A System for Real-time On-street Parking Detection and Visualization on an Edge Device

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***Abstract*—In recent years, street parking in prohibited areas has become a serious social problem, particularly in metropolitan and tourist areas where there are many on-street parked cars. In addition, because on-street parking can cause traffic congestion and accidents, real-time detection is considered necessary. In previous studies, fixed-point cameras have been mainly used for traffic control; however, a major disadvantage of these systems is their limited detection area. In this study, we developed a system that can detect and visualize on-street parking in real-time using video data captured by dashboard cameras, which have become widely used in recent years. We created a learned model to detect on-street parking and to recognize cars using an edge device. By displaying the location information of on-street parked cars on a map, their location can be visualized. This system could be used to obtain statistical data for crackdowns on on-street parking and to identify areas where on-street parking occurs.**

***Index Terms*—street parking, edge device, real-time sensing, dashboard camera, object detection**

I. Introduction

In recent years, street parking in prohibited areas has become a serious social problem, especially in metropolitan and tourist areas. According to a survey on street parking conducted by the Traffic Bureau of the National Police Agency (Japan) in 2019, the number of on-street parked vehicles in prohibited areas in the special wards of Tokyo was approximately 52,700 [1]. Illegal street parking is not only hazardous, but it can also cause a variety of other traffic problems, such as traffic jams and rear-end collisions.

To deal with on-street parking and its related problems, the extension of restricted parking zones and the implementation of time-limited zones are being considered. However, these measures are not a sustainable solution and they may complicate existing problems. In addition, they require large-scale cooperation from the government and administrative agencies, which is very costly and time-consuming [2]. A previous study proposed a system that uses multiple fixed-point cameras installed in the city to detect on-street parking. However, fixed-point cameras can only cover a limited area.

In this study, we sought to develop a system capable of detecting on-street parked cars more efficiently and widely than fixed-point cameras in real-time using dashboard camera video systems, which are increasingly being used in general vehicles [3]. A dashboard camera records every situation in a city and stores an overwhelming amount of information. Also, it is more efficient than traditional traffic monitoring methods because it is not limited by area. On the other hand, uploading all the collected videos to the cloud for analysis is problematic in terms of the loads placed on communications networks, communication cost, and real-time performance. To reduce communication costs, we sought to determine whether or not the vehicle has been parked illegally in real-time using an edge device that has been installed in the vehicle and only uploads parking-related information to the cloud. In this study, we also propose a real-time visualization system for determining the location of on-street parked cars using a video-learning model and a dashboard camera. This information is captured and processed on an edge device mounted on a vehicle.

The remainder of this manuscript is organized as follows. In Section 2, research related to the detection of on-street parking is reviewed and the problems associated with existing methods are summarized. Section 3 defines on-street parking and describes the issue of on-street parking in Japan. Section 4 provides an overview of a system for real-time detection and visualization of on-street parking. In Section 5, a method for on-street parking detection on an edge device is described. In Section 6, we describe the accuracy of instances of on-street parking by the model, and the speed required for recognition and processing on the edge device. In Section 7, a method for visualizing the location information of on-street parked vehicles is described. Finally, Section 8 presents the conclusions of this thesis and discusses future directions of this research.

II. Related Research

In this section, we review studies and existing technologies related to on-street parking. Although numerous studies have been conducted on on-street parking to date, few have examined how on-street parking can be detected [4] [5] [6].

Wen et al. proposed a system for vehicle recognition, location detection, and classification using Mobile Laser Scanning (MLS) point clouds [7]. Briefly, their method involved segmenting the recognition targets into point clouds and then fitting a vehicle recognition model to each target. The acquired information, such as position and orientation, was then compared with data acquired at different times to estimate the consistency of the features with their durations. The system was highly accurate in recognizing and classifying vehicles and detecting changes, but recognition was limited by the reach of the MLS and requires scanning through cars parked

