A 5G Cloud Platform and Machine Learning-based Mobile Automatic Recognition of Transportation Infrastructure Objects

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***Abstract*—Crack recognition is important in periodic pavement inspection and maintenance. The wide application of image recognition technology in daily inspection and maintenance makes the health monitoring of asphalt pavement defects more effective, intelligently, and sustainably. In this study, a mobile automatic system integrating 5th-generation wireless communication technology (5G), cloud computing and artificial intelligence (AI) was proposed for transportation infrastructure object recognition. The original dataset contained 344 images of pavement defects, including longitudinal cracks, transverse cracks, alligator cracks, and broken road markings. Three lightweight algorithms for automatic pavement crack identification were used and compared, including MobileNetV2, ShuffleNetV2, and ResNet50 networks respectively. The results showed that the model based on ShuffleNetV2 achieved the best overall predictive accuracy (ACC=95.52%). A mobile automatic monitoring system based on the cloud platform and Android framework was then established. With the help of 5G technology, the 'cloud-network-terminal' interconnection can be achieved to provide fast and stable information transmission between transportation infrastructure and road users. The proposed system provides an engineering reference for the transportation infrastructure inspection and maintenance using the 5G communication technology.**

***Index Terms*—5G cloud platform; Android detection system; Lightweight model; Mobile automatic recognition; Transportation infrastructure objects recognition.**

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I. Introduction

For advanced technologies such as 5G, the Internet of Things (IoT), and big data analysis technologies such as cloud computing and Artificial Intelligence (AI), the integration of them can significantly contribute to the development of smart transportation. Especially, smart functions can be achieved by connecting roads, vehicles and users with multidimensional perception and information exchange, such as transportation infrastructure monitoring, traffic real-time information control and automatic driving decision. To provide long-term services, the quality monitoring of transportation infrastructures, like road surfaces, have become a significant problem for engineers.

The traditional method is to use the manual visual recognition of road surface defects. However, there exist limitations of low efficiency, high cost, and low accuracy. Thus, engineers have tried to use Convolutional Neural Network (CNN) as a powerful tool for automatic road defects detection, which can automatically extract potential features of images to predict and identify pavement defects with satisfactory accuracy [1-3].

To now, common automatic pavement defect recognition networks are developed based on Deep Convolutional Neural Network (DCNN), which has a complex structure and many model parameters. To improve the training speed and detection efficiency of the model, the lightweight CNN models have been widely studied by engineers [4-5], where the lightweight network has the characteristics of reducing network parameters by compressing the network and can be deployed in the cloud or on mobile devices more flexibly.

Based on the above-mentioned researches, engineers have tried to further develop a more convenient mobile-based system for fast road distress recognition in recent years, where a series of mobile deep learning frameworks, enabling more real-time end-to-end image recognition have been proposed.

Tedeschi [6] developed a real-time Android mobile platform that can identify potholes, longitudinal cracks, and fatigue cracks with an accuracy of over 70%. Zhou et al. [7] used smartphones as sensors to collect road image data and proposed a road surface condition detection system based on CNN with 86.3% accuracy. Dogan et al. [8] used lightweight MobileNetV2 to conduct pixel-level crack identification, which can be applied in mobile systems. Zheng et al.[9] developed a sustainable monitoring system called SmartRoad using self-powered sensors and automatic identification technologies to determine the vehicle-load types. In sum, the realization of a mobile terminal defect identification system makes defect detection more convenient and mobile and can be widely used in transportation infrastructure detection in the future.

In this paper, MobileNetV2, ShuffleNetV2, and ResNet50 lightweight networks based on the convolutional neural network were employed to classify different asphalt pavement objects such as transverse cracks, longitudinal cracks, alligator cracks, and broken road markings, respectively. First of all, the recognition performances of different lightweight networks were compared to find the best classification model. Secondly, with the deployment of the cloud platform and Android application using the 5G communication technology, a real-time transportation infrastructure intelligent monitoring system was developed.

Fig.1 presents the analysis process of the transportation infrastructure objects recognition system in this study. Objects on asphalt pavement crack images collected by various sensors (e.g. smartphones) can be transmitted by a 5G wireless network to a centralized platform for data storage. Then, the Cloud Platform adopts AI-based algorithms to process and analyze traffic infrastructure images and delivers the real-time classification result to road users using an android mobile system.

