Smart *R*oad *D*amage Detection and Warning

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Abstract— Because road damage has resulted in numerous deaths, research into road damage detection, particularly hazardous road damage detection and warning, is essential for traffic safety. Existing road damage detection systems mostly process data on the cloud, which has a large latency due to long-distance transmission. Meanwhile, in these systems that require big, carefully labeled datasets to achieve outstanding performance, supervised machine learning methods are typically used. We suggest using Deep Learning to detect and warn about road damage in this study. The foundation of road surface analysis is visual observations by persons and quantitative analysis by pricey tools. Visual inspection, for example, not only necessitates the use of experienced road managers but also takes time and money. Furthermore, visual inspection is inherently unreliable and inconsistent, increasing the risk. Vi- visual inspection of roads by engineers takes a long time due to the length of roads or freeways. As a result, establishing an AI-based automated system that can determine the sort of damage can help to improve and enhance the way road conditions are assessed.

Keywords: Road Damage Detection, Deep Learning, Image Processing, CNN, etc.

I. Introduction

ROAD transportation networks area unit an important social element for all nations [1]. However, they are crumbling and typically even to a dangerous level everywhere on the planet because of aging, lacking periodic maintenance, or natural disasters [2]. Consequentially, poor road conditions have caused important economic losses and safety issues. As according in [3], numerous injuries are caused by road accidents each year, and around 300,000 of that area units seriously eviscerate and cause around one.5% to three economic losses everywhere on the planet. Poor road condition is one vital reason for road accidents [4]. Therefore, the detection of road damages and timely warning of drivers regarding unsafe road damages will considerably decrease road accidents and guarantee road traffic safety.

Nevertheless, it's still difficult to watch road conditions because of the large road network volume and untidy real-world environments. the present routine of road harm observance is usually performed by certified inspectors, which is subjective, labor-intensive, costly, and long. Moreover, most of the previous works like [5] solely concentrate on road harm (e.g., cracking) detection, whereas only a few researchers [6] address the matter of warning drivers regarding serious damages like massive holes in the period. However, the method knowledge in Cloud and sends alerts to drivers from Cloud so suffers from high latency.

Since an honest road condition offers facilities for transportation and business provision, road maintenance is one of the tasks to confirm traditional production and life. the premise of road maintenance is inspecting the road condition, during which the situation and therefore the style of harm ought to be detected. the standard urban administrator must rent specialists to manually notice the road damages sporadically and thoroughly, and therefore the urban administrator performs harm detection by the CNN classifier.

In this system, the first input is the Image dataset provided machine the hen next step is pre-processing. Pre-processing Phase is removing the noise from the data, rescaling, resize the image dataset. Then Feature Extraction is to extract features like edges, size, etc. from the dataset. After Feature Extraction next step is segmentation. In segmentation, we divide the images into multiple parts. Then after the all steps were done we used a classifier for the classification. We used CNN algorithm for the classification. Classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. After All the Training Phase Done Machine creates the model Then Model Goes To the testing Phase and Then outputs are Provide To the user. Output is to Detect Damage Roads

II. System Design

In this section, we present the design goals and architectural components.

A. *Design Goals*

We list the design goals of EcRD as follows:

1) **Safety:** It is crucial for a road damage detection and warning system to provide users with road danger information for accident prevention and ensure road traffic safety.
2) **Robustness:** A road damage detection and warning system should be able to handle unpredictable and unexpected complications arising from the surrounding environment, e.g., different weather conditions, illuminations, shadows, and obstacles like vehicles and pedestrians, etc.
3) **Accuracy:** A road damage detection and warning system should correctly detect road damages, especially hazardous damages with high accuracy to avoid accidents.
4) **Latency:** Fast detection and warning of hazardous road damages are critical to ensure traffic safety, especially in disaster areas such as earthquakes, floods, etc. If drivers cannot receive dangerous warning information timely, serious traffic accidents could happen when drivers hit or try to avoid damage. Therefore, hazardous road damage detection tasks should have very low latency. Due to long distance. Hence, a light-weighted approach with low latency should be developed for hazardous road damage detection.
5) **Resources:** Since video analysis is a highly resource-demanding task, the number of data increases quickly over time. Besides, storage space is expensive for Clouds and even worse for Edges. Therefore, designing an efficient storage strategy is critical.

