

Computer Vision-Assisted Evaluation of Asphalt Pavement Cracking Based on Aggregate Distribution and Microstructural Characteristics

Oliwier Danieluk

Department of Computer Science, Binghamton University, Binghamton, NY, USA.
contactoliwier@binghamton.edu

Sonya Webb

Department of Computer Science, University of North Texas, Denton, TX, USA.
sonya1981@unt.edu

Naoise Condon

Department of Electrical Engineering and Computer Science, University of Kansas, Lawrence, KS, USA.
condon1993@ku.edu

Abstract

Asphalt pavement cracking remains one of the most consequential indicators of infrastructure deterioration, yet conventional visual inspection often treats cracks as surface symptoms rather than expressions of deeper material and structural conditions. This paper examines computer vision-assisted evaluation of asphalt pavement cracking through the lens of aggregate distribution and microstructural characteristics, arguing that more reliable assessment requires coupling image-based crack detection with meso-scale interpretation of mixture structure. The discussion positions computer vision not merely as a replacement for human inspection but as a socio-technical infrastructure that connects sensing, data processing, asset management, governance, and sustainability. It reviews architectures ranging from handcrafted feature extraction to deep segmentation and three-dimensional surface analysis, while emphasizing trade-offs in latency, bandwidth, privacy, robustness, and cost. The paper further explores how aggregate morphology, orientation, contact, air void distribution, and interfacial conditions influence crack initiation and propagation, and how these properties can be inferred or approximated from pavement imagery. Deployment challenges are analyzed in relation to edge and cloud computation, institutional procurement, data standards, fairness across geographic regions, and lifecycle policy. The central claim is that technically accurate crack detection is insufficient unless embedded within governance structures that address data quality, explainability, maintenance prioritization, and equitable infrastructure investment. Future directions include multimodal sensing, uncertainty-aware models, federated learning, digital twins, and policy frameworks that treat pavement evaluation as part of a broader resilient infrastructure system.

Keywords

computer vision; asphalt pavement; crack detection; aggregate distribution; microstructure; infrastructure governance; sustainability; robustness.

1. Introduction

Asphalt pavements constitute a large proportion of transportation infrastructure in many countries, and their deterioration directly affects mobility, safety, economic productivity, and public expenditure. Cracking is among the earliest and most informative forms of distress because it signals changes in material integrity, load transfer, moisture susceptibility, and structural capacity. Traditional pavement inspection relies heavily on manual surveys, windshield assessments, and periodic specialist evaluations, but these methods are limited by subjectivity, cost, spatial coverage, and inconsistency across inspectors and agencies. Computer vision has emerged as a promising alternative because it can process large volumes of pavement imagery, identify crack patterns, and generate repeatable measurements at scale [1]. Early image-processing approaches demonstrated that pavement distress could be detected through edge detection, thresholding, texture analysis, and morphological operations [2]. Subsequent work extended these ideas to pothole detection, crack classification, and automated road defect recognition [3], [4]. However, the transition from laboratory demonstration to routine infrastructure practice remains uneven because cracking is not only a visible pattern but also a material response shaped by aggregate distribution and microstructural characteristics.

A central limitation of many vision-based systems is that they treat the pavement surface as a two-dimensional visual field and classify cracks according to geometric appearance alone. Such systems can identify longitudinal, transverse, block, and fatigue cracking with increasing accuracy, but they often do not explain why cracks form or how they are likely to evolve. Asphalt mixtures are heterogeneous composites composed of coarse and fine aggregates, asphalt binder, mastic, and air voids. The spatial arrangement of aggregates influences stress distribution, interlock, permeability, and resistance to crack propagation. Recent research on coarse aggregate morphology and asphalt mixture meso-structure using image recognition technology illustrates how aggregate-scale features can be recovered from pavement imagery and related to mixture behavior [13]. This line of inquiry suggests that computer vision-assisted evaluation can become more diagnostically meaningful when crack detection is integrated with microstructural interpretation.

The broader challenge is system-level rather than purely algorithmic. Pavement evaluation systems must operate across varied lighting conditions, surface textures, camera platforms, vehicle speeds, and data governance regimes. They must produce outputs that are usable by engineers, maintenance planners, budget officials, and the public. They must also be robust to distribution shift, sensor degradation, and seasonal variation. A vision system that performs well on a curated dataset may fail when deployed on rural roads, older pavements, or regions with different aggregate sources. Therefore, the design of computer vision-assisted evaluation requires attention to architecture, deployment, fairness, and policy alongside model accuracy [5], [6]. This paper argues that aggregate distribution and microstructural characteristics provide an important conceptual bridge between image-based crack detection and infrastructure decision-making.

