AI and Remote Sensing for Resilient and Sustainable Built Environments: A Review of Current Methods, Open Data and Future Directions

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***Abstract*— Critical infrastructure, such as transport networks, underpins economic growth by enabling mobility and trade. However, ageing assets, climate change impacts (e.g., extreme weather, rising sea levels), and hybrid threats—ranging from natural disasters to cyber-attacks and conflicts —pose growing risks to their resilience and functionality. This review paper explores how emerging digital technologies, specifically Artificial Intelligence (AI), can enhance damage assessment and monitoring of transport infrastructure. A systematic literature review examines existing AI models and datasets for assessing damage in roads, bridges, and other critical infrastructure impacted by natural disasters. Special focus is given to the unique challenges and opportunities associated with bridge damage detection due to their structural complexity and critical role in connectivity. The integration of SAR (Synthetic Aperture Radar) data with AI models is also discussed, with the review revealing a critical research gap: a scarcity of studies applying AI models to SAR data for comprehensive bridge damage assessment. Therefore, this review aims to identify the research gaps and provide foundations for AI-driven solutions for assessing and monitoring critical transport infrastructures.**

Keywords—damage assessment, machine learning, artificial intelligence, transport infrastructures, natural disasters.

1. Introduction

Transport networks are crucial for the integrity of the economy and social health of any region in the world, thus maintaining them in good condition is of high importance. Climate change is having a big impact on transport networks as well, as common climate threats include large precipitations, high temperatures and rising sea levels, which lead then to biophysical impacts such as floodings, erosion, and urban heat islands, which reduces road safety and durability (de Abreu et al., 2022). There are also direct impacts that refers to the actual damage to the infrastructures and indirect damages due to the cascading events (Rebally et al., 2021). Consequently, fostering climate-resilient infrastructure is becoming essential for the economic prosperity and social coherence of any country (Argyroudis et al., 2022), aligning with the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015).

Given these threats, critical infrastructures require quick damage assessment to enable informed decision making and on time restoration avoiding cascading impacts. This need is especially highlighted in challenging zones, such as areas under war or other disruptive events.

The use of remote sensing technologies and satellites is crucial here, as data collection in these areas is often defined by security risks and restricted access making on-ground data hard to obtain (Zhao & Morikawa, 2024).

Critical infrastructures require quick damage assessment to enable informed decision making and on time restoration, avoiding cascading impacts. Furthermore, there is a need for damage assessment especially in challenging zones and areas, such as under war or other challenging environments, using remote sensing technologies and satellites, as data collection in this area are often hindered by security risks and restricted access, making this data less available and hard to obtain (Zhao & Morikawa, 2024).

Key methods to address this challenge involve damage assessment using satellite images, which can be sourced from open-access platforms or commercial providers. A prominent example is the ESA (European Space Agency) Sentinel mission, which provides valuable data through radar imaging (Sentinel-1) and multispectral high-resolution imaging (Sentinel-2) (*European Space Agency*, n.d.). For instance, researchers have developed multi-scale approaches that integrate Sentinel-1 SAR images with high-resolution imagery and deep learning for rapid post-disaster infrastructure damage detection (Kopiika et al., 2025).

While there have been previous studies on damage detection, they have often focused on single transport infrastructures such as roads, bridges (Santaniello & Russo, 2023) or buildings in isolation. Existing literature reviews have also covered related topics, for example, (Abedi et al., 2023) provided a systematic review of Machine Learning for general civil infrastructure damage using methods like vibration and image analysis, while (Abduljabbar et al., 2019) presented a broader overview of AI applications across the transport sector without a specific focus on structural damage.

However, there remains a distinct need for a review that comprehensively examines and compares current AI models and datasets specifically tailored for assessing damage to both roads and bridges. Crucially, this review is motivated by another identified gap in the literature: while satellite technology like Synthetic Aperture Radar (SAR) is used for monitoring, its integration with advanced AI models for holistic bridge damage assessment remains largely unexplored. This review aims to address this gap. It will synthesize the latest emerging technologies and AI models, from the detection of localized road potholes to wider regional damage assessments, providing a foundation for developing AI-driven solutions that enhance the monitoring and resilience of critical transport infrastructures.

The rapid adoption of these technologies necessitates a careful consideration of ethical AI principles (Díaz-Rodríguez et al., 2023) (Radanliev, 2025). These concerns include fairness, transparency, privacy, and accountability. AI models for damage assessment could cause societal inequalities if trained on biased dataset. An AI system trained predominantly on urban or affluent area imagery might underperform in rural regions, leading to inequitable allocation of repair resources and marginalization of vulnerable groups. This raises the question for accountability, which demands mechanism to ensure responsibility for an AI system's outcome and provide compensation when its decision cause harm. Furthermore, the system must be transparent and explainable, making their functionality clear and understandable to build and maintain user trust. The use of high-resolution satellite imagery also introduces significant privacy and data governance concerns that must be addressed to protect individuals and ensure data is used responsibly.

The increasing use of AI in managing critical infrastructure demands significant policy and risk management reform, as some current regulations are inadequate for the technology's complexity. There is need for new policies that standardize data quality, model validation and operational transparency. It is also crucial to address the emerging landscape of AI-generated threats. The same technology can be used for malicious ends. Therefore, the successful application of these technologies for infrastructure assessment requires navigating the challenges of ensuring ethical performance, establishing robust governance and policy, and safeguarding the assessment process from digital interference.

2. Methodology

This review paper employs a systematic approach to evaluate existing research and compare the different findings and applications of AI models and datasets availability. While the literature demonstrates significant, particularly in road damage detection, our initial analysis confirmed a scarcity of research combining AI, SAR, and bridge damage assessment. Therefore, this review aims to provide a comprehensive evaluation of current findings and highlight directions for future research.

Articles were included based on a series of criteria which includes the relevance of AI models and their application for damage assessment on transport infrastructures (roads, bridges, etc.), availability of the datasets that correspond to the tables' columns (i.e. for AI models, the accuracy). As for the eligibility criteria for article searching, we considered the most recent articles, including up to 10 years old articles, except for same cases where articles were scarce. The language of these article is English, for ease of comparison and readability. The database we searched the articles from are Scopus and Google Scholar. The search terms are the titles identified for each table, which corresponds to a research question. We excluded articles that are older than 2010, and which are not relevant to the research question identified for each table.