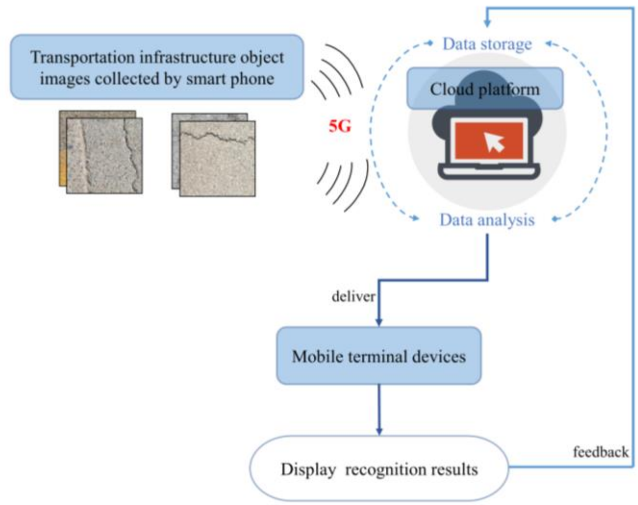


Fig. 1. 5G-based mobile system for transportation infrastructure objects recognition

(a) Longitudinal crack (b) Transverse crack (c) Alligator crack (d) Broken road marking

Fig. 2. Different pavement surface defect image dataset.

TABLE I
ASPHALT PAVEMENT DEFECTS AND OBJECTS DATASET

Class	Longitudinal crack	Transverse crack	Alligator crack	Broken Road marking	Total
Train	81	43	63	21	208
Valid	27	14	21	7	69
Test	26	14	20	7	67
Total	134	71	104	35	344

II. DATA PROCESSING AND ANALYSIS

A. *Image data preprocessing*

The data images adopted in this study were collected from the real asphalt roads around Beijing University of Technology, China and inspections on highways in Jiangsu Province, China. The original RGB image of 3648 * 2736 pixels needs to be pre-processed before input into the lightweight network. The processing steps are as follows: (1) Divide the original image into 16 sub-images equally; (2) Adjust the size of all images to 224 * 224 pixels. Finally, the asphalt defect image dataset of this paper is composed of 134 longitudinal cracks, 71 transverse cracks, 104 alligator cracks, and 35 broken road marking images, with a total of 344 images. The four typical images are shown in Fig.2a (a)~(d) represent pavement longitudinal crack, transverse crack, alligator crack and broken road marking image respectively.

In this paper, the original asphalt defect dataset was divided into the validation set and test set according to the ratios of 60%:20%:20%. The data sets of asphalt pavement objects are shown in Table I.

B. *Deep learning algorithms and analysis*

1) Deep learning methods

To apply lightweight CNN models to mobile terminals, the efficiency of the model should be evaluated first. The usual approach is to compress the network parameters of the trained model. At present, the commonly used lightweight networks have preliminary solve the problems. Besides, to achieve better classification performance, the transfer learning method was applied to transfer the general feature weight parameters from the pre-trained ImageNet-based model [10]. In this paper, the pre-trained MobileNetV2, ShuffleNetV2, and ResNet50 were used to identify the above four types of asphalt pavement objects.

(1) MobileNetV2 network

Like MobileNet, the MobileNetV2network uses Depthwise Convolution and Pointwise Convolution as two convolution steps to improve the training speed by reducing the amount of network weight parameters. On this basis, a Residual Connection is added to form the Inverted Residual Block, which contains an Expansion layer, Depth separable convolution layer, and Projection layer [11] to process images.

In this research, the pre-trained MobileNetV2 model first used a 3*3 convolution and a 3*3 Depthwise Separable Convolution. Then, a total of 19 stacked Inverted Residual Blocks were applied to extract the features of the input images. The expansion factor of the first block was 1, and the others were all set to 6. Each block used several 1*1 and 3*3 convolutions to increase the number of channels of the output features. Then, a 1*1 convolution, a global average pooling layer and a fully connected layer with Softmax activation function were added to reduce the size and channel number of the output image and classify images into requisite object categories.

(2) ShuffleNetV2 network

The ShuffleNetV2 [12] employs Group Convolution and Channel Shuffle to significantly decrease the weight parameters of the model. The model can effectively process images by separating the input image into two channel-dimension branches.