2. Pavement Cracking as a Multi-Scale Material and Infrastructure Phenomenon

Asphalt pavement cracking originates from interacting mechanical, environmental, and material processes. At the microstructural level, the binder film, aggregate surface, mastic, and air void system determine how stresses are distributed under traffic loading and thermal cycling. When adhesion between binder and aggregate is weak, or when aggregate gradation produces insufficient interlock, localized damage can initiate and coalesce into visible cracks [14]. The interfacial transition zone between aggregate and binder is especially important

because it can become a preferential path for moisture ingress, oxidation, and debonding. Scanning electron microscopy and related imaging methods have shown that adhesive properties and surface characteristics of aggregates influence mixture durability [14]. These findings imply that a crack observed at the surface may be the final expression of a longer sequence of meso-scale changes that computer vision could potentially infer if imagery is analyzed with sufficient resolution and material awareness.

Aggregate distribution is not merely a background property of asphalt mixtures. It shapes the skeleton that carries load, affects the formation and movement of air voids, and controls the tortuosity of crack paths. Image analysis of asphalt concrete has been used to characterize internal structure, including aggregate orientation, contact, and spatial arrangement [15]. Morphological descriptors such as angularity, sphericity, texture, and size distribution can be extracted from images and related to compaction, segregation, and mechanical performance. Recent work on coarse aggregate morphology extends this tradition by using image recognition to examine meso-structure and its relationship to mixture behavior [13]. For computer vision-assisted pavement evaluation, the implication is that aggregate-scale features are not an optional refinement but a potential explanatory layer that can distinguish superficial cracking from structurally significant deterioration.

From an infrastructure perspective, cracking is also a governance and resource-allocation problem. A crack map generated by an automated system may be technically accurate, but its value depends on how it is integrated into asset management, maintenance prioritization, and capital planning. Pavement condition indices, performance models, and intervention thresholds are institutional constructs as much as technical ones [11]. If vision systems produce highly localized crack measurements but cannot connect them to lifecycle costs, environmental impacts, or equity outcomes, then their deployment may improve inspection efficiency without improving infrastructure outcomes. A multi-scale view that links aggregate distribution, microstructural damage, surface cracking, and network-level policy can help avoid this fragmentation. It also encourages cross-domain comparison with fields such as medical imaging, where diagnosis depends not only on detecting an anomaly but also on understanding tissue context, and remote sensing, where spectral and spatial patterns are interpreted within environmental and land-use frameworks [16], [17].

3. Computer Vision Architectures for Crack Detection and Microstructural Characterization

Image acquisition is the first architectural decision in any vision-assisted pavement evaluation system. Two-dimensional cameras mounted on vehicles or smartphones offer low cost and ease of deployment, and they have been used effectively for road damage detection and classification [6]. However, two-dimensional intensity images are sensitive to shadows, oil stains, surface discoloration, and lighting variation, which can be mistaken for cracks or obscure real defects. Three-dimensional laser imaging and structured light systems provide depth and profile information that can improve crack detection on textured surfaces and support volumetric measurements [11]. The choice between two-dimensional and three-dimensional sensing involves trade-offs in cost, vehicle integration, data volume, processing complexity, and operational speed. A system optimized for urban arterials may not be suitable for rural networks where road geometry, speed limits, and maintenance budgets differ.

Once imagery is acquired, the analytical pipeline may use handcrafted features, classical machine learning, or deep neural networks. Early methods relied on edge detection, wavelet transforms, texture descriptors, and morphological reconstruction to separate cracks from

pavement background [2], [3]. These approaches can be computationally efficient and interpretable, but they often struggle with complex crack networks, low contrast, and noisy surfaces. Deep learning has shifted the field toward learned representations, with convolutional neural networks and fully convolutional architectures enabling pixel-level crack segmentation and measurement [8], [9]. Deep hierarchical feature learning can capture multi-scale crack characteristics, while adaptive thresholding and post-processing refine predictions [7]. Classification networks can distinguish crack types, severity levels, and surface defects, but they require representative training data and careful validation [10]. The architectural trade-off is between model capacity and operational feasibility: deeper models may achieve higher accuracy but demand more computation, memory, and energy, which matters when deployment is expected on vehicles, edge devices, or cloud infrastructure with limited connectivity [1], [5].