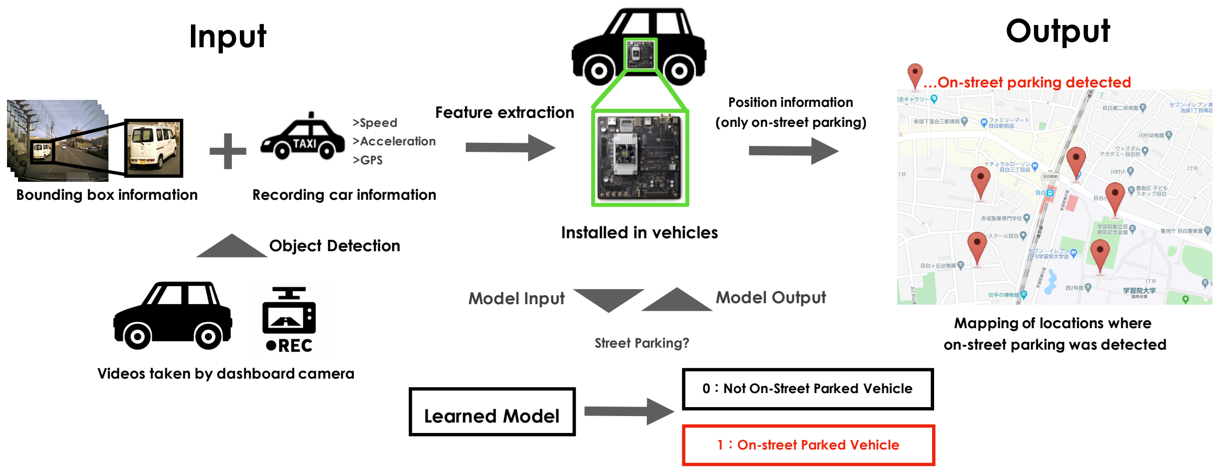

Fig. 1. Overall configuration of the proposed system

along the side of the street. Further, real-time recognition is difficult because of the need for different time data.

Xie et al. proposed a system for detecting illegal parking based on the Single Shot MultiBox Detector (SSD) algorithm [8]. SSD is used to detect and track vehicles in the region of interest and count the number of static objects. However, this system uses fixed-point camera images and the detection area is limited. In addition, it is difficult to judge whether a vehicle is engaged in on-street parking or waiting at a traffic signal (all stationary vehicles are counted). All of the abovementioned methods have limitations in terms of detection areas and detection conditions, making them suboptimal. In practical applications, on-street parked vehicles are spread out throughout the city and conditions vary. In this study, we propose a method for lane- and past-information-independent detection that uses video captured by dashboard-mounted cameras.

Specifically, we sought to develop a system that can efficiently and accurately make real-time decisions regarding on-street parking using an edge device, and to visualize the location of on-street parked vehicles to resolve the problems highlighted in the studies described in this section.

III. Street Parking

In this section, we discuss on-street parking. Specifically, we examine the distinguishing characteristics of vehicles engaged in on-street parking from images captured by a dashboard camera. We then define the common characteristics of on-street parking. Based on these definitions, we determine whether or not a vehicle is parked in the street.

A. Street Parking in Japan

On-street parking in prohibited areas is widespread in Japan, particularly in urban and tourist areas. An example of on-street parking is shown in Fig2. A vehicle parked on the left side of a lane, regardless of the number or width of lanes, is considered to be engaged in on-street parking. A wide variety of vehicles engage in on-street parking, and detailed descriptions of such situations are described in the following section.

Fig. 2. Street parking in Japan (red frame)

B. Definition of on-street parking

The common characteristic of on-street parking is define as a condition. This definition makes it possible to determine whether or not a vehicle is engaged in on-street parking. Further, in the conditions described below, it is assumed that the target vehicle is stationary.

1) Determination by brake lights: One of the characteristics of on-street parking is if the vehicle is stationary on a road and the vehicle's brake lights (tail lights) off. Normally, the brakes of a vehicle need to be applied in order for the vehicle to stop at a traffic light or pause in the road. A manual transmission (MT) car may maintain the vehicle in a stationary position without applying the brake, but these situations have become almost non-existent in recent years as automatic (AT) cars now account for most car sales. Furthermore, from a safety point of view, stopping without turning the brake lights on is dangerous because of the risk of rear-end collisions and other problems. Thus, if a vehicle on the road is stationary and its brake lights are not on, then that vehicle is considered to be an on-street parked vehicle.

2) Determination by hazard lights: One of the conditions that need to be met for on-street parking is if the vehicle is stopped at the side of the road with its hazard lights on. Many street-parked cars turn on their hazard lights to indicate that they are parked on the street. Most of these stationary cars have only their hazard lights on, and their brake lights off. Although hazard lights are often used in situations other than those for which they are intended, many vehicles parked on the side of the road with their hazard lights on are considered to be on-street parked vehicles.

