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An end-to-end computer vision system based on deep learning for pavement distress detection and quantification

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ABSTRACT

The performance of deep learning-based computer vision systems for road infrastructure assessment is hindered by the scarcity of real-world, high-volume public datasets. Current research predominantly focuses on crack detection and segmentation, without devising end-to-end systems capable of effectively evaluating the most affected roads and assessing the out-of-sample performance. To address these limitations, this study proposes a public dataset with annotations of 7099 images and 13 types of defects, not only based on cracks, for the confrontation and development of deep learning models. These images are used to train and compare YOLOv5 sub-models based on pure detection efficiency, and standard object detection metrics, to select the optimum architecture. A novel post-processing filtering mechanism is then designed, which reduces the false positive detections by 20.5%. Additionally, a pavement condition index (ASPDI) is engineered for deep learning-based models to identify areas in need for immediate maintenance. To facilitate decision-making by road administrations, a software application is created, which integrates the ASPDI, geotagged images, and detections. This tool has allowed to detect two road sections in critical need of repair. The refined architecture is validated on open datasets, achieving mean average precision scores of 0.563 and 0.570 for RDD2022 and CPRI, respectively.

1. Introduction

The abundance, condition, and level of service of road pavements significantly impacts economic development [1]. For instance, road density in low-income economies is approximately 0.4% of the typical level in high-income economies. However, pavements deteriorate over time, resulting in the emergence of surface defects such as potholes and cracks. These defects compromise traffic safety and shorten the service life of the road network [2]. Consequently, pavement health monitoring is of paramount importance for road agencies [3].

Current approaches rely on human-based visual inspections and sophisticated pavement inspection vehicles. These methods, however, have their limitations. Foot-on-ground surveys are inefficient and costly, often posing safety hazards for inspectors [4]. Moreover, data collection vehicles can be expensive to acquire and operate, placing a strain on the limited budgets of road preservation administrations [5]. Therefore, transportation departments are interested in the timely, high-frequent, automatic, and cost-effective recognition systems of road damages [6]. Intelligent systems hold promise for developing methodologies that optimize strategic maintenance plans, promoting preventive maintenance practices. Preventive preservation strategies can slash annual costs by up to 80% [3] while simultaneously curtailing the environmental harm of corrective maintenance [6].

The recent advancements in Artificial Intelligence (AI) across various fields [7–9] have ignited growing interest in its application for pavement distress recognition. More precisely, the utilization of deep learning-based computer vision systems has revolutionized pavement distress recognition, enabling automated and efficient defect identification. These systems excel in extracting relevant features from pavement images. The most common approaches perform image classification, segmentation, and object detection [10]. Classification algorithms predict the type of defect present in an image [11]. Segmentation models delineate the defect's boundaries at the pixel level [12]. Object detection algorithms encircle the defect with a bounding box and provide distress label [13]. In the following, the current state-of-the-art in computer-aided road damage detection is

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