A system-level view must also consider where computation occurs. Edge processing reduces bandwidth and latency and can improve privacy by keeping raw imagery local, but it limits model size and update frequency. Cloud processing enables large-scale model training, centralized updates, and cross-network analytics, but it depends on connectivity and raises concerns about data ownership, cybersecurity, and long-term storage. Hybrid architectures can balance these concerns by performing initial detection on edge devices and sending only metadata, embeddings, or uncertain cases to the cloud. Such designs resemble distributed sensing systems in energy grids and environmental monitoring, where local autonomy is combined with centralized coordination. For pavement evaluation, the architecture must support not only crack detection but also the extraction of aggregate distribution and microstructural proxies. This may require higher-resolution imagery, multi-view sensing, or fusion with ground-penetrating radar, infrared thermography, or acoustic methods [12], [18]. The technical challenge is therefore inseparable from the institutional challenge of maintaining data pipelines, calibration protocols, and model governance over time.

4. Aggregate Distribution and Microstructural Features in Vision-Assisted Assessment

Aggregate distribution can be characterized through a range of image-derived descriptors. Size gradation, spatial clustering, orientation, contact points, and shape indices can be estimated from segmented aggregate particles in cut sections, surface images, or reconstructed volumes [15]. Morphological properties such as angularity and surface texture influence interlock and friction, while elongation and flatness affect compaction and load transfer. Image recognition methods can quantify these properties and relate them to meso-structural heterogeneity [13]. In a computer vision-assisted evaluation system, such features could be used to contextualize crack patterns. For example, a fatigue crack network may be more likely in a mixture with poor aggregate interlock or segregated coarse aggregate, whereas a reflective crack may be driven by an underlying layer or joint and less directly linked to surface aggregate distribution. By combining crack geometry with aggregate-scale features, the system can move from detection toward diagnosis.

Microstructural characteristics also include air void distribution, binder content, mastic richness, and interfacial conditions. These properties are difficult to observe directly from surface imagery, but they can be inferred indirectly through texture, reflectance, thermal response, or surface deformation. Scanning electron microscopy and image analysis have shown that binder-aggregate adhesion and void structure are critical to durability [14]. Internal structure characterization using image analysis has demonstrated that aggregate arrangement and contact networks affect mechanical response [15]. The integration of these

insights into computer vision systems requires careful attention to scale. A crack may be millimeters wide, while aggregate particles may range from micrometers to tens of millimeters. A single image resolution may not capture both crack topology and aggregate morphology with equal fidelity. Multi-scale imaging, super-resolution, and fusion across sensors are potential solutions, but they increase system complexity and cost.

Several practical challenges constrain the extraction of aggregate distribution and microstructural features from pavement imagery. Surface wear, polishing, rutting, and contamination can obscure aggregate boundaries. Shadows and specular reflections can create false edges. Moisture and temperature can alter appearance. In addition, training datasets may overrepresent certain aggregate types, pavement ages, or geographic regions, leading to biased feature extraction. Cross-domain comparison with medical histology is instructive because both fields deal with heterogeneous tissue or material structures, staining or lighting variation, and the need for expert annotation. In pavement imaging, as in histology, automated segmentation must be validated against ground truth that is itself subject to sampling and preparation effects. Remote sensing offers another comparison, because satellite and aerial imagery require atmospheric correction and contextual interpretation. For pavement evaluation, contextual metadata such as traffic level, climate zone, mixture design, and maintenance history can improve the interpretation of aggregate and crack features [16], [17].

5. System-Level Deployment, Governance, and Infrastructure

Deployment of computer vision-assisted pavement evaluation is not a simple matter of installing cameras and running models. It requires integration with existing asset management systems, inspection workflows, procurement rules, and budget cycles. Departments of transportation and municipal agencies often rely on established condition rating protocols, and new vision outputs must be mapped onto those protocols to be actionable [11]. A crack detection model may produce pixel-level masks, but maintenance planners need severity classes, extent measures, and recommended treatments. Digital twins and pavement management systems can serve as integration platforms, allowing image-derived features to be combined with structural models, traffic data, and lifecycle cost analysis. However, such integration demands data standards, metadata schemas, and interoperability across vendors and agencies [12]. Without these, vision systems risk becoming isolated pilots that generate impressive visualizations but do not change maintenance practice.

