# Road Damage Acquisition System based on RetinaNet for Physical Asset Management

**Anonymous Author(s)**
Affiliation
Address
email

## Abstract

Research on damage detection of road surfaces has been an active area of research, but most studies have focused so far on the detection of the presence of road damages, without integrating an end-to-end solution for managing their status an localization. However, in real-world scenarios, municipalities need to clearly understand the type of damage, its extent and location in order to take effective action in advance. In this work, we present solution geared towards the management such physical road assets, which can aid governmental agencies to create digital replicas of the city's infrastructure and leading to a "digital twin" framework for the implementation of a smart cities. Such solution has to be affordable and easy to use, and therefore, we have trained and tested a state of the art object detector (RetinaNet) for automating the otherwise expensive and tedious road inspection process. Our proposal is amenable for implementation on mobile devices and achieves a high detection accuracy and low inference times, making it suitable for the real-time systems required for on-board road inspections systems.

## 1 Introduction

Research on damage detection of road surfaces using image processing and machine learning techniques is an active area of research [1-4]. Road maintenance is of paramount importance due to the inherent economic implications; many countries have implemented inspection standards to carry out this process. Nonetheless, both the inspection and journaling processes of road damages remain daunting problems, as cities still struggle to maintain accurate and up-to-date databases of such structural damages, making it hard to allocate resources for repair works in an informed manner.The problem is exacerbated as the number of experts that can assess such structural damages is limited, and furthermore, methods typically used to collect data from the field are time-consuming, cost-intensive, require a non-trivial level of expertise, and are highly-subjective and prone to errors.

### 1.1 Motivation

Both academic endeavors and commercial initiatives have been conducted to facilitate the road inspection, making use of a combination of sophisticated technologies [5, 6]. Most of these surveying systems combine various sensors (i.e. inertial profilers, scanners), but also imaging techniques, which have demonstrated to be particularly fit for the task [7, 8]. The information gathered by these sensors and cameras can be fed to machine learning algorithms and combined with mobile acquisition systems and cloud computing approaches to automate the process or to create end-to-end solutions.

Such endeavors had demonstrated promising results [9, 10], but the field has seen a a great progress with the advent of deep learning algorithms, in particular progresses in generic object detection (GODs), which have achieved astounding performances for very challenging tasks, as we will discuss next.

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### 1.2 Related Works

The automation of road damage inspection generally requires robust computer vision algorithms with a high degree of intelligence, which can be easy to use and run in real-time. The biggest challenge for automated road damage detection systems is to consistently achieve high performance, in terms of accuracy, under various complex environments (due to changes in illumination, weather conditions, among other challenges). Despite these problems, several systems for detecting individual structural damages have been proposed in the literature [10-13]. As datasets for road damage detection have become larger, there has been a growing interest in deploying deep learning-based (DL) generic object detectors (GOD) [15], but most works have focused on specific types of damages [16-18].

## 2 Proposed approach

One advantage of DL methods over traditional approaches is that cheaper or less sophisticated imaging devices (i.e. smartphones) can be used for acquiring the training samples. This is due to recent advances in GOD algorithms that make possible to implement very sophisticated and resource efficient algorithms in constrained devices. In this sense, it is also possible now to carry out the deployment phase (acquisition and detection of structural damages) in real-time using mobile devices, either for individual inspections in situ or mounted on an car or a UAV, as depicted in Figure 1.

Considering the progresses made road damage inspection, its integration into "smart cities" paradigms such as physical asset management (PAM) systems was only question of time, and some government and private service companies have started to make use of the information collected into road damage databases in various ways [19, 20]. The main idea of our work is to leverage the progresses made in several domains (i.e. AI, IoT, mobile and cloud computing) for creating systems that can ease the labor of road inspectors on the one hand, but which can also be used to implement end-to-end solutions for creating a large database of structural damages from individual roads, to streets in medium to large cities, leading to the so-called "digital twins, as depicted in Figure 1. This "digital transformation" shift can have multiple benefits for municipalities, as the solution is cheaper than other surveying methods and the information can easily be transmitted to the cloud for further processing and big data analyses. Having this information is also vital for optimizing the resources allocated to inspection and repairing works, as prognosis mechanisms can be readily implemented.

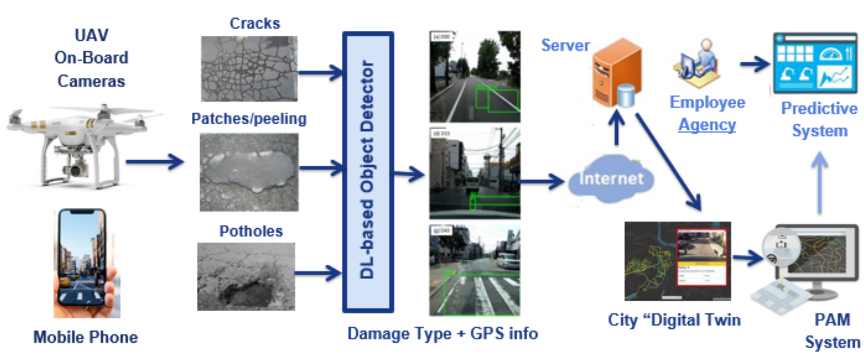


Figure 1: Proposed system for people counting based on smart cameras and dilated CNNs

## 3 Discussion and future work

The system depicted on Figure 1 is still on development, a project in collaboration with UK company *removed for blind review*. So far, we have collected a large dataset of structural damages (cracks, alligator cracks, peelings, patches, potholes, etc.) accounting for 18,000 labelled images that have been augmented to over 100,000 samples. We have tested several state of the art two-stage and one-stage object detectors and we have chosen RetinaNet [21] for its superior performance compared to others in the literature (mAPs of about 0.92 for the considered classes) and due to the fact that can be run in real-time in constrained devices (inference time of less than 0.5s). The next step in our project is the integration of this solution onto a large IT system for realizing a complete PAM system.