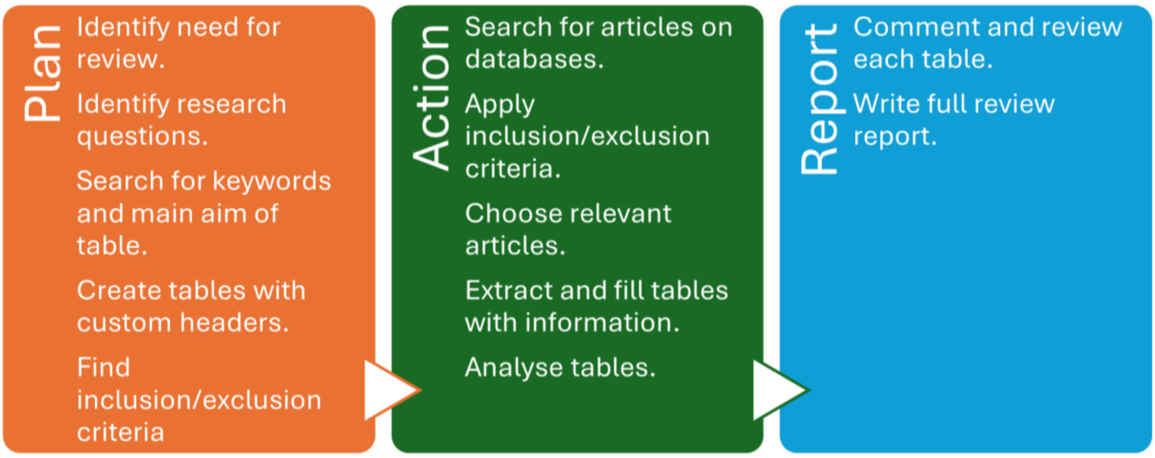


Figure 1, Review process diagram methodology

For wider damage assessment, we looked into technologies that use satellite imagery as well, and more specifically SAR (Synthetic Aperture Radar) (Kopiika et al., 2025) (Nettis et al., 2023) (Markogiannaki et al., 2022). This technology has been used in some variations depending on applications, such as MTInSAR (Multi-Temporal Interferometric SAR), InSAR (Interferometric SAR) and D-TomoSAR (Differential Tomographic SAR). MTInSAR, for instance, has been used for monitoring of structural deformation in bridge portfolios, like in (Nettis et al., 2023), while InSAR has also been used for similar application, such as Long-term deflection and thermal dilation of bridges (Jung et al., 2019). D-TomoSAR is similar to the other, but it uses multiple radar images acquired from different viewing angles to create 3D model of the deformed infrastructure. In (Markogiannaki et al., 2022), the authors have used D-TomoSAR for monitoring of landmark bridge suing displacement products deformation trends. Another application of SAR includes using coherence products for assessing the damage on infrastructures, as in (Kopiika et al., 2025) and (Sun et al., 2020), more specifically using Coherence Change Detection, or CCD, in which two time-lapsed high-res SAR images are compared to detect and measure changes to a specific geographic area, as described in Figure 2.

Table 1, SAR RGB decomposition (Schultz, 2021)

Colour	Band	Polarization	At small scale pixel indicates	At large scale pixel indicates
Red	Co-Pol (VV)	Surface scattering (polarized/simple)	Smooth surface	Rough surface
Green	Cross-Pol (VH)	Volume scattering (depolarized/random)	Low volume (water, roads, plowed or newly planted fields)	High volume (trees, buildings, mature crops, built up areas)
Blue	C-Pol when Cross-Pol near 0dB	Surface scattering when volume scattering is very low	Scattering measurable in red channel, no value	Co-Pol backscatter values near -24dB (smooth water, roads)

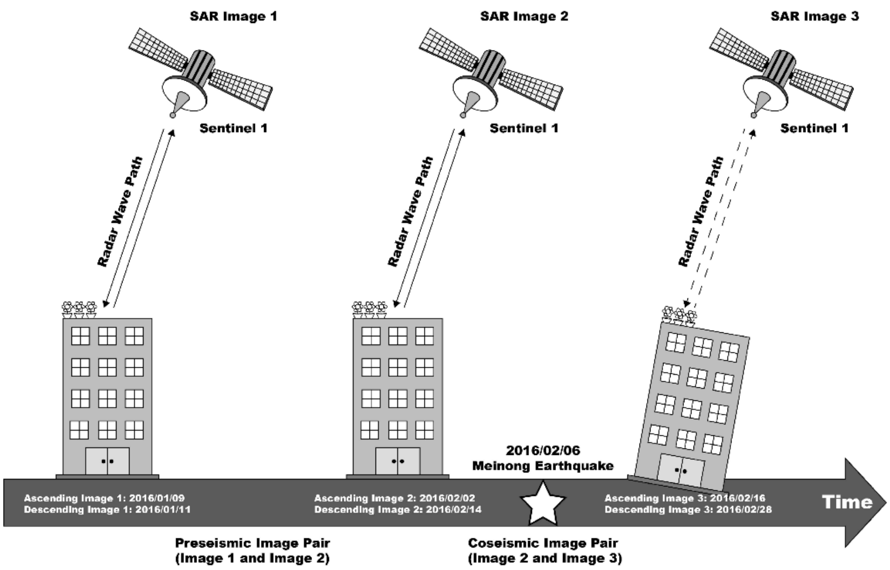


Figure 2, SAR acquisition for CCD (Lu et al., 2018)

Some applications of SAR for have used RGB composite images using various SAR data parameters, where different polarizations and frequencies of radar signals are combined into a multi-band visualization (Heiselberg, 2020). These RGB composite images can be used in AI models using computer vision to enhance damage assessment on transport infrastructures. In Table 1, the difference between colours is shown, with what object indicates.

3. Results and Discussion

In this section, an analysis of current available AI models and datasets in this field are carried out along with an investigation on robust solutions for data collection. Through the literature review, the emerging digital technologies and system resilience will be also explored. The findings are presented in table style, along with a discussion regarding the damages on civil infrastructures that have been studied, along with available datasets and AI models employed. Consequently, an analysis on the use of SAR for damage detection is presented, and lastly a discussion on natural hazards related to damaged civil infrastructures.

3.1 Damages in critical civil infrastructure used for analysis in AI approaches

Table 2 summarises the most common civil infrastructure damages that have been identified, which allows us to have a clear view of what are the most common ones. Although some have used different criteria, such as good, fair and poor (referring to the state of the road) like in (Ma et al., 2017). When searching for publications, we found that most of the damage detection models were applied on road infrastructure instead of buildings. When searching on Google Scholar "Road Damage Detection" since 2012 to 2025 the search gives us 26,400 results, whereas when searching "Building Damage Detection", we get 17,900 results. This explains that there has been more research and applications on road infrastructures, detecting cracks and potholes. The above table tells us that most of the cracks identified are classified into lateral, longitudinal, alligator, and other general cracks.

Table 2, Damages in critical civil infrastructure used for analysis in AI approaches

Author / Year	**Roads**				
	Longitudinal cracks	**Lateral cracks**	**Alligator cracks**	**Cracks**	**Other road components**
(Paramasivam et al., 2024)				x	Potholes
(Zeng & Zhong, 2024)	x	x		x	Potholes, mesh cracks
(Guo & Zhang, 2022)	x	x		x	Mesh cracks, pothole, longitudinal and lateral construction joint, crosswalk blur, white line blur.
(Stricker et al., 2021)	x	x	x	x	Patches, scratches, bleeding, manholes, curb, cobblestone, drill holes, vegetation, joints, water drains.
(Du et al., 2021)	x	x	x	x	Patches, nets, manholes
(Mei & Gül, 2020)				x	
(Majidifard et al., 2020)	x	x	x	x	Reflective crack, block crack, sealed reflective crack, lane

					long. crack, sealed long. crack
(Hegde et al., 2020)	x	x	x		
(Stricker et al., 2019)			x	x	
(Angulo et al., 2019)	x		x	x	
(Weng et al., 2019)	x	x	x	x	
(Maeda et al., 2018)	x	x	x		
(Dorafshan et al., 2018)				x	
(Ma et al., 2017)					Good, Fair, Poor
(Ouma & Hahn, 2017)			x		
(L. Zhang et al., 2016)				x	
(Shi et al., 2016)				x	
(L. Li et al., 2014)	x	x	x		
(Oliveira & Correia, 2014)	x	x		x	
(Zou et al., 2012)				x	
			Buildings		
	Minor	Major	Destroyed	Ruin	Other
(Y. Zhang et al., 2023)			**x**	**x**	
(Wang et al., 2022)	**x**	**x**	**x**		
(C. Liu et al., 2022)			**x**		Debris, Spalling, Cracking
(C. Wu et al., 2021)	**x**	**x**	**x**		
(Weber & Kané, 2020)	**x**	**x**	**x**		
(Gupta et al., 2019)	**x**	**x**	**x**		
(J. Z. Xu et al., 2019)					UNOSAT 5-level scale

Regarding damage criteria for buildings, we can observe from Table 2 that, like for the roads, there is a common pattern. Most of these publications used criteria such as “Minor”, “Major” and “Destroyed”. When we analyse these papers, we found out that they used this classification because they used the same dataset, named “xBD”, which is a large-scale dataset of building damage assessment used for humanitarian relief and disaster rescue. We will analyse other datasets in the tables below.

