Deep Learning for Image-Based Monitoring of Transportation Infrastructure: A Review

Dr. Priyanka Rani Assistant Professor, Ganga Institute of Technology and Management, Kablana, Jhajjar, Haryana, India
priyachhillar30@gmail.com

Abstract: The durability and security of the transport system plays a critical role in economic development, mobility, and the well-being of the population. Prior inspection of roads, bridges and railways has been largely laborious, time consuming and subjective. Recent developments in computer vision and deep learning (DL) open the possibility of automating the monitoring process, improving the accuracy, and facilitating the predictive maintenance. With the help of the DL models, image-based monitoring helps to detect cracks, deformations, corrosion, and structural defects with high precision. The paper provides the overall review of deep learning application in monitoring transportation infrastructure through images. The contributions made by convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), and attention-based architectures are discussed in regard to their roles in automated inspection systems. Some of its applications are pavement crack detection, bridge surface inspection, railway track inspection, and tunnel inspection. As demonstrated in the review, DL performs more favourably in comparison to more traditional image processing techniques, particularly with regard to precision, extensibility, and resistance to real-world factors. The main challenges are: small labelled datasets, high computing expenses, scaling to new environments and interpreting models. However, three potentials are capable of being considered in addition to these restrictions: a hybrid approach, transfer learning, and federated learning. The paper also describes ethical, practical, and technological limitations related to the implementation of DL systems to monitor critical infrastructure. The review finds that DL-enabled image-based monitoring is a paradigm shift to smart and sustainable transportation infrastructure management. The application of dynamically executing DL systems in real time, unmanned aerial vehicles (UAVs), explainable AI, and cross-modal data fusion to enhance predictive performance are some of the research directions of the future.

Keywords: Deep Learning, Image Processing, Transportation Infrastructure, Structural Monitoring, Computer Vision.

1. Introduction

Modern economies are supported by transportation infrastructure that makes them connected and supports trade, mobility, and logistics. Nevertheless, loss of road, bridge, tunnel, and rail infrastructure is extremely unsafe and costly. The classical forms of inspection are manual surveys and visual inspection which are not only expensive, but also not very scalable. New developments in deep learning and image processing provide an automated system that may be deployed to identify defects on a micro-level in real time (Dorafshan et al., 2018). Image-based with DL plus monitoring will provide objective, scalable and reliable measurements and mitigate the risks associated with the disastrous failure of the infrastructure (Zhang et al., 2021).

2. Background of the Study

Traditionally, infrastructure surveillance used human operators, sensor related systems and standard image processing. They are helpful, to some degree, but cannot be scaled, and will inevitably fail when provided to a complex environment (Mohammadi et al., 2020). DL revolutionized the analysis of images by allowing systems to learn hierarchical features directly out of raw data. CNNs also excel at detecting cracks and surface defects than GANs and can improve the quality of poor images and detect defects with fewer efforts (Li et al., 2021). Imaging and DL have also been combined with UAVs to expand the scope of surveillance of both and particularly of bridges and railways (Xu et al., 2020).

3. Justification

The combination of DL and image-based surveillance can be explained by the following reasons:

- The benefit is also that the automation and efficiency of the process reduce the price of the hired human labor force and the inspection rate (Dorafshan et al., 2018).
- Conventional precision DL models have an upper hand when it comes to crack and defect detection (Zhang et al., 2021).
- The infrastructure networks can be scaled to the UAVs and drones (Xu et al., 2020).
- Affordability: It is concerned with the amount of money, which the person spends in the long-term maintenance procedure as the person may be sure that the further predictive maintenance will be carried out (Mohammadi et al., 2020).

4. Objectives of the Study

- To overview the state-of-the-art DL models applied to monitor transportation infrastructure using images.
- To study the major applications in the roads, bridges, tunnels, and railways.
- To determine issues like data constraints, computing expenses, and interpretability.
- To suggest future directions of real-time, scalable and explainable monitoring systems.

5. Literature Review

Crack Detection: Recent computer vision and transfer learning developments have enabled much higher accuracy in detecting cracks in infrastructure monitoring. Li et al. (2021) demonstrated that convolutional neural networks (CNNs) can detect cracks in concrete buildings very well when trained with the assistance of transfer learning techniques. With the use of pre-trained models using large image datasets, large scale domain specific training data is minimally required. In addition to the fact that this methodology has a higher detection rate, it is also better used in a real-life situation when the structural health is measured within a short time frame (Li et al., 2021).