B. **Cost:** Due to the high cost of video data collection and transmission, the data should be well used. Moreover, the cost of Internet communication and bandwidth is also unneglectable, thus the newly developed systems need to consume low communication costs and bandwidth in order to apply in the real world.

I. *Architectural Components*

The planned sensible road harm detection and warning, that satisfies the mentioned style goals is. The parts of this framework are represented thoroughly as follows:

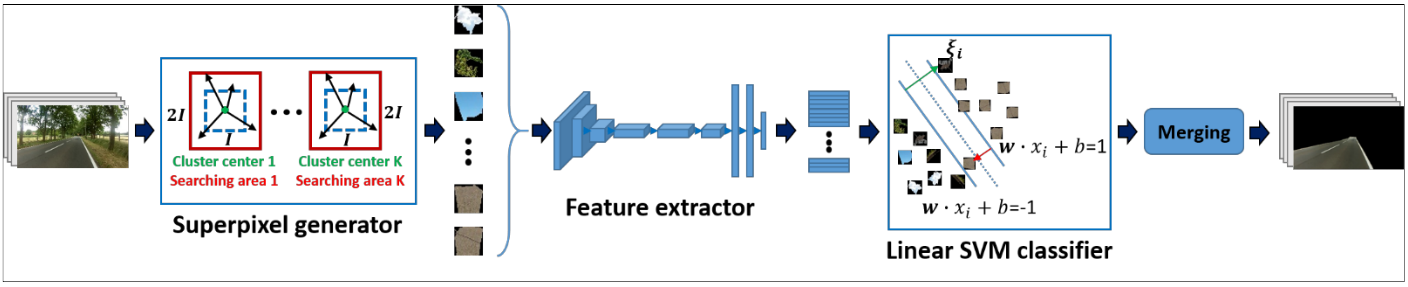
–Devices: This part gathers image information from the pervasively used database.

–Edges: The dangerous road harm detection task is deployed at Edges for speedy data broadcasting and receiving that satisfies the need for low latency. to boot, the developed approaches enhance the performance of EcRD that meets the wants of high lustiness and accuracy. Once dangerous harm is detected at a foothold, it broadcasts a warning message together with the damages' location to the near users and road administrations WHO will repair the harm at intervals a brief time that improves traffic safety.

CNN: A convolutional neural network, or CNN, may be a deep learning neural network sketched for processing structured arrays of knowledge like portrayals. CNN is satisfactory at memorizing style within the input image, like lines, gradients, circles, or maybe eyes and faces. This characteristic produces a convolutional neural network therefore strong for laptop vision. CNN will run directly on a half-baked image and doesn't want any preprocessing. A convolutional neural network may be a feed-forward neural network, rarely with up to twenty. The neural network is therefore strong for laptop vision. CNN will run directly on a half-baked image and doesn't want any preprocessing. A convolutional neural network may be a feed-forward neural network, rarely with up to twenty. The strength of a convolutional neural network comes from a specific reasonable layer referred to as the convolutional layer. CNN contains several convolutional layers assembled on the prime of every alternative, all competent in recognizing additional refined shapes. With 3 or four convolutional layers it's viable to acknowledge written digits and with twenty-five layers, it's the potential to differentiate human faces. The agenda for this sphere is to activate machines to look at the planet as humans do, understand it in an alike fashion, and even use the information for a mess of duties like image and video recognition, image examination and classification, media recreation, recommendation systems, linguistic communication process, etc.