3.2 AI approaches used for damage detection on infrastructures

A wide range of AI models have been applied in damage detection algorithms on civil and transport infrastructures. These models include both traditional machine learning methods such as Random Forest

(Shi et al., 2016), as well as more advanced deep learning models, for instance CNNs (Waseem Khan et al., 2025), (Paramasivam et al., 2024), (Majidifard et al., 2020) citing few examples.

In Table 3, Overview of AI approaches for damage detection in buildings, bridges and roads, including algorithms, datasets, and data sources. Abbreviations, a series of these AI model are presented and compared. The references are presented in the first column, the name of the model in the second column, and lastly, the performance in the last column. Here the infrastructures are roads, buildings, bridges, and other (which is only a steel structural model, to show an example of simulation of damage detection).

Table 3, Overview of AI approaches for damage detection in buildings, bridges and roads, including algorithms, datasets, and data sources. Abbreviations[1]

Author / Year	Algorithm	Dataset	Source
		Roads	
(Waseem Khan et al., 2025)	YOLOv9s-Fusion	RDD2022	Terrestrial
(Shakhovska et al., 2024)	YOLO_tinyv4	Potholes or Cracks on Road Image Dataset	Terrestrial
(Zanevych et al., 2024)	YOLOv11+FPN+Crad-CAM	Multiple publicly available	Terrestrial
(Khan et al., 2024)	Faster R-CNN, YOLOv5, SSD MobileNet V1, EfficientDet D1	RDD2022	Terrestrial
(Ji et al., 2024)	LRDD-YOLO	Pothole dataset, Road Damage Dataset	Terrestrial
(Paramasivam et al., 2024)	Faster R-CNN	Custom	Terrestrial
(Y. ; Li et al., 2024)	RDD-YOLO	RDD2022	Terrestrial
(Zeng & Zhong, 2024)	YOLOv8-PD	RDD2022	Terrestrial
(Chen et al., 2024)	LAG-YOLO	RDD2020	Terrestrial
(Ni et al., 2023)	YOLOv7	RDD2022	Terrestrial
(Guo & Zhang, 2022)	YOLOv5s	RDD2020	Terrestrial
(Arya, Maeda, Ghosh, Toshniwal, Mraz, et al., 2021)	YOLOv5	RDD2020	Terrestrial
(Du et al., 2021)	YOLOv3	LIST dataset	Terrestrial
(Hegde et al., 2020)	u-YOLO with EM&EP	GRDDC	Terrestrial
(Yang et al., 2020)	FPHBN	CRACK500, GAPs384, Cracktree200, CFD, (Aigle-RN & ESAR & LCMS)	Terrestrial
(Mei & Gül, 2020)	ConnCrack (GANs)	EdmCrack600	Terrestrial
(Majidifard et al., 2020)	YOLOv2, Faster RCNN	PID (pavement image dataset)	Terrestrial
(Angulo et al., 2019)	RetinaNet	Custom	Terrestrial
(Weng et al., 2019)	Edge detector and segmentation	Custom	Terrestrial
(Stricker et al., 2019)	ResNet34 160x160	GAPs V2	Terrestrial
(Dorafshan et al., 2018)	AlexNet DCNN	SDNET2018	Terrestrial
(Maeda et al., 2018)	SSD-Inception v2	RoadDamageDetector	Terrestrial
(Ouma & Hahn, 2017)	Fuzzy c-means	Custom	Terrestrial

[1] EM: Ensemble Model, EP: Ensemble Prediction, ASPP: Atrous Spatial Pyramid Pooling, U-BDD++: Improved unsupervised building damage detection, FV: Fisher vector, FPN: Feature Pyramid Network, RSF: Random Structured Forests, RDF: Random Decision Forests, BPNN: Back-Propagation NN, FPHBN: feature pyramid and hierarchical boosting network, SCWT: Synchrosqueezing Continuous Wavelet Transform, YOLO: You Only Look Once, CNN: Convolutional Neural Network, GAN: Generative Adversarial Network, SSD: Single Shot Detector

(Ma et al., 2017)	FV-CNN	Cusatom – Google street view	Terrestrial
(Shi et al., 2016)	CrackForest (RSF+RDF)	CFD, AigleRN	Terrestrial
(L. Zhang et al., 2016)	Convnets	Custom	Terrestrial
(L. Li et al., 2014)	BPNN	ARAN dataset	Terrestrial
	Buildings		
(Y. Zhang et al., 2023)	U-BDD++	xBD	Satellite
(C. Liu et al., 2022)	LA-YOLOv5	GDBDA	Terrestrial
(Weber & Kané, 2020)	Mask R-CNN with FPN	xBD	Satellite
(Gupta et al., 2019)	ResNet50, CNN	xBD	Satellite
	Bridges		
(Abubakr et al., 2024)	Xception Vanilla	CODEBRIM	Terrestrial
(Santaniello & Russo, 2023)	SCWT & ResNet with signal splitting	Z24 bridge	Terrestrial
(Gao et al., 2023)	GoogleNet	Crack-detection	Terrestrial
(Ni et al., 2023)	YOLOv7	RDD2022	
(Tazarv et al., 2022)	Mask R-CNN	RC-bridge	Terrestrial
(Mundt et al., 2019)	MetaQNN and ENAS	CODEBRIM	Terrestrial
(H. Xu et al., 2019)	CNN with ASPP	Crack-detection	Terrestrial

In the case of buildings, (Y. Zhang et al., 2023) have presented an innovative model, where the authors have achieved an F1 score of 0.582 for the tasks of localization and segmentation, and an F1 score of 0.638 for the tasks of damage classification. Here the data used consisted of unlabelled pre and post disaster satellite images pairs. Using satellite images sometimes is not the ideal solution due to its complexity, so the authors have implemented a novel self-supervised framework, named U-BDD++. Other findings, (C. Liu et al., 2022), show higher accuracy on a different dataset, such as the GDBDA(Ground-level Detection in Building Damage Assessment), where an average (between different classes) F1 score of 0.911 was achieved, using a improved version of YOLOv5 object detection model. A term has been found for the application of Artificial Intelligence to geospataial data from remote sensors such as satellites, aerial drones, and this is GeoAI (Agbaje et al., 2024). GeoAI brings a big potential for Rapid and scaled-up building damage assessment. This GeoAI concepts includes methods that use Artificial Intelligence, Machine Learning and Computer Vision.