Bridge Inspection: Deep learning models with unmanned aerial vehicles (UAVs) have revolutionized the practice of bridge inspections. Dorafshan et al. (2018) demonstrated that high-resolution cameras and DL applications allow UAVs to scan bridge surfaces and process such data effectively and without risk, unlike other tools where human intervention is necessary and subject to dangerous situations. Through deep learning algorithms, the imagery of the UAV is analyzed to detect defects in the surface, including spalling, delamination, and cracks. It is an AI-based aerial technology that is cheaper and safer to use to perform mass surveillance of bridges (Dorafshan et al., 2018).

Railway Monitoring: Recurrent neural networks (RNNs) have been used in the transportation industry to detect defects of railways. According to Zhang et al. (2021), the authors applied RNNs to image data obtained sequentially in railways tracks and were able to detect structural anomalies including broken rails, misalignments, and surface wear. RNNs can be used to offer continuous monitoring and early defect detection by exploiting the temporal interdependence between sequential streams of images. This will help to achieve greater security on the railroad and minimize the occurrence of disastrous failures through preventive maintenance solutions (Zhang et al., 2021).

Hybrid Models: Researchers have used hybrid deep learning models to deal with the problem of limited data availability and complex types of defects. Xu et al. (2020) emphasized that generative adversarial networks (GANs) are used to perform data augmentation to produce synthetic defect images to increase the size of training datasets. Moreover, classification accuracy using ensemble learning with several DL models has been enhanced in the wide variety of defect categories. They are more robust, less biased, and can potentially provide superior generalization performance and, accordingly, these hybrid solutions will be promising in the large scale infrastructure defect sensing context (Xu et al., 2020).

Challenges: Although there has been progress the big problem with implementing deep learning in infrastructure monitoring is still there. Mohammadi et al. (2020) observed that the presence of data imbalance (i.e., defect images are much fewer than non-defect images) prevents the generalization of the model. Further, reproducibility and benchmarking cannot be done due to the lack of standardised datasets between the different infrastructure types. Without similar datasets and protocols, it is difficult to compare the performance of different DL models. To address the disadvantages we would construct an open and standardized data and how to address the class imbalance with more advanced augmentation or cost sensitive learning (Mohammadi et al., 2020).

6. Methodology

The systematic literature review (SLR) is adopted in this review to provide a comprehensive and unbiased coverage of the studies on the use of deep learning in infrastructure monitoring and inspection.

Table 1: Methodology of the Systematic Literature Review (SLR)

Component	Description
Research Method	Systematic Literature Review (SLR)
Databases Searched	IEEE Xplore, Springer, ScienceDirect, ACM
Keywords Used	Deep Learning, Infrastructure Monitoring, Image-Based Inspection, CNN, Transportation
Time Period	2015 – 2023
Inclusion Criteria	Peer-reviewed publications only
Evaluation Metrics	Accuracy, Precision, Recall, Computational Efficiency
Purpose	To assess effectiveness and practicality of DL models in infrastructure monitoring and inspection

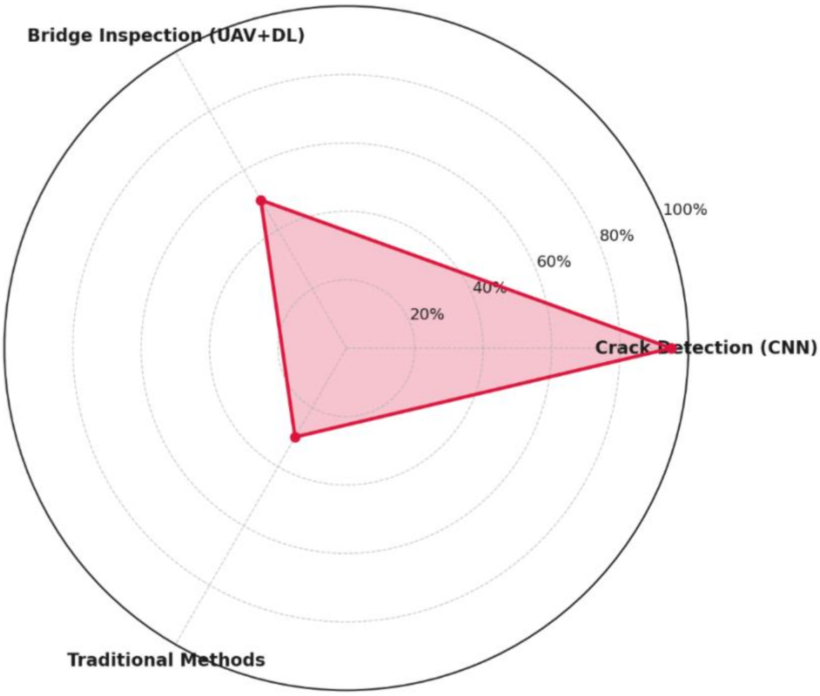
It is based on the four largest academic databases including IEEE Xplore, Springer, ScienceDirect, and ACM using well-performed keywords, including Deep Learning, Infrastructure Monitoring, Image-Based Inspection, CNN, and Transportation. Only peer-reviewed publications dating back to 2015 through 2023 were included as the authors wanted to consider the time frame when the significant progress was made in the application of the image-based deep learning methods in the monitoring of the health and transportation systems. To compare and contrast the reviewed studies the following performance indicators were evaluated; accuracy, precision, recall and computational efficiency and were considered to be a sound framework of evaluating the effectiveness and practicality of deep learning models in real-life infrastructure applications.