3) Determination by lane occupancy: Another condition that needs to be met for on-street parking is if the lane occupancy is low, or if the front and back tires of the vehicle are near or extend beyond the line indicating the outer edge of the roadway opposite the centerline. This happens because vehicles park on the street and stop at the side of the road. Street parking occurs at the left side of the travel lane and the distance between the vehicle's tires and the centerline of the lane is typically far. Therefore, for on-street parking, which is the object of detection for the video on the dashboard camera, increased attention is given to the area left of center in the video. Therefore, if the vehicle is in the leftmost area of the video frame and the lane occupancy is low, or if the vehicle's tires straddle the line that demarcates the outer edge of the roadway, it is considered to be an on-street parked vehicle.

IV. System Overview

In this section, we describe the proposed system. An overview of the system is shown in Fig1. The input consists of dashboard camera video and the data of the vehicle (recording car) from which the video was recorded. Also, when installed in the vehicle, the inputs consist of a camera video connected to the edge device, and the sensor values. The output is visualized on a map and all of these processes are performed entirely on the edge device.

A. System Requirements

We describe the requirements for a real-time on-street parking detection system using an edge device. The three main requirements of the proposed system are listed below.

- A simple edge device that can be installed in a vehicle
- Real-time processing for object recognition and parking-position acquisition
- Ability to recognize a wide range of on-street parking cars with high accuracy

For the first requirement, the device must be simple so that it can be installed in a vehicle to perform on-device processing. Previous studies experienced problems with equipment, such as the need for large equipment to be installed in vehicles [4]. In this study, we used an NVIDIA Jetson platform, a compact publicly available, vehicle-mountable device to fulfill the first requirement. Sensing is performed by a simple device that mimics a dashboard camera that can capture video, vehicle acceleration, and GPS information by connecting a camera to a sensor module.

For the second requirement, real-time recognition and rapid location of parking positions are required to accurately identify instances of on-street parking. Previous studies experienced problems with real-time processing, such as when scenes need to be compared with images that have been captured previously [9]. In this study, scene recognition and processing was performed on the device to satisfy the second requirement. We used a lightweight recognition model and a learned decision model to restrict processing to on-street parking positions only, while taking pictures using a device similar to a dashboard camera. The GPU-equipped device increases the processing speed and reduces the processing load by converting image data to text data and then inputting them into the decision model. Also, we reduced communication loads by uploading the location information of on-street parked vehicles only to the real-time database. By reducing the communication load of each process, we can achieve real-time performance from vehicle recognition to visualization.

For the third requirement, it was necessary to identify vehicles with high accuracy, even in a wide range of complex situations, from a moving vehicle. Previous studies experienced problems with vehicle identification, such as only being able to recognize a limited range of and number of vehicles [8]. In this paper, to satisfy the third requirement, we analyzed many dashboard camera videos provided by a taxi company and used them to create a decision model capable of learning vehicle data captured in a variety of situations to make accurate decisions. Also, we intend to transfer-learn the object recognition model to improve recognition accuracy.

B. System Configuration

The camera and sensor module was attached to a recording device to record and acquire various types information. Then, real-time vehicle recognition was performed using an object recognition model. The coordinates of the Bounding Box (BB) that are assigned to a vehicle at the time of recognition are acquired in chronological sequence and converted to text data for each vehicle. In addition, the speed and acceleration of the device with the BB information is also calculated and stored chronologically. With this information as inputs, we used a trained model for on-street parking decisions. Using the trained model, if a vehicle is on-street parking, then the location information of that vehicle is stored for mapping. The entire flow from recognition to processing is performed on the edge device.

C. Devices

The platform used was a Jetson TX2[1], an embedded single-board computer produced by NVIDIA. The specifications of the Jetson TX2 platform are given in table I. The Jetson TX2 was selected as the AI computing device for this study because of its portable size, light weight, and because it is a GPU edge IoT device. Also, using the Development Tool Kit for the Jetson TX2, a variety of connectors can be supported. In automotive devices that are intended for use with sensor modules, scalability was also a consideration.