The study adopted ShuffleNetV2 to classify the type of asphalt pavement objects. As shown in Fig.3a, the network first included a 3*3 convolution layer and a max-pooling layer with a stride of 2. Then, there were 3 stages composed of several repeated Shuffle unit modules to ensure the feature map and the number of channels were constant. The repeated time was 4, 8, and 4 respectively for each stage. Finally, 1*1 convolution, global average pooling and full connection were used to output the predicted result.

(3) ResNet50 network

When deeper networks are able to start converging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated and then degrades rapidly. Unexpectedly, such degradation is not caused by over-fitting, and adding more layers to a suitably deep model leads to higher training error [13]. ResNet, short for Residual Network is a specific type network that was introduced in 2015 to solve this problem. The Residual Learning and Identity Mapping by Shortcuts are the key parts in ResNet. [14]. ResNet50 is a 50-layer Residual Network. It includes Plain Networks and Residual Networks. The Plain Networks is mainly inspired by VGG nets: (I) the 48 convolutional layers have 3×3 filters (the layers have the same number of filters for the same output feature map size, and have the doubled layers for the halved feature map size); (II) one down-sampling layers that have a stride of 2; and (III) the network ends with a global average pooling layer and a 1000-way fully-connected layer with Softmax. And the Residual Networks are based on the Plain Networks, expect that a shortcut connection is added to each pair of 3×3 filters.

2) Training Parameter Setting

The lightweight classification models were based on a deep learning framework developed by Google called TensorFlow 2.0. The whole classification models were conducted on a laptop computing workstation (CPU: Intel Core i7-9700K@ 3.60GHz; GPU: NVIDIA GeForce RTX2080, 16 GB of RAM). In the training process, the adaptive learning rate adjustment algorithm RMSProp (Root Mean Square Prop) [15] was adopted as the optimization algorithm of gradient descent in the process of backpropagation. This algorithm preliminarily solves the problem of large swings in the optimization, which can adaptively adjust the learning rate during gradient descent to minimize the value of the loss function. The model hyper-parameters are as follows: (1) The Batch Size was set as 10; (2) The learning rate was 0.001 and the learning decay rate was 1×10^{-6}. The learning rate decayed constantly after each generation to avoid the network parameters falling into local optimum.

3) Results and analysis

In this study, the lightweight model introduced the above-recognized objectives on 134 images of longitudinal cracks, 71 images of transverse cracks, 104 images of alligator cracks, and 35 images of broken road marking. Accuracy (ACC), precision (P), recall rate (R), F1-score value (F1) and confusion matrix were further adopted to evaluate the classification results of asphalt pavement defects based on lightweight models.

After 100 epochs of training with the best model monitored by validation loss selected, the classification results, training parameters and training time of each lightweight network are shown in Table II. The ShuffleNetV2 demonstrated the best performance by achieving 95.52% recognition accuracy and a relatively faster speed of an hour, 8 minutes and 39 seconds on the test dataset.

TABLE II
TEST RESULTS OF LIGHTWEIGHT MODELS AFTER TRAINING WITH DIFFERENT DATASETS

Group	Lightweight model	Total accuracy			Training parameters	Training time
		Training	Validation	Testing		
1	MobileNetV2	92.79%	81.16%	80.60%	2,228,996	3m16s
2	ShuffleNetV2	100.00%	97.10%	95.52%	1,257,704	8m39s
3	ResNet50	100.00%	94.20%	94.03%	23,542,788	18m19s

TABLE III
EVALUATE RESULTS OF SHUFFLENETV2 MODEL

Evaluation	Class	Precision	Recall	F1 score	Test samples
Each defect category	longitudinal crack	96.30%	100.00%	98.11%	26
	transverse crack	93.33%	100.00%	96.55%	14
	alligator crack	100.00%	85.00%	91.89%	20
	broken road marking	87.50%	100.00%	93.33%	7
Overall model	Micro-average ACC	95.52%	95.52%	95.52%	67
	Macro-average ACC	94.28%	96.25%	94.97%	67
	Weighted-average ACC	95.86%	95.52%	95.43%	67

The evaluation metrics for each pavement defect type classified by ShuffleNetV2 are shown in Table III. It can be seen that the ShuffleNetV2 classifier can identify almost all transportation infrastructure objects, where the value of precision, recall and F1 score are satisfactory. Specifically, the classification precision for longitudinal crack, transverse crack, alligator crack and broken road marking were 0.9630, 0.9333, 1.0000 and 0.8750 respectively. The recall values were all over 0.85. The F1 score reached 0.9811, 0.9655, 0.9189 and 0.9333. In addition, the comprehensive evaluation results of different average accuracy methods (i.e. Micro-average, Macro-aver and Weighted-average) all reached above 0.94.