As for bridges, we observe that most of the publications used CNNs, deep learning models, for damage identification. Some authors have used an improved version of Convolutional Neural Networks, such as Xception, a deep learning model based on extreme version of the Inception architecture (Abubakr et al., 2024). The authors have utilized Xception model and Vanilla model, achieving respectively an accuracy of 0.9495 and 0.8571 for defect classification of concrete bridges. Other authors have experimented with different models, such as Meta-QNN (Mundt et al., 2019), a meta-modelling algorithm based on reinforcement learning that generated higher performance CNNs architectures automatically, and Synchrosqueezing Continuous Wavelet Transform with deep learning (Santaniello & Russo, 2023), using acceleration responses for multi-class damage detection.

When it comes to roads, there has been a lot of competitions, such as the Global Road Damage Detection, which happened on multiple occasions, like in 2020 and 2022. In fact, we have presented the relative datasets in the below tables, under RDD2020 and RDD2022. There has been some variation to these datasets and competitions, such as the Optimized Road Damage Detection Challenge (ORDDC'2024) or the Crowdsensing-based Road Damage Detection Challenge (CRDDC) (Arya, Maeda, Ghosh, Toshniwal, Omata, et al., 2022). From the table we understand that most of the models used are based on YOLO (You

Only Look Once) models, which are two stage detectors: in the first pass it generates the potential object locations, and in the second pass it refines these proposals. A recent study presents a model specifically developed for road damage detection, where the authors based on a previous object detection model YOLOv8n, have proposed an improved version, YOLOv8-PD for Pavement Distress, demonstrating lower computational load and higher detection accuracy (Zeng & Zhong, 2024). Most recent versions have also been used such as YOLOv11 (Zanevych et al., 2024) and YOLOv9 (Waseem Khan et al., 2025), and recently, as the weight of the models are being considered more and more, particularly for edge applications, lighter versions are also being considered, such as YOLO_tinyv4 (Shakhovska et al., 2024).

An experiment have been conducted on simulated structures, such as an eight-level steel frame structure, where in (Jiang et al., 2022), a two-stage structural damage detection method is used (a 1D-CNN model in the first stage to extract the damage features, and a SVM model to quantify the damage), and achieved a high accuracy of 0.9988. However, it has not yet been applied to real world infrastructure, where additional factors influence the performance. Lastly, the majority of these papers have relied on terrestrial data, with limited use of satellite imagery, despite its value in scenarios where access to transport infrastructure is restricted.

3.3 Datasets used for infrastructure damage detection

In the previous sections, the AI models have been presented, along with what datasets have been used. In this part, these datasets are more deeply analysed. In Table 4 the datasets for the different infrastructures are presented. We can observe how the section for roads is bigger compared to buildings and bridges. This is because the datasets for roads are easier to create compared to buildings and bridges, which requires more sophisticated and advanced acquisition techniques, as we will see later in the table about technologies used for data collection. Therefore, we can observe that to create a road dataset, a smartphone with a camera is sufficient. Furthermore, there has been a lot of competitions for road damage detection like the RDD2020 and RDD2022, which had a huge success and motivated for more advanced datasets, i.e. including other countries' roads to improve the model. For instance, in RDD2020 dataset (Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021), the data was collected from three different countries: India, Japan and Czech Republic. However, in RDD2022 dataset (Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2022), the data was collected from six countries: India, Japan, Czech Republic, Norway, the United States and China, with more than 55,000 instances of road damage.

Table 4, Datasets of damaged infrastructures used for detection.

Authors/Year	Dataset	Classes	No. of Images	Images resolution
		ROADS		
(Shakhovska et al., 2024)	Potholes or Cracks on Road Image Dataset	Longitudinal, transverse, alligator crack, potholes, rutting, surface distress.	1,000+	1920x1080
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2022)	RDD2022 CRDDC2022	Longitudinal, Transverse, Alligator cracks, Potholes.	47,420	512x512, 600x600, 720x720, 3,650x2044
(Du et al., 2021)	LIST	Crack, Pothole, Net, Patch-Crack, Patch-Pothole, Patch-Net, Manhole.	45,788	1,920x1080
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021)	RDD2020	Longitudinal cracks, Transverse cracks, Alligator cracks, and Potholes.	26,336	600x600, 720x720
(Stricker et al., 2021)	GAPs 10m	22 classes[2].	394	5,030x11,505

[2] Void, Inlaid patch, Applied patch, Scaled crack, Crack, Open joint, Pothole, Raveling, Scratch, Bleeding, Road marking, Surface water drain, Manhole, Expansion joint, Curb, Cobblestone, Drill hole, Object mobile, Object fixed, Joint, Road verge, Vegetation, Induction loop, Normal.

(Yang et al., 2020)	Crack500	Crack.	500	2,000x1500
(Mei & Gül, 2020)	EdmCrack600	Crack.	600	1,920x1080
(Majidifard et al., 2020)	PID	Block, Lane longitudinal, Longitudinal, Sealed Longitudinal, Pothole, Alligator, Sealed reflective, Reflective, Transverse.	7,237	640x640
(Stricker et al., 2019)	GAPs v2	Intact, Cracks, Applied patches, Inlaid patches, Potholes, Open joints.	2,468	1,920x1080
(Angulo et al., 2019)	Modified RDD2018	Wheel mark, Construction joint long. , Equal interval, Construction joint lat., Partial/Overall pavement, Bump/Rutting, Crosswalk blur, White line blur.	18,034	600x600
(Weng et al., 2019)	G45	Transverse, Longitudinal, Block, Alligator	217	2,048x1,536
(Dorafshan et al., 2018)	SDNET2018	Cracked, Non-cracked	56,000	256x256
(Ma et al., 2017)	NYCDT	Poor, Fair, Good.	711,520	640x640
(Ouma & Hahn, 2017)	Own	Illumination and light intensity variations, Background asphalt variations, Cracks, Oil stains, Patches, Pebbles, Shadows, other.	75	1,080x1,920
(Shi et al., 2016)	CFD	Crack, Non-crack.	118	480x320
(L. Zhang et al., 2016)	Own	Crack, Non-crack.	500	3,264x2,448
(L. Li et al., 2014)	Own	Alligator crack, Linear crack:(Longitudinal, Transversal crack).	400	n/a
(Oliveira & Correia, 2014)	CrackIT	Crack, Non-crack.	84	1,536x2,048
		BUILDINGS		
(C. Liu et al., 2022)	GDBDA	Debris, Collapse, Spalling, Crack.	8,340	800x800
(Gupta et al., 2019)	xBD	No damage, Minor damage, Major damage, Destroyed, Unclassified.	22,068	1,024x1,024
		BRIDGES		
(Flotzinger et al., 2023)	Dacl10k	12 classes[3].	9,920	Min: 336x245 Max: 6,000x5,152
(Santaniello & Russo, 2023)	Z24	Undamaged, 20mm, 40mm, 80mm, 95mm displacement.	1,422	Time-series
(H. Xu et al., 2019)	Crack-detection	Crack, Non-crack.	6,069	224x224
(Mundt et al., 2019)	CODEBRIM	Crack, Spallation. Efflorescence, Exposed Bars, Corrosion.	1,590	2,592x1,944 to 6,000x4,000
(Dorafshan et al., 2018)	SDNET2018	Cracked, Non-cracked.	56,000	256x256

From the table we can observe how there are many images with different sizes. Some images were collected using specific advanced systems with very high images resolution, such as "Mobile mapping system" named S.T.I.E.R. and RoadSTAR (Stricker et al., 2021), which have been used in Austria, Switzerland and Germany.

For buildings there aren't many datasets, but there is one that used satellite that is very extensive, including around 22 thousand images over 45 kilometres squared of polygon labelled pre and post disaster imagery, the xBD dataset (Gupta et al., 2019).