[1]Jetson:https://www.nvidia.com/ja-jp/autonomous-machines/embedded-systems/

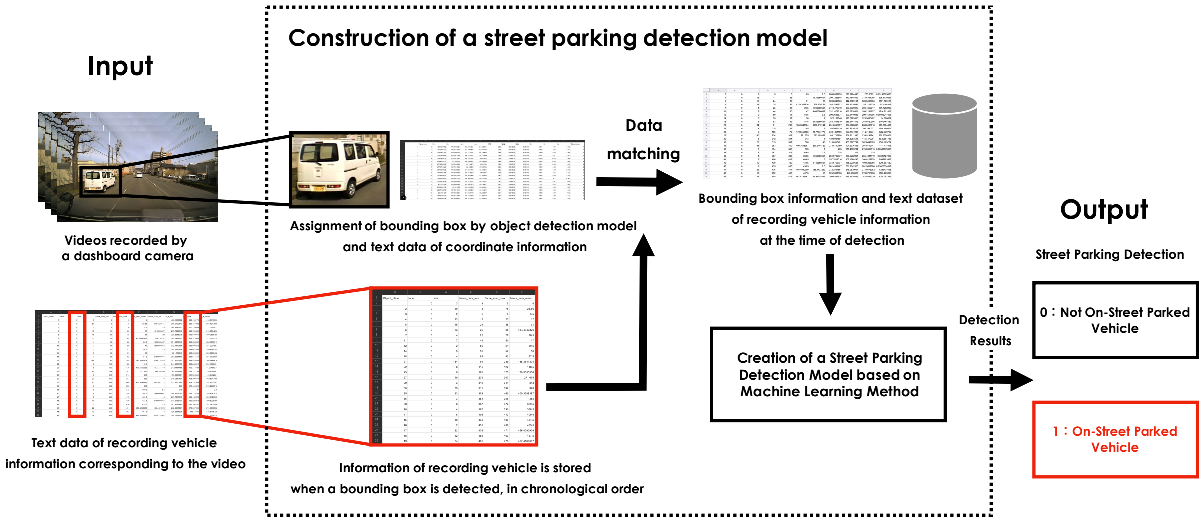

Fig. 3. Constructing a street parking decision model

TABLE I
DEVICE SPECIFICATIONS

Item	Jetson TX2
Size	87×50mm, 170×170mm(board)
Weight	85 g (core)
OS	Ubuntu
CPU	Dual-Core NVIDIA Denver 2 Quad-Core ARM Cortex-A57
GPU	256-core NVIDIA Pascal™ GPU with 256 NVIDIA CUDA cores
Memory	8GB 128-bit LPDDR4 Memory3
Connector	USB, HDMI, SD, Ethernet
Bluetooth	Bluetooth
Wireless LAN	IEEE802.11ac
Power	5.5-19.6V
Consumption	7.5W|15W

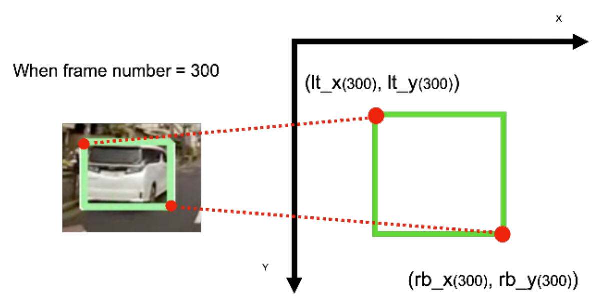

Fig. 4. BB coordinates

V. AN ON-STREET PARKING DECISION MODEL

In this section, we describe the construction of a model for detecting on-street parking. The model building procedure is shown in Fig3. To decide whether the vehicle is parked in the street, we used an object recognition model YOLOv3 to acquire information such as the coordinate value of the BB and the acceleration of the recording vehicle (device) at the time [10]. We then performed feature generation and created a training model, and made a decision using the model.

A. Data

A total of 1,765 vehicles were used to train the model using 12 videos (about 24 minutes) captured by dashboard cameras. The original size of the video, which was 1280×720 [px], was resized to 512×288 [px] while maintaining the 16:9 aspect ratio to reduce the computational load. Most of the video was captured in Kyoto Prefecture on sunny and cloudy days. A breakdown of the video results revealed that there were 56 on-street parked vehicles and 1,709 vehicles that were not parking on the street. However, this ratio varies depending on the time of year and time of day.

