updated in real-time. Such framework can prove effective in reducing resource consumption and overall operational cost involved in street cleaning. Disadvantage is it is not carried out an urban street cleanliness assessment.

[4] L. J. C. Brinez, A. Rengifo, and M. Escobar., "Automatic waste classification using computer vision as an application in colombian high schools", this paper presents a system to classify waste in an automatic way as an application of computer vision in Colombian high schools. This is in order to introduce this kind of topics into the high school education, making young students learn about things in this field that could facilitate the student performance later in university. Such process is consistent with the standards proposed by the Colombian government, and developed in the In Andres Bello educative institute or high school. The teaching topics in technology are modified according to an application of computer vision that classifies waste in three stages. The first one corresponds to the image acquisition system, the second one is the image processing module, and the third one is the robotic classification module. The system developed classifies three kinds of waste with a performance over 70 percent, which indicates that the system could be used in scholar contexts to teach people about the waste classification process, and to get students involved in research projects. Disadvantage is it is limited to the school environment.

[3] C. Balchandani, R. K. Hatwar, P. Makkar, Y. Shah, P. Yelure, and M. Eirinaki., "A deep learning framework for Smart Street cleaning", Conventional street cleaning methods include street sweepers going [5] Taylor Buck, N. and White, A., "Competitive urbanism and the limits to smart city innovation: The UK future cities initiative", the technological vision of smart urbanism has been promoted as a silver bullet for urban problems and a major market opportunity. The search is on for firms and governments to find effective and transferable demonstrations of advanced urban technology. This paper examines initiatives by the UK national government to facilitate urban technological innovation through a range of strategies, particularly the TSB Future Cities Demonstrator Competition. This case study is used to explore opportunities and tensions in the practical realisation of the smart city imaginary. Tensions are shown to be partly about the conjectural nature of the smart city debate. Attention is also drawn to weakened capacity of urban governments to control their infrastructural destiny and also constraints on the ability of the public and private sectors to innovate. The paper contributes to smart city debates by providing further evidence of the difficulties in substantiating the smart city imaginary. Disadvantage is it doesn't support for image data, it consumes more time.

III. METHODOLOGIES

This paper consists of 6 modules, which are,

1. DATA COLLECTION: During the data collection stage, the main task is to collect 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 collected includes mainly two parts: street image information and local management information. For street image information, the cleaning vehicle equipped with a high-resolution camera is shot on each street according to the administrator'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 administrator responds in time and arranges cleaning staff to clean.

2. MOBILE EDGE PROCESSING: We use edge servers to complete two tasks. The first task is to improve the performance of the entire system. During this stage, when object detection is performed, image data collected is first input into the CNN network and then the size of pictures are modified to the suitable size. We believe that if image data is preprocessed in the edge server, it can reduce the overall time of the entire system. We design an algorithm to modify the size of images automatically in the edge server when image data is transmitted to the edge server. The street image data preprocessing in mobile edge environment. Edge server j receives street image data from mobile device i. We define t_{i-j} as the time street image data transferred from mobile device i to edge server j. t_{j-c} is the time from edge server j to cloud c. t_{edge} is described as the time picture processed in the edge server.

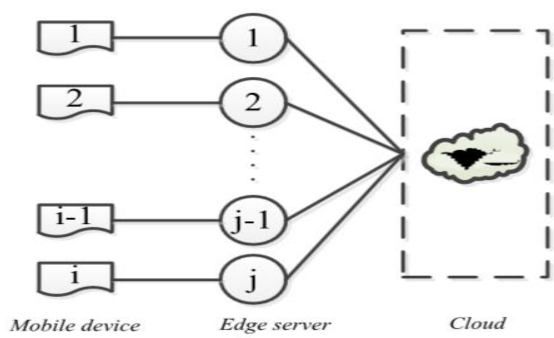

FIG 1: Mobile edge processing.

3. IMAGE DETECTION USING NEURAL NETWORK (R-CNN): Faster R-CNN algorithm. Below, we describe the detection algorithm in detail from three parts: network design, network training, and street garbage detection.

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 224×2243-channel RGB image, and the first layer contains 96 convolution kernels. In order to avoid the first layer convolution kernels mixing high-frequency, low frequency 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 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 performed, the stride is set to 2. The normalized operations are compared, and 96 different feature templates produced are 55 × 55 size. Layer 2,3,4and 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.

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 Image Net 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 Image Net model is used to initialize network parameters.
- Re-initialize the RPN training with the network fine tuned 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.

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. 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.

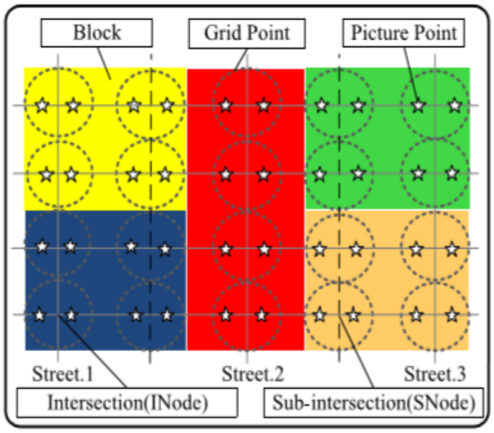

FIG 2: Street garbage detection.