In the context of bridges, there is a noticeable scarcity of publicly available image datasets specifically capturing overall structural damage. This scarcity is particularly acute for datasets suitable for advanced remote sensing techniques like SAR, which directly hinders the development and validation of corresponding AI models. However, several datasets focused on localised defects, particularly concrete cracks in bridge components, are available, such as the widely used CODEBRIM dataset (Mundt et al., 2019). Vibration based approaches have also been

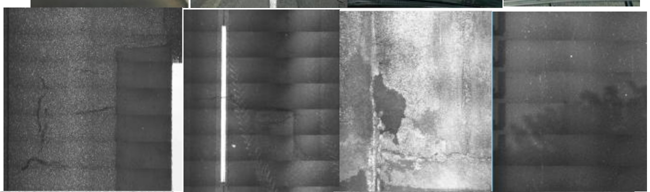
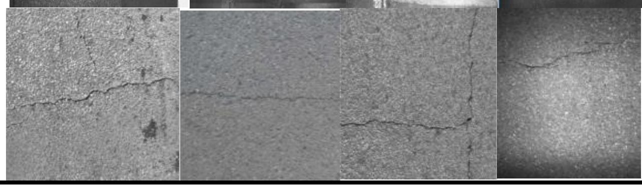
[3] Crack, Alligator crack, Efflorescence, Rockpocket, Washouts concrete corrosion, Hollowareas, Spalling, Restformwork., Wetspot, Rust, Graffity, Weathering, ExposedRebars, Bearing, Expansion joint, Drainage, Protective equipment, Joint tape.

investigated for bridge damage assessment. For example, (Santaniello & Russo, 2023) applied deep neural networks to time-frequency representations of vibration signals to detect structural damage. Their study utilized the Z24 dataset, a well-known benchmark in the field; however, this dataset is not publicly accessible, limiting its broader use in comparative studies. Another notable dataset for bridge damage detection is DACL10 (Flotzinger et al., 2023), a comprehensive dataset comprising 9,920 images collected from real-world bridge inspections. It supports multi-label semantic segmentation and includes annotations for 12 damage types across 6 distinct bridge components, making it a valuable resource for developing and evaluating deep learning models in realistic inspection scenarios.

We iterate here again, the importance of monitoring these structures, like bridges and roads, and identifying the right dataset and model is crucial for efficient restoration works, traffic load management and avoiding disruptions on major routes.

Table 5 shows some samples of the data/images in the different roads datasets here showed in Table 4. The images showed are taken randomly from different classes. In the GAPs 10m dataset by (Stricker et al., 2021), a system of high-resolution imaging was used, and we can see the sample images in Table 5. Another example is the building dataset xBD (Gupta et al., 2019), which by looking at the table of images, we can understand that the authors have used some sort of aerial imaging system or a satellite system, and in fact they used multi-band satellite imagery. In summary, this table shows some samples of how the data looks like, without the need of searching the dataset and looking at the images. In Table 6, samples of the bridge datasets used for damage detection are presented as well.

Table 5, Samples images from road datasets and aerial/satellite

Author/Year	Open-source Dataset Name	Samples
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2022)	RDD2022	
(Du et al., 2021)	LIST	
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021)	RDD2020	
(Stricker et al., 2021)	GAPs 10m	
(Yang et al., 2020)	Crack500	

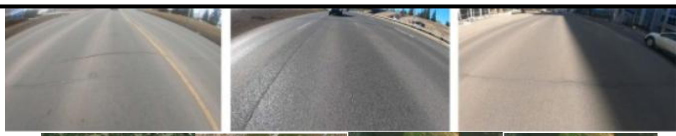
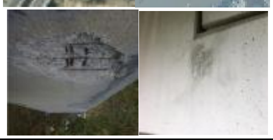
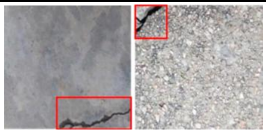
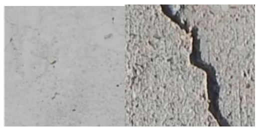
(Mei & Gül, 2020)	EdmCrack600	
(Gupta et al., 2019)	xBD	
(Stricker et al., 2019)	GAPs v2	
(Angulo et al., 2019)	Modified RDD2018	
(Dorafshan et al., 2018)	SDNET2018	
(Shi et al., 2016)	CFD	

Table 6, Samples of images from bridge datasets

Author/Year	Classes	No. of images	Samples
(IADF TC & GRSS IEEE, 2025) DOTA	Multiple classes, including Bridge	11,268	
(IADF TC & GRSS IEEE, 2025) Bridge Dataset	Bridges	500	
(IADF TC & GRSS IEEE, 2025) AID	Multiple classes, including Bridge	10,000	
(Flotzinger et al., 2023) Dacl10k	12 classes (see footnote 2 above)	9,920	

(H. Xu et al., 2019) Crack-detection	Crack, Non-crack	6,069	
(Mundt et al., 2019) CODEBRIM	Crack, Spallation, Efflorescence, Exposed Bars, Corrosion	1,590	
(Dorafshan et al., 2018) SDNET2018	Cracked, Non-cracked	230	

We looked at what datasets about general transport infrastructures are available previously in Table 4 however here in Table 6 we are visualizing sample images of the damaged bridges datasets we previously saw. As shown in the table, most of these datasets concern concrete cracks on bridges, but not analysing the bridge as a whole or from a wide perspective. The “Image Analysis and Data Fusion Technical Committee (IADF TC) of the IEEE Geoscience and Remote Sensing Society (GRSS)” created a centralized platform where researchers can find and explore datasets collected using remote sensing imagery for various applications, such as agriculture, disaster monitoring and climate change analysis (IADF TC & GRSS IEEE, 2025), and the three datasets at the top (DOTA, Bridge Dataset, AID) are taken from this platform, but they don’t have damage information. This is therefore useful for an analysis of transport infrastructures too, as these are open source labelled aerial dataset (satellite view).

As these datasets have been analysed, we need to look at what technologies have been used to collect these data, understanding what is the most used one and which one is more restricted.

3.4 Data collection technologies used for infrastructure damage detection

The data collection technologies are presented in Table 7, where we can see that for roads, most of the datasets have been collected using normal smartphones camera, which means collecting data about roads is generally easier compared to collecting data about bridges and other transport infrastructures, and that is because any person could use their devices with camera to capture the status of the roads. In fact, the RDD dataset as we saw in Table 4, it increased from 26,336 images in the 2020 version, to 47,420 in the 2022 version, which also included more countries.