# References

[1] Koch, C., Asce, A.M.; Jog, G.M.; and Brilakis, I.: Automated Pothole Distress Assessment Using Asphalt Pavement Video Data, J. of Comp. in Civil Engineering, V. 27, 4, (2013)

[2] Oliveira, H. and Correia, P.L.: Automatic Road Crack Detection and Characterization, in IEEE Transactions on Intelligent Transportation Systems, vol. 14, no. 1, pp. 155-168, 2013.

[3] Radopoulou, S.C and Bralakis, I.: Patch Detection for pavement assessment, Automation in Construction, Volume 53, May 2015, Pages 95-104

[4] Geiger, A., Lenz, P., Stiller, C., and Urtasun, R.: Vision meets robotics: The KITTI dataset. The International Journal of Robotics Research, 32(11), 1231–1237 (2013)

[5] Medina, R., Llamas, J., Zalama E. and Gómez-García-Bermejo, J.: Enhanced automatic de-tection of road surface cracks by combining 2D/3D image processing techniques, IEEE In-ternational Conference on Image Processing (ICIP), Paris, 2014, pp. 778-782 (2014)

[6] Seung-Ki, R., Taehyeong, K. and Young-Ro, K.: Image-Based Pothole Detection System for ITS Service and Road Management System, Math. Problems in Engineering, (2015)

[7] Mathavan, S., Kamal, K., and Rahman, M.: A Review of Three-Dimensional Imaging Tech-nologies for Pavement Distress Detection and Measurements, IEEE Transactions on Intelli-gent Transportation Systems, vol. 16, no. 5, pp. 2353-2362 (2015)

[8] Schnebele, E., Tanyu, B. F., Cervone, F., and Waters, G.: Review of remote sensing meth-odologies for pavement management and assessment, Eur. Transp. Res. Rev. (2015)

[9] Koch, C., Giorgieva, K., Kasireddy, V., Akinci, B., and Fieguth, P. A review of computer vision based defect detection and condition assessment of concrete and asphalt civil infra-structure, Advanced Engineering Informatics, (2015)

[10] Mohan, A., and Poobal, S. Crack detection using image processing: A critical review and analysis, Alexandria Engineering Journal, Volume 57, Issue 2, June 2018, Pages 787-798

[11] Hoang, N.D., and Nguyen, Q.L.: A novel method for asphalt pavement crack classification based on image processing and machine learning, Engineering with Computers, April 2018, Volume 35, Issue 2, pp 487–498 (2018)

[12] Hoang, N.D.: An Artificial Intelligence Method for Asphalt Pavement Pothole Detection Using Least Squares Support Vector Machine and Neural Network with Steerable Filter-Based Feature Extraction, Hindawi Advances in Civil Engineering, (2018)

[13] Cha, Y.J., Choi, W., and Büyüköztürk, O.: Deep Learning-Based Crack Damage Detection Using Convolutional Neural Network, Computer-Aided Civil and Infrastructure Engineer-ing, Volume 32, Issue 5, May 2017, pp. 361-378 (2017)

[14] Liu, L., Ouyang, W., Wang, X., Fieguth, P., Liu, X., and Pietikäinen, M.: Deep Learning for Generic Object Detection: A Survey, arXiv:1809.02165v2, (2016)

[15] Tedeschi, A., and Benedetto, F.: A real time pavement crack and pothole recognition system for mobile Android-based devices, AEI, Volume 32, , Pages 11-25 (2017)

[16] Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer,I. , Wojna, Z., Song, Y., Guadarrama, S., and Murphy, K.: Speed/accuracy trade-offs for modern convolu-tional object detectors, arXiv:1611.10012v3, 2018

[17] Ale, L., Zhang, N., Li, L. : Road Damage Detection Using RetinaNet. International Confer-ence on Big Data 2018: 5197-5200, (2018)

[18] Pereira, V., Tamura, S., Hayamizu, S., and Fukain H.: A Deep Learning-Based Approach for Road Pothole Detection in Timor Leste, 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 2018, pp. 279-284.

[19] Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., and Omata, H: Road Damage Detection Using Deep Neural Networks with Images Captured Through a Smartphone, (2018)

[20] RoadBotics, https://www.roadbotics.com/company/, Revised in June 2019

[21] Lin, T.Y., Goyal, P., Girshick, R., He, K. and Dollár, P.:Focal Loss for Dense Object Detection, 2017 IEEE International Conference on Computer Vision (ICCV) arXiv:1708.02002v2 (2017)