II. *Deep Feature-based mostly Road Detection model (DFRD)*

To expeditiously implement the model, we tend to plan a road detection algorithmic program named DFRD to get rid of the screaming background. rather than directly victimization image pixels as input, we elect superpixels as they preserve additional compact object options (e.g., color, texture, etc.) and fewer sensitive to noises than pixels [10]. Therefore, we tend to reform our road detection task to a super pixel-level image classification drawback-based road detection model (DFRD)



System Architecture

I. LITERATURE REVIEW:

The literature concerned with road damage caused by heavy commercial vehicles is reviewed. The main types of vehicle-generated road damage are described and the methods that can be used to analyze them are presented. Attention is given to the principal features of the response of road surfaces to vehicle loads and mathematical models that have been developed to predict road response.
According to the authors Jeevitha, Himanshu Sharma, and Vivekanand S Gogi [1], In this paper, has created a model which can detect road damage and classify it into different categories.

To compare and calculate the efficiency of deep learning algorithms (Mobile Net SSD and YOLOV5). To identify various factors that cause road damage. To replace traditional methods of identifying damages with efficient and reliable deep learning models. The secondary objectives include the Automation of Road Damage Detection using Deep Learning Object Detection Models.[4]

The authors M.Kawano Takuro Yonezawa, J. Nakazawa This study focuses on official city vehicles, especially garbage trucks, to detect damaged lane markings (lines) which is the simplest case of road deterioration. . In addition, this system utilizes a camera, and since garbage trucks almost run through the entire area of a city every day, we can constantly obtain road images covering wide areas. Our model, which we call Deep on Edge (DoE), is a deep convolutional neural network that detects damaged lines from images [26].

According to the authors Hiroya Maeda, Yoshihide Sekimoto,
Toshikazu Seto, Takehiro Kashiyama, Hiroshi Omata This study makes three contributions to address road damage detection issues. First, a large-scale road damage data set was prepared to comprise 9,053 road damage images captured using a smartphone installed on a car, with 15,435 instances of road surface damage included in these road images. Next, they used state-of-the-art object detection methods using convolutional neural networks to train the damage detection model with their data set, and compared the accuracy and runtime speed on both, using a GPU server and a smartphone. Finally, they have demonstrated that the type of damage can be classified into eight types with high accuracy by applying the proposed object detection method[5].

Authors Kristina Doycheva, Christian Koch & Markus König have proposed a methodology for automated pavement distress detection based on computer vision. Thereby, images obtained by cameras installed in common passenger vehicles are analyzed in real-time, resulting in cost savings and a reduced amount of stored data. For this purpose, the wavelet transform was implemented on Graphics Processing Units (GPU). In addition, median filtering and top-hat transform were also implemented on GPU to enable real-time noise removal and correction of non-uniform background illumination. To distinguish between surface types, they have incorporated textural features into our methodology and deep learning was utilized to determine the distress type (cracks, potholes, or patches) [7].

The Authors Weidong Song,1Guohui Jia, 1 Hong Zhu,2Di Jia, 3 and Lin Gao1 They have proposed the CrackSeg—an end-to-end trainable deep convolutional neural network for pavement crack detection, which is effective in achieving pixel-level, and automated detection via high-level features. In this work, they introduced a novel multiscale dilated convolutional module that can learn rich deep convolutional features, making the crack features acquired under a complex background more discriminant. Moreover, in the up-sampling module process, the high spatial resolution features of the shallow network are fused to obtain more refined pixel-level pavement crack detection results. We train and evaluate the CrackSeg net on their Crack Dataset, the experimental results prove that the CrackSeg achieves high performance with a precision of 98.00%, recall of 97.85%, -score of 97.92%, and a mIoU of 73.53%. Compared with other state-of-the-art methods, the CrackSeg performs more efficiently, and robustly for automated pavement crack detection [8].

The author's Noa Garnett; Shai Silberstein; Shaul Oron; Ethan Fetaya; Uri Verner; Ariel Ayash; Vlad Goldner have presented a unified deep convolutional network combining these two complementary functions in one computationally efficient framework capable of real-time performance. Training the network uses both manually and automatically generated annotations using Lidar. In addition, they have shown several improvements to existing column-based obstacle detection, namely an improved network architecture, a new dataset, and a major enhancement of the automatic ground truth algorithm[24].