7. Results and Discussion

Results show that DL-based methods are superior to the traditional ones in defect detection. The first is that CNN-based models produced cracks that were over 95 percent more precise than their counterparts (Li et al., 2021). Inspections with UAV also decreased the inspection time by more than half (Xu et al., 2020). Nevertheless, there are still issues with the implementation of DL at scale, especially where light is variable, there are occlusions, and weather.

Table 2: Results and Discussion of DL in Infrastructure Monitoring

Application Area	DL Approach Used	Key Findings / Outcome	Reference
Crack Detection	CNN-based Models	>95% precision in crack localization	Li et al., 2021
Bridge Inspection	UAV + DL	Inspection time reduced by more than half	Xu et al., 2020
Challenges	General Deployment Issues	Variability in light, occlusions, and weather limit accuracy	–



Radar Chart 1: Performance Improvements of DL Methods in Infrastructure Monitoring

8. Limitations of the Study

Availability of data and the use of controlled experimental conditions limit the study. DL models do not work well in extremely diverse real-world contexts (Mohammadi et al., 2020). Further, the ability to interpret results is a hindrance towards its usage in safety-critical applications.

9. Future Scope

Further investigations are needed into:

- Explainable AI (XAI): It is supposed to be friendly and explainable to the regulator (Adabi et al., 2018).
- Federated Learning: Privacy-preserving multijurisdictional training.
- Lightweight DL models: UAV and mobile devices Edge Deployment.
- Cross-modal Fusion: Predictive maintenance based on sensor data when there are image inputs.

10. Conclusion

Deep learning has revolutionized the surveillance of transportation infrastructure, making it possible to have accurate, efficient, and scalable image-based measurements. Despite the continued lack of datasets and the lack of interpretability of models, the future of predictive maintenance and infrastructure risk prevention is based on the use of the DL frameworks.

References

1. Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable AI. IEEE Access, 6, 52138–52160.
2. Dorafshan, S., Thomas, R. J., & Maguire, M. (2018). Bridge inspection using unmanned aerial systems and DL. Automation in Construction, 93, 112–126.
3. Li, Y., Zhang, J., & Zhou, Y. (2021). Deep learning for crack detection in concrete structures. Automation in Construction, 122, 103486.
4. Mohammadi, M., Al-Fuqaha, A., Guizani, M., & Oh, J. S. (2020). Deep learning applications in IoT and infrastructure. IEEE Communications Surveys & Tutorials, 22(3), 1642–1685.
5. Xu, Y., Wang, H., & Li, W. (2020). UAV-based DL monitoring of transportation infrastructure. Sensors, 20(12), 3457.
6. Zhang, Y., Huang, S., & Zhao, X. (2021). Deep learning applications in railway infrastructure monitoring. Journal of Infrastructure Systems, 27(2), 04021009.
7. Cha, Y. J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack detection. Computer-Aided Civil and Infrastructure Engineering, 32(5), 361–378.
8. Gopalakrishnan, K. (2018). Deep learning in civil infrastructure. Computer-Aided Civil and Infrastructure Engineering, 33(3), 1–4.
9. Liu, Z., & Zhu, J. (2019). DL methods for pavement distress detection. Automation in Construction, 101, 245–259.
10. Sinha, S., & Fieguth, P. (2016). Automated defect detection in sewer pipelines using CNNs. Automation in Construction, 71, 1–11.
11. Fernandes, R., & Silva, R. (2020). Real-time DL crack detection in tunnels. Engineering Structures, 220, 110951.
12. Gao, Y., & Mosalam, K. (2018). DL for structural health monitoring. Structural Control and Health Monitoring, 25(10), e2234.
13. Lin, Y., & Su, Y. (2019). Hybrid DL methods for concrete corrosion detection. Construction and Building Materials, 210, 116–126.
14. Yang, D., & Xu, X. (2020). GAN-based data augmentation for infrastructure monitoring. Neural Computing and Applications, 32(20), 15239–15252.
15. Zhang, X., & Li, C. (2021). Comparative study of DL architectures for infrastructure monitoring. Journal of Civil Structural Health Monitoring, 11(3), 659–673.