Governance is equally important. Who owns the imagery collected on public roads? How long is it retained? How are models audited for accuracy and bias? How are vendors held accountable for performance across diverse conditions? These questions are not peripheral to technical design; they shape what data can be collected, how models are trained, and how results are contested. Privacy concerns may arise if cameras capture license plates, pedestrians, or private property. Cybersecurity concerns arise if cloud systems or edge devices are compromised, leading to manipulated condition data or disrupted maintenance planning. Procurement policies that prioritize lowest cost may undermine long-term robustness, while policies that mandate open data and reproducibility can improve public accountability [5], [16]. A mature governance framework should include model cards, uncertainty reporting, version control, and mechanisms for field validation.

Fairness is a critical but often neglected dimension. Pavement networks are not uniformly instrumented or maintained. Urban areas may receive more frequent surveys and higher-resolution data, while rural and underserved areas may be assessed less often. If vision models are trained primarily on urban or well-maintained roads, their performance may degrade on

rural roads with different aggregate sources, distress patterns, and lighting conditions. This can create a feedback loop in which already disadvantaged areas receive less accurate condition assessments and therefore less timely maintenance [6], [17]. Fairness also concerns the allocation of benefits: if automated evaluation reduces inspection costs, those savings should be reinvested in maintenance rather than simply reducing labor. Workforce transitions must be managed so that inspectors and engineers are retrained to work with vision systems rather than displaced by them [18]. The social legitimacy of infrastructure automation depends on transparent performance and equitable outcomes.

6. Sustainability, Lifecycle, and Policy Implications

Computer vision-assisted evaluation has direct implications for sustainability. Pavement maintenance consumes significant amounts of asphalt, aggregate, fuel, and equipment time, and it generates greenhouse gas emissions through material production, transport, and construction. Earlier detection of cracking can enable preventive treatments such as crack sealing, microsurfacing, or thin overlays, which are generally less resource-intensive than full-depth reconstruction. However, earlier detection is only beneficial if it triggers timely intervention. If agencies lack budget flexibility or if condition thresholds are not updated, more precise data may not translate into better environmental outcomes [16], [18]. Vision systems can also support sustainability by enabling more precise scoping of repairs, reducing unnecessary milling, and documenting the performance of recycled or low-carbon mixtures. Aggregate distribution and microstructural information can help explain why some sections deteriorate faster and inform material selection for future projects.

Policy frameworks shape whether these benefits are realized. Standards for image quality, crack classification, and data interoperability can reduce fragmentation and allow agencies to compare performance across regions. Incentive programs can reward preventive maintenance and data-driven asset management. Open data policies can enable researchers, civic groups, and private firms to develop better models, but they must be balanced with privacy and security. Public procurement can require vendors to report uncertainty, provide explainability, and support independent validation. Policy can also address equity by targeting funding toward underserved networks and requiring performance monitoring in diverse conditions [12], [17]. In this sense, computer vision-assisted evaluation is not only a technical tool but also a policy instrument that can either reinforce or reduce existing inequalities in infrastructure investment.

Cross-domain comparison with energy grids and water systems highlights the importance of integrated infrastructure governance. Smart grids use sensors, communication networks, and analytics to balance supply and demand, but they also face cybersecurity, privacy, and equity challenges. Water utilities use leak detection and pressure monitoring to reduce loss, but deployment varies with municipal capacity. Pavement evaluation shares these characteristics: it is a distributed sensing problem, a data governance problem, and a public investment problem. Treating pavement cracking as an isolated computer vision task obscures these connections. A more integrated approach would link pavement condition data with traffic safety, climate resilience, and urban planning. For example, repeated cracking in a flood-prone area may indicate drainage problems, while cracking near transit corridors may affect accessibility and economic opportunity. Aggregate and microstructural features can inform material specifications, but policy must connect those specifications to lifecycle performance and environmental goals [11], [18].