III. EXPERIMENTAL SETUP AND DATASET

A laptop (HP ZBook 15 G5, 64-bit windows 11 Operating system, 64GB RAM, Intel Core i7-8850H CPU with 2.60GHz 12) is used as our edge computer to simulate a CNN, and a high-performance server (125.8 GB of RAM, 1GB TB of hard disk, and 8 GTX 1080 Ti GPUs) is used as our Cloud server. The client application is implemented using Python 3.6.

A. Datasets:

In this system, the first instance is the Image dataset provided by the machine then the next step is pre-processing. Pre-processing Phase is removing the noise from the data, rescaling, resize the image dataset. Then Feature Extraction is to extract features like edges, size, etc. from the dataset. After Feature Extraction next step is segmentation. In segmentation, we divide the images into multiple parts. Then after the all steps were done, we used a classifier for the classification. We used CNN algorithm for the classification. Classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. After All the Training Phase Done Machine creates the model Then Model Goes To the testing Phase and Then outputs are Provide To the user. Output is to Detect Damage Roads.

C. Evaluation Metrics

The following metrics are employed to estimate the perform- mane of EcRD and the baseline approaches.

1)Precision: It represents how correct a road damage detection model is, by measuring the proportion of the true positive predictions out of the total number of the model's positive output.

Precision = TP/ TP + FP

where TP is True Positives (TP) and FP is False Positives (FP)

2)Recall: It is a measure of how many instances are identified correctly and is given as follows:

Recall = TP,

TP + FN

where FN is False Negatives (FN).

3)Accuracy: It measures how correctly a road damage detection system operates by the percentage of TP and TN along with the number of false alarms and true predictions in terms of FP, FN, TP, and TN that the system produces [28] and is given as follows:

Accuracy = TP + TN/ TP + FN + FP + TN

where TN is True Negatives (TN).

1) F1-score: It is the harmonic mean of precision and recall and is given as follows:

F1-score = 2/(1/precision+1/recall)

2) FNR: It is the False Negative Rate measuring the proportion of FN concerning the sum of TP and FN as shown in the following equation:

FNR = FN/TP+FN

3) FPR: It is short for False Positive Rate that represents the percentage of FP along with the number of TN and TP which is given as follows:

FPR=FP/TN+FP

IV. RELATED WORK

In this section, we review the related literature include- ing road segmentation techniques, and road damage detection result is bad. While when K is very high. e.g. K > 100, the quality of superpixels is good, however, the computation time and storage requirement are very high. As shown in Fig. 6. the quality of superpixels is not sufficient when K = 10 and K 30 since some of them contain both road and non-road, while the superpixels are good when K =100. but it is resource-inefficient as it needs more processing time and storage space. In addition, when K 200, unique features of the road are not preserved well thus resulting in low road segmentation performance. Therefore, we set the desired number of superpixels as K = 50.

Road Segmentation Techniques: Traditional Road segmentation methods rely on specific information such as location priors, structured information (e.g., lane markings, vanishing point, and road boundary), or visual characters (e.g., texture, edge, and color) to detect road region. Chacra et al. [34] utilize location priors to detect road parts but with the assumption that roads are present at the lower part of images, which is not practical in the real world.

In [35], many low-level cues such as color intensity, entropy, and local binary pattern histograms are used for road segmentation. The work of [36] estimates vanishing points for road direction estimation to detect drivable roads. However, low-level hand-crafted features may not be suitable for complex images with cluttered backgrounds. Additionally, location priors and structured information cannot hold when the specified situation does not appear in images, for example, occlusion on road or no lane markings. With the recent development of DCNNs, many DCNN-based methods, for example [25], [16], and [37], have been successfully applied in road segmentation. In [16] and [25], the authors present a DCNN-based network that simultaneously performs road boundary detection and road segmentation utilizing the predicted results of both tasks to improve each other's performance.