Table 7, Data collection technologies used for damage datasets

Author/Year	Smartphones	Mobile mapping system	High-res cameras	Optical Device	Camera	Google Street view API
			Roads			
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2022)	x		x			x
(Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021)	x					
(Majidifard et al., 2020)						x

(Mei & Gül, 2020)				x
(Yang et al., 2020)	x			
(Stricker et al., 2019)		x		
(Dorafshan et al., 2018)				x
(Ouma & Hahn, 2017)	x			
(Shi et al., 2016)	x			
(L. Zhang et al., 2016)	x			
(Oliveira & Correia, 2014)			x	

Buildings

	Smartphones	Satellite
(C. Liu et al., 2022)	x	
(Gupta et al., 2019)		x

Bridges

	Vibration sensors	Camera	Satellite
(IADF TC & GRSS IEEE, 2025) DOTA			x
(IADF TC & GRSS IEEE, 2025) Bridge Dataset			x
(IADF TC & GRSS IEEE, 2025) AID			x
(Flotzinger et al., 2023)		x	
(Santaniello & Russo, 2023)	x		
(H. Xu et al., 2019)		x	
(Mundt et al., 2019)		x	

Natural Disasters

	Social media	News portals	Google API
(Weber et al., 2022)	x		x
(Niloy et al., 2021)	x	x	x
(Giannakeris et al., 2018)	x		
(Mouzannar et al., 2018)	x		

We can observe from Table 7 that for buildings and bridges there aren't many methods for data collection, as satellites are usually the easier way to get imagery data for these infrastructures. Therefore, for buildings the data collection primarily relies on aerial images and satellite imagery, where the last one is noted for the high efficiency of capturing building damage, especially where access is restricted like in warzones. As for bridges, data collection is also limited, where technologies used are images or vibration sensor, which suggests the reliance on more specialized equipment to capture structural data and suggests the critical importance of bridge structural health as it is a more fragile infrastructure compared to roads. Here there is also data collected from satellite, but it hasn't been used for damage detection yet. In the case of Natural

Disasters, data collection in this context includes the use of social media (crowdsourcing), news portals and google API. These sources are particularly useful for rapid data gathering, where for a specific study case, the data collector will most likely not be near the disaster, compared to people posting on social media and news journalists.

In summary, while buildings and bridges require more sophisticated equipment for data collection, for roads damages even smartphones are enough to gather data, and in the case of natural disasters, unconventional sources like social media and crowdsourcing plays an important role.

3.5 Types of bridge damages

In the analysis of bridge damages, we wanted to search for what terms are usually used for these damages on bridges, and for the recent studies, we found some types, which are shown in the below table. These include deflection, deformation and displacement.

Table 8, types of bridge damage and location

Author/Year	Damage type	Bridge studied	Country
(Nettis et al., 2023)	Structural deformation	Albiano Magra, Fossano	Italy
(Yunmei et al., 2023)	Deflection	Custom	/
(Markogiannaki et al., 2022)	Displacement, deformation	Polyfytos	Greece
(Schlögl et al., 2021)	Deformation	Seitenhafenbrücke	Austria
(Tian et al., 2021)	Deflection	Southside of Jingtai Bridge	China
(Y. Wu et al., 2021)	Deflection	Custom	/
(Jung et al., 2019)	Deflection	Kimdaejung and Muyoung bridges	S. Korea
(W. Zhang et al., 2017)	Deflection	Custom	/
(Pan et al., 2016)	Deflection	Shuohuang railroad	China
(Sousa et al., 2013)	Deflection	Sorraia Bridge, Leziria Bridge	Portugal

From Table 8, deflection is the dominant damage type, appearing in many entries of the table. This indicates that bending under load is a critical concern in bridge engineering, possibly due to heavy traffic, aging infrastructure or inadequate design. These bridges' locations indicate that damage types are not limited to specific areas and to specific bridge function, such as railroad or highway. The prevalence of deflection suggests that AI models trained on deflection-specific datasets can be effective for bridge monitoring. This can be enhanced also with InSAR, MTInSAR or D-TomoSAR, which will be mentioned in the next chapters, where they can measure minute displacements. In summary, from this table we can understand what the most common damage type is related to bridges and, more recently we see also damages labelled as displacement and deformation.

3.6 Methods used to detect bridge damages

In regards of the methodologies used for detecting bridge damage, we show these in the below Table 9, along with the scope and key finding from each entry. There are three methods: satellite-based methods (MTInSAR, InSAR, D-TomoSAR), image-based methods (Digital Image

Correlation), and sensor-based methods (Laser, inclinometer). These are also better summarized in the below Table 10.

Table 9, Methodologies used to detect bridge damages

Author/Year	Method	Scope	Findings
(Nettis et al., 2023)	MTInSAR: Multi-Temporal satellite-based differential interferometry	Monitoring of structural deformations in bridge portfolios	Bridge with ongoing deformations have been identified and prioritized for inspection
Yunmei et al., 2023 (Yunmei et al., 2023)	Multi-point Chain Laser Reference	Real-time dynamic deflection detection	Measuring accuracy can reach 1 mm, and the dynamic response is good
Markogiannaki et al., 2022 (Markogiannaki et al., 2022)	D-TomoSAR with engineering data and forensics	Monitoring of landmark bridge	Different measurements have been taken, such as displacement products deformation trends.
(W. Liu et al., 2021)	Using two temporal SAR images and verifying using satellite optical image.	Damage Assessment of Bridge after flood	Four washed-away bridges were identified successfully. Three were missed due to location in radar shadow.
(Schlögl et al., 2021)	Time-series analysis (Persistent Scatter Interferometry)	Analysis of bridge deformation using SAR	Promising results when post-processing is correctly applied, extraction of horizontal & vertical deformations, results aggregated. Further research is needed to test transferability to other infrastructures.
(Tian et al., 2021)	Off axis Digital Image Correlation	Deflection measurement with Digital Image Correlation	The full-field image displacement maps can be efficiently and accurately calculated
(Y. Wu et al., 2021)	Secant inclination	New measurement method based on inclination of two points	Error of proposed methos is less than 1%
(Jung et al., 2019)	InSAR with Sentinel-1 SAR and COSMO-SkyMed data	Long-term deflection and thermal dilation of bridges	Downward movements at mid-spans, implying need for periodic monitoring
(W. Zhang et al., 2017)	Finite-element model with partial least-square regression	Bridge deflection estimation	The method is accurate with deflection estimation, also provides rough damage localization
(Pan et al., 2016)	Off-axis digital image correlation	Real-Time measurement of vertical deflection	Advanced video deflectometer is developed and can be used for field measurement of bridge deflection
(Sousa et al., 2013)	Strain and rotation measeuements, inclinometer	Analysis of deflection of bridge	On bridges, using 6th deg. Polynomial function, can predict vertical displacement

MTInSAR leverages multi-temporal satellite data to detect changes over time, and similarly InSAR is applied for long term deflection and thermal dilation analysis, focusing on continuous monitoring. D-TomoSAR is the Differential Tomographic Synthetic Aperture Radar, and it's used to monitor ground deformation by analysing the differences in radar images taken at different times (M. Liu et al., 2018). A study has used two temporal SAR images to assess bridge damage due to a flood and verified the result using satellite optical imagery (W. Liu et al., 2021).

In the case of image-based methods, Digital Image Correlation and Off-axis DIC have been utilized (Tian et al., 2021) (Pan et al., 2016). This is used for deflection measurement by analyzing image displacement maps. The Off-axis DIC uses a video deflectometer to measure this.

As for sensor-based methods, an inclinometer has been used to analyze deflection using polynomial functions to predict vertical displacement (W. Zhang et al., 2017). Also, secant-inclination is also used, which measures inclination between two points to estimate deflection, with an error less than 1%.

Satellite-based methods like InSAR and D-TomoSAR are valuable for inaccessible or large-scale infrastructures, which aligns with remote sensor for challenging environments such as warzones, whereas image-based offer also high-precision for specific damage types such as deflection. The data generated from these satellite-based methods can be further analysed using AI model to classify and quantify damage, which is mentioned in the next tables. The main difference between satellite-based and image-based is the time of monitoring, since methods like Multi-chain laser reference and DIC can get immediate response to structural issues, which makes them near real-time, whereas for satellite-based, some processing steps are required to be able to analyze and visualize the results, making them far from real-time, therefore more for long-term monitoring.