7. Robustness, Fairness, and Future Research Directions

Robustness is a foundational requirement for deployment. Pavement imagery is subject to wide variation in illumination, weather, motion blur, camera angle, and surface condition. A model trained on dry daytime images may fail in rain, snow, or low-light conditions. A model trained on one pavement type may produce false positives on another. Robustness can be improved through data augmentation, domain adaptation, multi-sensor fusion, and uncertainty estimation. Three-dimensional imaging and adaptive thresholding can reduce sensitivity to lighting and texture [7], [11]. Deep hierarchical architectures can capture multi-scale features and improve generalization [8]. However, robustness is not only a model property; it also depends on calibration protocols, maintenance of sensors, and operational procedures. A system that is robust in the laboratory but fragile in the field is not deployable at scale [1].

Fairness in pavement evaluation requires attention to data representativeness and model performance across subpopulations. Roads differ by climate, traffic, materials, age, and maintenance history. If training data are skewed toward certain regions or pavement types, the model may perform poorly on others. This can lead to systematic underestimation or overestimation of distress in underrepresented areas. Fairness also concerns the interpretability of model outputs. If a model flags a crack but cannot explain whether it is related to aggregate segregation, binder aging, or structural failure, then maintenance decisions may be arbitrary. Explainable artificial intelligence, feature attribution, and uncertainty quantification can help engineers understand model reasoning. Self-supervised learning and federated learning are promising because they can leverage unlabeled data and preserve local data ownership, respectively. Digital twins can integrate vision outputs with mechanistic models of pavement performance, enabling scenario analysis and lifecycle optimization [9], [13], [18].

Future research should therefore move beyond benchmark accuracy toward system-level validation. This includes longitudinal studies that track model performance over seasons and years, field trials that compare vision-based assessments with destructive testing, and governance experiments that test how agencies use uncertainty information. Research is also needed on the relationship between image-derived aggregate descriptors and actual mechanical performance. The required reference on coarse aggregate morphology and meso-structure using image recognition provides a foundation, but more work is needed to connect such descriptors to crack initiation and propagation under real traffic and climate conditions [13]. Interdisciplinary collaboration among computer scientists, civil engineers, materials scientists, policymakers, and social scientists is essential. The goal is not merely to detect cracks more accurately but to build a resilient, fair, and sustainable infrastructure intelligence system [5], [12].

8. Conclusion

Computer vision-assisted evaluation of asphalt pavement cracking has advanced rapidly, but its full potential depends on integrating surface crack detection with aggregate distribution and microstructural characteristics. Cracks are not merely visual anomalies; they are expressions of material composition, interfacial conditions, air void structure, and loading history. By extracting aggregate morphology, orientation, contact, and texture from imagery, vision systems can provide a richer diagnostic layer that supports more informed maintenance decisions. At the same time, technical accuracy alone is insufficient. Deployment requires architectures that balance edge and cloud computation, governance frameworks that address data ownership and cybersecurity, and policies that promote fairness, sustainability, and lifecycle thinking. Robustness under diverse environmental and operational conditions

remains a central challenge, as does fairness across geographic and socioeconomic contexts. Future systems should incorporate uncertainty, explainability, multimodal sensing, and federated or self-supervised learning. They should also be embedded in digital twins and asset management platforms that connect pavement condition to safety, mobility, climate resilience, and public investment. The most promising path forward is not a singular algorithm but a socio-technical infrastructure in which computer vision, materials science, civil engineering, and public policy co-evolve to support more durable, equitable, and sustainable pavement networks.