Design: Design consists of three levels

In the first level it escribes the overall process of this project. we are passing street image as a input the system will classify the type of garbage and assist to the city manager to clean garbage. In the second level it describes the first stage process of this project. we are passing street image as a input the system will preprocess and remove noise and extract features. In the third level Describes the final stage process of this project. we are passing extracted features from level 1and trained data as a input the system will classify the types of garbage using RCNN model.

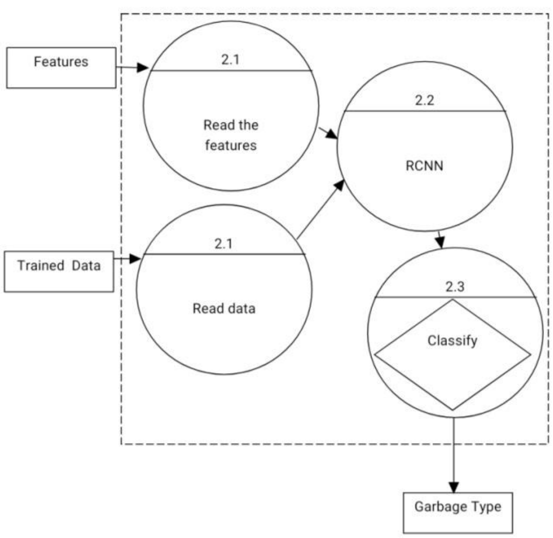

FIG 3: Dataflow Diagram

Algorithm used is Faster Region-Convolutional Neural Network

We propose a novel urban street cleanliness assessment model using mobile edge computing and deep learning. The high-resolution cameras installed on the vehicle collect street images. Meanwhile, the edge servers located at the edge of the network are used to store and process the street image information temporarily, and then these processed data is transferred to the remote cloud center through city network. Faster R-CNN (Faster Region- Convolutional Neural Network) is used to identify street garbage categories and count the number of garbage. The results are sent to the street cleanliness level assessment model for evaluation. Finally, the approach visualizes street cleanliness level, which provides convenience for city managers to arrange cleaners in time.
We describe a novel edge computing framework. There is an edge layer between cloud servers and mobile terminals. We configure edge servers (micro-data centers) to handle a part of services from mobile devices at the edge layer. It can also store data resources temporarily and transmit data resources in time.

Faster R-CNN is used to identify street garbage categories and count the number of garbage. A multi-layer assessment model across different layers is used. The whole city is divided into 5 layers: city, area, block, street, point. Every layer will carry out street cleanliness calculation.

We provide a public garbage data set1 collected by ourselves, which can be used as a benchmark for evaluating street garbage detection and street cleaning. Furthermore, The application validates the feasibility and usability of the proposed approach. The results are useful for improving and optimizing city street cleanliness.

I. 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.

Working process of RNN: Combined with region suggestions and region scores, classification probabilities and bounding box regression are trained, the classification scores of the region are output, and the results are finally tested. Faster R-CNN is considered as one of the most precise image detection approaches. It has high detection accuracy and speed.

• The image is input to the Convolutional neural network, and spread to the shared Convolutional layer to get the feature map;

• The feature map extracted by the shared Convolutional layer generates a suggestion window through RPN network, and gives region suggestions and region scores;
• The feature map of the first step is input to the pooling layer in Fast R-CNN to extract area features.

IV. RESULT

The result shows the output image with classification of garbage using Faster R-CNN in which the output image consisting of blue and green boxes around the garbage to show the wet and dry waste separately.

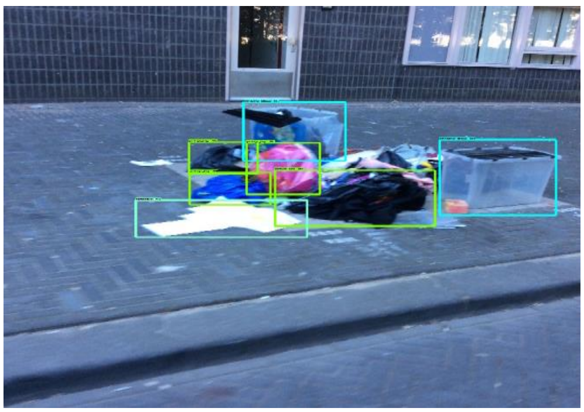

FIG 4: Classification of garbage present.

V. CONCLUSION

The development of novel technologies has driven a number of cities into the way to smart cities. Street cleanliness is one of the concerns for smart cities. Consequently, this paper proposes a novel urban street cleanliness assessment approach using mobile edge computing and deep learning. A visual street cleanliness road diagram is presented; such an automated system can help city administrators to know the cleaning state of the street easily.

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