B. Features

The features used in this study are listed in table II. For the features, we used the coordinate information of the BB that was assigned to the recognized vehicle, and the speed and acceleration of the recording vehicle (device). The coordinate values of the BB, as a feature, are shown in Fig4. A total of four BB coordinates are captured: the upper-left and lower-right X- and Y-coordinates. These coordinates were used to create features, such as width, height, and area for each recognized car. The maximum, minimum, mean, and variance of the coordinates, as well as the vehicle information were then used to create 45 features. We constructed a trained model using the features.

C. Constructing a learned model

For the analyzed data, we sampled cars randomly to perform equilibration. The ratio of off-street and on-street parking was balanced and trained by Random Forest (RF) and Logistic Regression (LR) methods. We used scikit-learn, a Python machine learning library, to construct the model. For the model parameters, we used the default settings of the scikit-learn library [11]. The Hold-out and Stratified K-fold Cross-Validation methods were used for data set partitioning and

TABLE II
FEATURES

Domain	Features name
Frame	Number
Bounding Box	Top left X-coordinate
	Top left Y-coordinate
	Bottom right X-coordinate
	Bottom right Y-coordinate
	Width
	Height
	Area
Recording car	Speed
	Acceleration(x,y,z direction)

TABLE III
RECOGNITION RESULTS FOR EQUILIBRIUM DATASETS

Method	Accuracy	Precision	Recall	F-measure
RF-holdout	0.94	1.00	0.88	0.93
RF-5-fold	0.92	0.92	0.92	0.92
LR-holdout	0.90	1.00	0.81	0.90
LR-5-fold	0.88	0.93	0.82	0.87

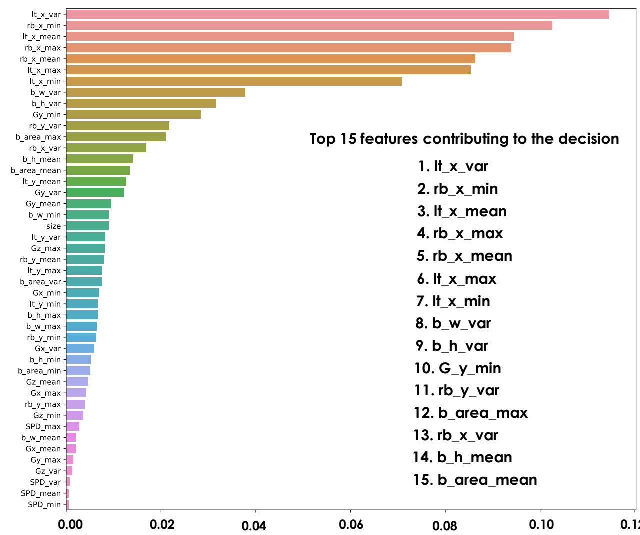

Fig. 5. Feature importance

validation. In this study, the ratio used for the holdout method was set to 7:3 and the value of K for the K-split validation method was set to 5.

VI. ACCURACY AND ANALYSIS/PROCESSING SPEED

In this section, we describe the recognition accuracy of on-street parking by a trained model. We also examine the speed of video analysis for creating a learning model and the processing speed required to recognize instances of on-street parking using the learning model.

A. Recognition accuracy

The recognition accuracy of the trained model described in the previous section is shown in table III. The maximum F-value of 93% was confirmed by the RF holdout method. As a whole, all four results showed F-values of approximately 90%, suggesting that it is possible to recognize on-street parking using the model. The importance of the features in the RF-holdout with the highest F-value is shown in Fig5. The contribution of features to the decision of on-street parking, especially those related to the X-coordinates of the BB, were high. Since a characteristic of the position of the street parking, and the position of the recording vehicle is considered to have a marked effect on the decision.

B. Analysis speed

The analysis of the dashboard camera videos was performed using the Google Colaboratory (Colab) GPU environment, which had an average analysis speed of 15 [fps] for 12 videos. The PC used was a MacBook Pro 2018 with 8 GB of memory, and the processing time was approximately 1.5 [fps].