Table 10, technologies used for detection of bridge damage

Author/Year	Type of data used			
	Media	Sensor	SAR	Laser
(Nettis et al., 2023)			MTInSAR	
(Yunmei et al., 2023)				Chain Laser beam
(Markogiannaki et al., 2022)			D-TomoSAR	
(W. Liu et al., 2021)			SAR	
(Schlögl et al., 2021)			SAR	
(Tian et al., 2021)	Video deflectometer side of bridge			Rangefinder
(Jung et al., 2019)			InSAR	
(W. Zhang et al., 2017)		Inclinometer		
(Pan et al., 2016)	Video deflectometer side of bridge			Rangefinder
(Sousa et al., 2013)		Inclinometer		

3.7 Applications of satellite data methods and Synthetic Aperture Radar (SAR)

Satellite imagery and Synthetic Aperture Radar (SAR) have been analysed and seen in the previous tables, however this Table 11 summarises some applications of SAR and the integration with AI where possible. The table is divided into three sections, including General SAR applications, SAR with Coherence and long-term monitoring.

Table 11, applications of satellite SAR methods and uses of AI models

Author/Year	Application	AI	Satellite
(Markogiannaki et al., 2022)	Monitoring of a landmark bridge	No	Sentinel-1A/B
(Huang et al., 2022)	Marine oil spill detection	Faster R-CNN	Sentinel-1 Radarsat-2
(Heiselberg, 2020)	Ship-Iceberg classification (multispectral images)	SVM & CNN	Sentinel-1 Sentinel-2
(R. Wu et al., 2020)	Mapping glacial lakes (with optical satellite)	CNN	Landsat 8 (opt) Sentinel-1A
(Nemni et al., 2020)	Rapid flood segmentation	FCNN	Sentinel-1
(Winsvold et al., 2018)	Regional glacier mapping	No	Sentinel-1A Radarsat-2
(Henry et al., 2018)	Road segmentation in satellite images	FCNN	TerraSAR-X
(Rahman & Thakur, 2018)	Detection, mapping and analysis of flood propagation with GIS	No	Radarsat
(Markert et al., 2018)	Surface water mapping (with optical satellite)	No	Sentinel-1 Landsat (opt)
(Chang et al., 2017)	Nationwide Railway monitoring	No	Radarsat-2

	With Coherence product		
(Kopiika et al., 2025)	Rapid post-disaster infrastructure damage characterization enabled by remote sensing and deep learning technologies	SAM (Segment Anything Model)	Maxar Sentinel-1
(Lopez-Sanchez et al., 2023)	Multi-Annual Evaluation of Time Series of Sentinel-1 Inter. Coherence as a tool for Crop Monitoring	No	Sentinel-1
(ElGharbawi & Zarzoura, 2021)	Damage detection using SAR coherence statistical analysis, application to Beirut, Lebanon	No	Sentinel-1
(Sun et al., 2020)	Deep Learning Framework for SAR Interferometric Phase Restoration and Coherence Estimation	CNN	TerraSAR-X
(Sharma et al., 2017)	Earthquake Damage Visualization for Rapid Detection of Earthquake-Induced damage	No	JAXA ALOS-2
(Yun et al., 2015)	Rapid Damage Mapping for 2015 Gorkha Earthquake	No	COSMO-SkyMed, JAXA ALOS-2
(Bouaraba et al., 2012)	Detection of surface changes using Coherence Change Detection	No	COSMO-SkyMed
(Preiss et al., 2006)	Detection of scene changes with Change in Coherence	No	DSTO Ingara X-Band SAR
	Long Term Monitoring		
(Tonelli et al., 2023)	Interpretation of Bridge Health Monitoring Data from Satellite InSAR	No	COSMO-SkyMed
(Nettis et al., 2023)	Multi-Temporal satellite-based differential interferometry for monitoring structural deformations of bridge portfolios	No	Sentinel-1 COSMO-SkyMed
(Jung et al., 2019)	Long-Term Deflection Monitoring for Bridges Using X and C-Band Time-Series SAR Interferometry	No	COSMO-SkyMed

In the first section it's presented how SAR is useful when it comes to detecting marine oil spills, ship-iceberg detection, glacial lake mappings, road segmented and water/flood mapping. Here the satellites that have been used include two missions from ESA (European Space Agency), Sentinel-1 and Sentinel-2, TerraSAR-X, Landsat and Radarsat. Some of these cases have utilised AI models, such as Faster R-CNN, Support Vector Machine (SVM) and Convolutional Networks for automated detection and classification (Huang et al., 2022) (Heiselberg, 2020) (R. Wu et al., 2020) (Nemni et al., 2020) (Henry et al., 2018).

In SAR interferometry, coherence indicates a measure of correlation between two SAR images at different times, where high coherence indicates better interferences and therefore more accurate phase measurements (Y. Zhang & Prinet, 2004). This is here used for rapid-post disaster infrastructure damage characterization (Kopiika et al., 2025), crop monitoring (Lopez-Sanchez et al., 2023), earthquake damage visualization (Sharma et al., 2017) (Yun et al., 2015) and scene change (ElGharbawi & Zarzoura, 2021) (Bouaraba et al., 2012) (Preiss et al., 2006). The coherence product is mainly taken from Sentinel-1 mission, but also from the German TerraSAR-X, the Japanese JAXA ALOS-2 and the Italian COSMO-SkyMed mission (see Table 12 for available satellites used for monitoring infrastructures along with more specifics). Some AI models have been used here as well, but less frequent compared to general SAR application. In this case, SAM (Segment Anything Model) and CNN are used for tasks like phase restoration and coherence estimation. Therefore, coherence product can be highly useful when comparing pre- and post-event SAR images.

Lastly, for Long-term monitoring, there are two cases of bridge health monitoring and multi-temporal monitoring of structural deformations, using mainly Sentinel-1 and COSMO-SkyMed, without any case of using AI models.

The table shows the versatility of SAR and its usage across different domains. Also, AI integration shows the potential of machine learning to automate and scale SAR data analysis. The frequent use of Sentinel-1 mission from ESA shows the accessibility of high-quality radar imagery which is crucial for researchers. We also saw how the coherence product can be invaluable for post disaster assessment in challenging environments (Kopiika et al., 2025).

The absence AI usage for Long-Term monitoring suggests a gap in utilising Machine Learning for continuous infrastructure monitoring, possibly due to the fact that SAR requires long processing times and expertise.

Therefore, while SAR offers unique advantages for infrastructure monitoring, it has some challenges, as mentioned above. The complexity of SAR data that arises from the multiple dimensions, polarizations and frequency, impacts image resolution, sensitivity to surface features and penetration depth. Atmospheric conditions also further complicate it, with effects such as attenuation, ionospheric disturbances, and tropospheric distortions leading to signal loss and reducing image quality. It is also hard to interpret, due to its signal noise, speckle, distortion and scattering effects, presented in grayscale which requires advanced training (Deep Block, 2023).