It improves the segmentation accuracy, however, extra information such as road contour maps and location priors are required. Despite the great success of DCNNs in road segmentation, it may not be the best solution for the task because DCNNs inherently require large precisely labeled datasets to learn parameters while data labeling is time-consuming and costly. Therefore, we develop a simple but efficient road segmentation method called DFRD for our EcRD framework.

Road Damage Detection Techniques: Most recent state-of-the-art road damage detection methods can be summarized into two groups, low-level feature-based methods, and pattern-based methods, depending on the noise level of the background. Most of the low-level feature-based method is relatively simple and requires less processing time (e.g., [38]), while many pattern-based methods are relatively complex and usually need large datasets (e.g., [7]). Hence, for images with simple and clean backgrounds like road damage images, low-level feature-based methods combining low-level features like intensity [38] or structure information [39] provide relatively fast and accurate results; while pattern-based methods like DCNNs [7] require large training time and much slower on normal computers, but they are more robust in detecting damages from images with cluttered backgrounds. Therefore, combining the advantages of both methods, low-level feature-based methods are relatively complex

and usually need large datasets (e.g., [7]). Hence, for images with simple and clean backgrounds like road damage images, low-level feature-based methods combining low-level features like intensity [38] or structure information [39] provide relatively fast and accurate results; while pattern-based methods like DCNNs [7] require large training time and much slower on normal computers, but they are more robust in detecting damages from images with cluttered backgrounds. Therefore, combining the advantages of both methods, low-level feature-based methods along with noise reduction (e.g., road segmentation) pre-processing is used at Edges for hazardous road damage detection, and a state-of-the-art DCNN model is employed at Cloud for multi-types road damage detection.

In summary, so far, most of the existing works propose Cloud-based solutions. Only a limited number of researchers exploited Edge-based solutions [44] and no research work leverages the advantages of both Edge and Cloud to improve the detection of both hazardous and detailed road damage. In addition, vision-based road damage detection challenges and service requirements in computational offloading schemes have not been studied. Therefore, in this paper, we study the limitation and advantages of both Edge and Cloud and exploit the benefits of the Edge-cloud framework in providing high QoS road damage detection and warning services with minimum cost and resources.

TABLE VII: Representative Works in Road Damage Detection.

Category	Main Techniques	Advantages	Disadvantages
Road segmentation techniques	Hand-craft feature based methods [34], [35], [36]	Low computation cost	Rely on specific information like location, structure or visual characters
	DCNN-based methods [25], [16], [37]	High accuracy	Large labeled training set, high computational cost
Road damage detection techniques	low-level feature based method [38], [39]	More fast and accurate	Not robust with significant changes
	Pattern based method [7]	More robust	More complex, requiring extra training process
Cloud/Edge computing systems	Cloud-based [40]	High storage and computational resources	High response delay

V. Conclusion

In this work, we studied the importance of road damage detection and warning and the limitations of existing approaches, for example, high latency, high computational cost, and high data labeling cost. To tackle these problems, we proposed a novel EcRD framework to exploit the benefits of Edge computing, especially the combination of Edge and Cloud for fast, efficient, and cheap smart road damage detection and warning applications. The Edge-cloud based structure of EcRD provides high-quality services with optimum resource consumption. Besides, to timely detect hazardous road damages, DFRD and HDD are developed. Finally, MDD is developed to effectively detect multi-types road damage in Cloud with very limited human effort. Extensive experiments show that EcRD can accurately detect both hazardous road damage at Edge and multi-type damage at Cloud. Further, our EcRD is 579 times faster than cloud-based approaches for hazardous road damage detection and only needs limited resources and cost. As part of future work, we will explore and incorporate new lightweight models or learning techniques (e.g., few-shot- learning techniques) that can perform better with limited data for hazardous road damage detection, and check the benefits compared to the current design. We will also test the proposed system in a real-world setup to further verify its robustness and address the challenges.

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