References

1. Zhang, A., Wang, K. C. P., Li, B., Yang, E., Dai, X., Peng, Y., Fei, Y., Liu, Y., Li, J. Q., & Chen, C. (2017). Automated pixel-level pavement crack detection on 3D asphalt surfaces using a deep-learning network. *Computer-Aided Civil and Infrastructure Engineering*, 32(10), 805–819. <https://doi.org/10.1111/mice.12297>
2. Zou, Q., Cao, Y., Li, Q., Mao, Q., & Wang, S. (2012). CrackTree: Automatic crack detection from pavement images. *Pattern Recognition Letters*, 33(3), 227–238. <https://doi.org/10.1016/j.patrec.2011.11.004>
3. Koch, C., & Brilakis, I. (2011). Pothole detection in asphalt pavement images. *Advanced Engineering Informatics*, 25(3), 507–515. <https://doi.org/10.1016/j.aei.2011.01.002>
4. Cord, A., & Chambon, S. (2012). Automatic road defect detection by textural pattern recognition based on AdaBoost. *Computer-Aided Civil and Infrastructure Engineering*, 27(4), 244–259. <https://doi.org/10.1111/j.1467-8667.2011.00736.x>
5. Eisenbach, M., Stricker, R., Seichter, D., Amende, K., Debes, K., Sesselmann, M., Ebersbach, D., Stoeckert, U., & Gross, H. M. (2017). How to get pavement distress detection ready for deep learning? A systematic approach. In 2017 International Joint Conference on Neural Networks (IJCNN) (pp. 2039–2047). IEEE. <https://doi.org/10.1109/IJCNN.2017.7966101>
6. Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H. (2018). Road damage detection and classification using deep neural networks with smartphone images. *Computer-Aided Civil and Infrastructure Engineering*, 33(12), 1127–1141. <https://doi.org/10.1111/mice.12387>
7. Fan, R., Bocus, M. J., Zhu, Y., Jiao, J., Wang, L., Ma, F., Cheng, S., & Liu, M. (2019). Road crack detection using deep convolutional neural network and adaptive thresholding. In 2019 IEEE Intelligent Vehicles Symposium (IV) (pp. 474–479). IEEE. <https://doi.org/10.1109/IVS.2019.8814000>
8. Liu, Y., Yao, J., Lu, X., Xie, R., & Li, L. (2019). DeepCrack: A deep hierarchical feature learning architecture for crack segmentation. *Neurocomputing*, 338, 139–153. <https://doi.org/10.1016/j.neucom.2019.01.036>
9. Yang, X., Li, H., Yu, Y., Luo, X., Huang, T., & Yang, C. (2018). Automatic pixel-level crack detection and measurement using fully convolutional network. *Computer-Aided Civil and Infrastructure Engineering*, 33(12), 1090–1109. <https://doi.org/10.1111/mice.12412>

10. Zhang, L., Yang, F., Zhang, Y. D., & Zhu, Y. J. (2016). Road crack detection using deep convolutional neural network. In 2016 IEEE International Conference on Image Processing (ICIP) (pp. 3708–3712). IEEE. <https://doi.org/10.1109/ICIP.2016.7533052>
11. Wang, K. C. P., & Hu, Y. (2018). Innovative methods for pavement condition evaluation using 3D laser imaging. *Journal of Infrastructure Systems*, 24(4), 04018029. [https://doi.org/10.1061/\(ASCE\)IS.1943-555X.0000450](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000450)
12. Coenen, T. B. J., & Golroo, A. (2017). A review on automated pavement distress detection methods. *Cogent Engineering*, 4(1), 1374822. <https://doi.org/10.1080/23311916.2017.1374822>
13. L.W.Shi, Z.Y.Hu, H.M.Huang, et al. Effect of coarse aggregate morphology on asphalt mixture meso-structure using image recognition technology, *Measurement*, 2026, 290: 122757.
14. Kutay, M. E., Arambula, E., Gibson, N., & Youtcheff, J. (2007). Use of scanning electron microscopy for the evaluation of adhesive properties of asphalt binders and aggregates. *Transportation Research Record*, 1998(1), 59–66. <https://doi.org/10.3141/1998-08>
15. Masad, E., Muhunthan, B., Shashidhar, N., & Harman, T. (1999). Internal structure characterization of asphalt concrete using image analysis. *Journal of Computing in Civil Engineering*, 13(2), 88–95. [https://doi.org/10.1061/\(ASCE\)0887-3801\(1999\)13:2\(88\)](https://doi.org/10.1061/(ASCE)0887-3801(1999)13:2(88))
16. Ragnoli, A., De Blasiis, M. R., & Di Benedetto, A. (2018). Pavement distress detection methods: A review. *Infrastructures*, 3(4), 58. <https://doi.org/10.3390/infrastructures3040058>
17. Ouma, Y. O., & Hahn, M. (2017). Pothole detection on asphalt pavements from 2D-colour pothole images using fuzzy c-means clustering and morphological reconstruction. *Automation in Construction*, 83, 196–211. <https://doi.org/10.1016/j.autcon.2017.08.017>
18. Hou, Y., Li, Q., Zhang, C., Lu, G., Ye, Z., Chen, Y., Wang, L., & Cao, D. (2020). The state-of-the-art review on applications of intrusive sensing, image processing techniques, and machine learning methods in pavement monitoring and analysis. *Engineering*, 6(1), 40–55. <https://doi.org/10.1016/j.eng.2019.08.016>