III. 5G CLOUD PLATFORM AND MOBILE TERMINAL SYSTEM DEVELOPMENT

A. Cloud Platform deployment

The cloud platform contains two main parts: the back-end server and the front-end website. The severing of the cloud control platform was deployed using Python programming language in Pycharm and the front-end website was established based on a VUE framework of Webstorm on the same computing workstation.

1) Back-end server

It consists of a series of databases named MongoDB and MySQL that uses a sample dataset of defect images. In addition, the messaging protocol Message Queuing Telemetry Transport (MQTT) was also deployed to realize data transmission between the cloud platform and terminal equipment.

2) Front-end website

In the front end, users can view users' information, AI model information, APP device information and the running results of AI-based models, etc. over the Hypertext Transfer Protocol (HTTP). Furthermore, the operational management of terminal devices, deep learning models and real-time distress-type identification information can be also realized.

B. Mobile infrastructure monitoring system

In recent years, mobile devices are playing an increasingly significant role in informing decision-making in daily life. This work aimed to develop a real-time mobile monitoring system for road distresses.

1) Android-based automatic recognition system

With the help of the Android Studio development software, Activity, Layout, UI interface and Service, etc. were designed through the Android-JAVA language. After virtual compiling and debugging by the API26 AVD simulator, a software package (APK file) mobile application was automatically generated. The application can then be deployed on any common mobile terminal device. In this study, the Android application was installed on a 5G smartphone (Version: Vivo Pro5G, V1916A; CPU: Snapdragon 855Plus, eight-core, and 2.96GHz).

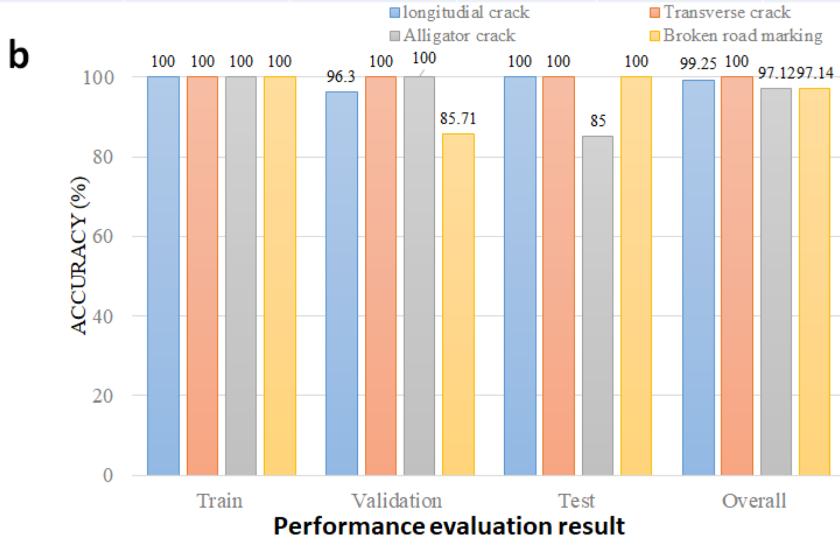
2) Results display of the mobile system

In the mobile defect recognition system, the communication between mobile terminal devices and the cloud platform was realized by 5G wireless technology. The designed specific process of the traffic infrastructure objects identification is as follows: 1) Smartphones use their cameras to collect defect images from real pavement surfaces (where the same datasets are used in the current study for convenience) and transmit them to the cloud platform through 5G communication; 2) Based on the vast storage and computing power of the platform, the image dataset can be processed and analyzed efficiently using AI-based models; 3) The final operating results of transportation infrastructural defect types will be sent back to the mobile phone for display.