C. Processing speed

We used three object recognition models, YOLOv3, YOLOv3-tiny, and YOLOv4 and ran them on PC and Jetson TX2 platforms to determine the time required, in frames per second (fps), for recognition and processing using the trained model [12]. The PC environment was the same as that described in the previous section. The results are shown in Table IV. The target video was captured on a main street and multiple vehicles were detected successfully. The original video was 1280×720[px]* and was resized to 1024×576[px]** and 512×288[px]***. The fps was calculated as the average of the 10th, 20th, and 30th frames of the movie. The results showed that YOLOv3-tiny achieved a near-real-time recognition speed on both PC and Jetson TX2 platforms. No significant differences in processing speed were observed between platforms in the other two models. Reducing the video resolution improved the processing speed, especially for YOLOv3-tiny. In the video, the time required by the Jetson TX2 was approximately 7 [fps], which is sufficient for real-time recognition and processing. We therefore selected YOLOv3-tiny for recognition and processing on the edge device, and we performed real-time object recognition by reducing the resolution of the acquired video.

VII. LOCATION VISUALIZATION

In this section, we describe the visualization of on-street parking. Specifically, the process involved in acquisition of location information of vehicles that have been identified as being parked in the street and their visualization on a map. Visualization makes it easy for a third party to identify the location of an on-street parked vehicle and to take effective countermeasures. The procedures from acquiring location information to visualizing data are shown in Fig6.

First, location information of on-street parked cars is obtained and stored in a real-time database. To reduce the communication load on the database, location information is uploaded as text data. We also reduced the frequency of communication by updating the database only with newly

TABLE IV
RESULTS OF RECOGNITION AND PROCESSING SPEED COMPARISONS

Model \ Device	PC	Jetson TX2
YOLOv3	1.73 [fps]* 1.79 [fps]** 1.89 [fps]***	1.54 [fps]* 1.67 [fps]** 1.90 [fps]***
YOLOv3-tiny	8.14 [fps]* 9.10 [fps]** 10.89 [fps]***	3.84 [fps]* 4.89 [fps]** 6.99 [fps]***
YOLOv4	0.63 [fps]* 0.63 [fps]** 0.66 [fps]***	0.81 [fps]* 0.81 [fps]** 0.90 [fps]***

* 1280×720 [px]
** 1024×576 [px]
*** 512×288 [px]

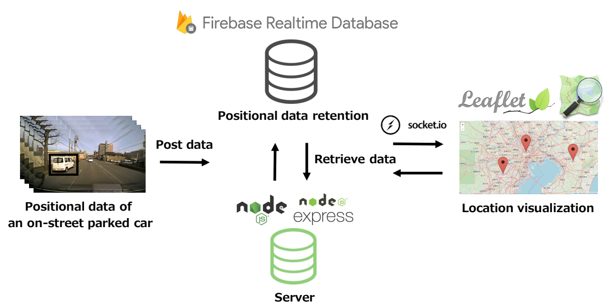

Fig. 6. Visualization of on-street parking location

detected vehicle data. The stored location information is sent to a webserver and visualized on a map in real-time using socket.io.

The on-street parking location visualization system can be installed in multiple vehicles for more accurate and extensive coverage. Previous studies have experienced difficulties disseminating location information to multiple vehicles. This system provides everything from on-street parking recognition to location visualization using a single system, and can be installed in multiple vehicles. However, vehicles in traffic jams or vehicles waiting at traffic lights may be misidentified as vehicles that have parked in the street. In such situations, detection using several independent systems operating simultaneously could increase the accuracy of recognition and visualization. For example, if the first system identifies the on-street parking position and the second system subsequently detects on-street parking at the same position, then the vehicle is not considered to be in a traffic jam or waiting at a traffic light. We aim to increase the effectiveness of the system by simultaneously visualizing independently obtained on-street parking data on a map.

VIII. CONCLUSION

In this study, we proposed a real-time visualization system for detecting the location of on-street parked cars using a model that learns from video captured by a dashboard camera, and then recognizes and processes the video on an edge device installed in the same vehicle. The study focused primarily on the following aspects of the system: (i) model construction by learning from dashboard camera video, (ii) processing the video using the learned model on an edge device, and (iii) visualization of the on-street parking location.

We confirmed that the trained model recognized on-street parking with an F-value of 93% and a processing speed of 7 [fps] on the edge device.We also implemented a flow from recognition to visualization of on-street parking using a common edge device. From the above, we considered that this study was able to improve the three problems that were not solved in the related studies mentioned above.

In the future, it will be necessary to increase the number of training samples to provide a more versatile decision model. Improvement of the processing flow is also necessary to improve real-time recognition and decision making. As a next step, the entire system will be mounted on a vehicle to streamline the process from recognition to visualization.

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