A total of 134 longitudinal crack images, 71 transverse crack images, 104 alligator crack images and 35 broken road marking images were delivered to the cloud by 5G communication techniques. Then, the cloud platform analyzed and identified each asphalt defect type by using the ShuffleNetV2 deep learning model. The datasets of asphalt pavement objects for mobile system detection are shown in Fig. 3a. The values in red represent the numbers for the specific category that the platform could correctly identify and the values in the bracket are the number of samples inputted into the model. Final performance accuracy for training, validation, and test set of each defect category are shown in Fig. 3b. Overall samples of longitudinal crack, transverse crack, alligator crack and broken road marking can be classified by the intelligent deep learning-based algorithm with the accuracy of 99.25%, 100%, 97.12%, and 97.14%, respectively. For all defect samples in the overall dataset, the overall accuracy analyzed by the cloud platform reached 98.55%. It can be demonstrated that the lightweight ShuffleNetV2 classifier can accurately identify almost all the defects and objects on the transportation infrastructure. In addition, the a

Cloud computing dataset

Class	Longitudinal crack	Transverse crack	Alligator crack	Broken Road marking	Total
Training	81 (81)	43 (43)	63 (63)	21 (21)	208 (208)
Valid	26 (27)	14 (14)	21 (21)	6 (7)	67 (69)
Test	26 (26)	14 (14)	17 (20)	7 (7)	64 (67)
Total	133 (134)	71 (71)	101 (104)	34 (35)	339 (344)



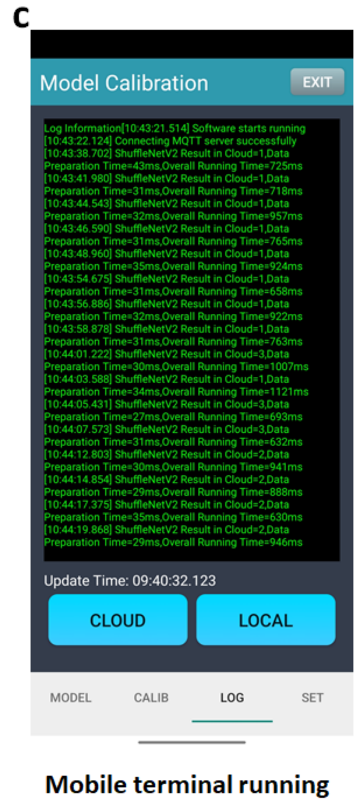


Fig. 3. The mobile application result display. a) asphalt pavement defect dataset for clouding computing in the mobile system; b) performance evaluation result of the cloud; c) mobile terminal running interface, which shows the overall time spent in the whole mobile system.

total operating time of the mobile system, including three steps of a mobile device collection, cloud computing analysis and mobile phone display was also counted in this part. As shown in Fig. 3c, the time required for identifying one defect image via the whole mobile system operation is around 1000ms. It should be noted that, in the current studies, we haven't considered the time of taking photos and all the process is computed based on the existing images of transportation infrastructure objects stored in the phone for conveniences.

In general, with the mobile road object recognition system developed based on the cloud platform and Android framework proposed in the paper, engineers and road users can obtain road defect-type information accurately and remotely.

IV. Conclusions and Outlook

This study proposed a 5G-based automatic mobile system for asphalt pavement object detection based on lightweight network. The original dataset consisted of 344 images, including longitudinal crack, transverse crack, alligator crack and broken road marking. Then, the MobileNetV2, ShuffleNetV2 and ResNet50 were respectively trained and verified for the dataset. The experimental results showed that the asphalt pavement objects classification network based on ShuffleNetV2 achieved the best prediction accuracy (ACC=95.52%). On this basis, a real-time mobile intelligent recognition system of pavement objects was developed with Android, which can be deployed on any Android mobile device. The study provides a low-cost system that can monitor and analyze defect and object types on transportation infrastructures in real-time using smart terminal device sensors and deep learning-based methods operating in the cloud. The application is capable of identifying a road defect test image for approximately 1000ms using a 5G communication system and obtaining a real-time evaluation of pavement defect and object category with relatively high accuracy (overall accuracy = 98.55%). The implementation of the system provides a real-time approach for periodic pavement inspection for engineers using mobile phones instead of heavy workstation in the road site.

Future studies will consider to design a mobile pavement defect monitoring system based on the 5G cloud platform and mobile deep learning framework. The mobile recognition application will be developed using TensorFlow Lite, which can be deployed on any mobile computation device. Different from a desktop-level deep learning analysis system, the mobile system enables road users to get fast and reliable pavement defect information by running a mobile deep learning algorithm using its CPU. It is expected that the wide application of this system can provide real-time road defect information to engineers and promote the development of smart transportation.

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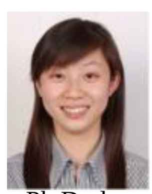

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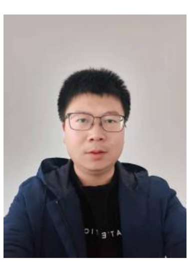

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