Table 12, Available satellite data for monitoring infrastructures. GSD: Ground Sample Distance

Author	Satellite data source	Data resolution in GSD	Features
Gupta et al., 2019)	Maxar	0.3m	Assessing building damages after natural disasters. MDA.
(Mari et al., 2018)	COSMO-SkyMed	1m - 100m	High resolution imagery, multi-mode operation and dual polarization capability. Italian Space Agency.
(Motohka et al., 2017)	JAXA ALOS-2	1m x 3m (spotlight), 3m,6m,10m (strimap)	High resolution imagery, L-band SAR, Compact InfraRed Camera, Automatic Ship Identification System. Japanese Aerospace Exploration Agency.
(Chabot et al., 2014)	RADARSAT-2	3m – 100m	High resolution imaging, flexible polarization and left/right looking imaging capabilities. C-Band SAR. Canadian Space Agency.
(Roy et al., 2014)	Landsat 7/8	15/30m	Landsat 8 has narrower spectral bands, improved calibration and signal-to-noise characteristics, high radiometric resolution and more precise geometry compared to Landsat 7. NASA and US.
(Space Agency, 2012a)	Sentinel-1, ESA	5m - 40m	Radar imagery, dual polarization, short revisit times, fast product delivery. ESA.
(Space Agency, 2012b)	Sentinel-2, ESA	10m	Wide-swath, high resolution and multi spectral imager for earth surface monitoring. ESA.
(Werninghaus & Buckreuss, 2010)	TerraSAR-X	1m - 40m	Radar imagery, various imaging modes, high resolution, rapid switching between modes and polarizations. German Aerospace Centre and Airbus.

Some of the studies above have used damage quantification methods, which have been listed here in Table 13, highlighting their application in real-world scenarios for assessing infrastructure damage, especially in the context of natural disasters. We can see there are 3 methods used for roads infrastructures, such as PASER, PCI and SDI which are standardized visual survey methods that are crucial for systematic infrastructure maintenance planning. Methods like Hazus and UNOST are relevant for post disaster assessment.

Table 13, Damage quantification methodologies

Author/Year	Damage quantification methods	Data source used	Infrastructure	Case study applications
(Teopilus & Amrozi, 2023)	PASER	Visual survey, Bina Marga	Roads	Dandels road, Java island
(Teopilus & Amrozi, 2023)	PCI	Visual survey, Bina Marga	Roads	Dandels road, Java island

(Teopilus & Amrozi, 2023)	SDI	Visual survey, Bina Marga	Roads	Dandels road, Java island
(Gupta et al., 2019)	Hazus Fema	Maxar	Natural disasters	xView2 competition
(J. Z. XU ET AL., 2019)	UNOSAT	UNITAR	Buildings	Indonesia 2018, Mexico City 2017, Haiti 2010

3.8 Natural hazards in studies using AI models

Having detailed the specific damages, AI models, and data technologies, the focus now shifts to the broader context of the causal events. The type of natural hazards, such as flood, earthquake, or wildfire, directly influences the natura and scale of damage to transport infrastructure. This link is critical, as the hazard determines the most suitable remote sensing data and consequently, the design and application of AI models for assessment. To understand the current state of research from this perspective, the following sections analyse the specific natural hazards that have been the focus of using AI models.

The following table summarizes a selection of studies that identify the specific natural hazard stressors investigated. This illustrates the area of focus within the scientific community regarding use of AI for disaster management and risk assessment.

Table 14, Natural hazards stressors analysed

Author/Year	Wild-Fire	Flood	Land disaster	Nature disaster	Earthquake	Hurricane	Volcano	Human-induced	Tsunami
Weber et al., 2022 (Weber et al., 2022)	x	x	x		x	x	x	x	
(Niloy et al., 2021)	x	x	x					x	x
Arif et al., 2020 (Arif et al., 2020)	x	x		x				x	
(Gupta et al., 2019)	x	x			x	x	x		x
(Rizk et al., 2019)				x					
(Barz et al., 2019)		x							
Giannakeris et al., 2018 (Giannakeris et al., 2018)	x	x							
(Mouzannar et al., 2018)	x	x		x				x	
Muhammad et al., 2017 (Muhammad et al., 2017)	x								

(Alam et al., 2017)	x	x	x

The hazards listed in Table 14 directly threaten the integrity of transport infrastructures, which are vital for economic and social connectivity. The table suggests that most of these natural hazards are floods and hurricanes, which can cause direct damage to roads and bridges, and as well as indirect impacts through cascading events like traffic disruptions. As presented in Table 13 a range of methods have been employed for damage quantification. In the context of natural disasters, methodologies such as HAZUS (developed by FEMA) and UNOSAT are frequently adopted. Specifically, HAZUS-FEMA has been applied for multi-hazard damage classification, encompassing events such as floods, hurricanes, and earthquakes (Gupta et al., 2019). These tools leverage geospatial data and standardized assessment protocols to support large-scale disaster impact evaluation.

In the table there are entries also for human-induced hazards, which connects to the discussion of using remote sensing in challenging situations such as warzones. Technologies such as SAR can operate in these areas and are valuable for assessing infrastructure damage in these contexts, as in (Kopiika et al., 2025). The constraint here is the suitability of methodologies and data in these contexts, i.e. the suitability of AI model for SAR based monitoring is limited by the slow acquisition and processing of SAR data, and therefore in the case of rapid-onset hazards like the ones above, timely damage assessment is critical. In Table 15 and Table 16 the datasets and AI models used are presented.

A further constraint is the resolution of the satellite technologies, where open-source satellite missions have worse resolution compared to commercial satellites, such as MAXAR, which can achieve a resolution of 0.3m GSD (Ground Sample Distance), as presented in Table 12. This has an impact on the accessibility of resources, especially in the field of research where these are limited.

The suitability of the technologies shown so far are constrained by practical challenged mentioned before, like data unreadiness, need for faster processing, and better access to high-quality resources. Addressing these gaps through extended datasets and innovative processing techniques will be crucial for advancing infrastructure resilience, in line with supporting sustainable and climate-aware transport networks.

Table 15, Available natural disaster datasets

Author/Year	Dataset Name	Classes	Size	Geo area
(Weber et al., 2022)	Incidents1M	43	977,088	Worldwide
(Niloy et al., 2021)	Disaster-Dataset	Fire, Water, Infrastructure, human damage, land disaster, non-damage.	13,720	India, Japan, Australia, California, Brazil
(Arif et al., 2020)	SAD	Fire, Flood, Infrastructure, Nature, Human damage, non-damage.	493	South Asia

(Barz et al., 2019)	EU-Flood	Flooding, Inundation depth, water pollution.	3,435	Europe
(Rizk et al., 2019)	Home-grown + Sun dataset	Infrastructure, Natural disaster.	2,344	Nepal, Chile, Japan, Kenya
(Giannakeris et al., 2018)	3F-emergency dataset	Fire, Flood.	12,000	N/a
(Mouzannar et al., 2018)	UCI	Fire, Flood, Infrastructure, Nature, Human damage, non-damage.	5,880	Worldwide
(Muhammad et al., 2017)	(Chino et al., 2015) (Foggia et al., 2015) (Verstockt et al., 2013) (Ko et al., 2011)	Fire, non-damage.	68,457	N/a
(Alam et al., 2017)	Image4act	Earthquakes, Typhoon, Hurricane.	34,562	Nepal, Ecuador, Philippines, Haiti

Table 15 presents datasets regarding natural hazards that included use of AI model for detection, and it varies significantly in scale and scope, reflecting the diversity of natural hazards impacting infrastructures. Incidents1M stands out as the largest one, however it included many classes not related to natural disasters such as “bus accident” “motorcycle accident” and other similar accidents, but apart from this it contains a large number of natural disaster classes, such as “dust devil”, “heavy rainfall”, “storm surge” and so on (Weber et al., 2022). The scale of this datasets makes it ideal for AI training. In contrast, other datasets such as SAD (Arif et al., 2020) and Home-grown + Sun dataset (Rizk et al., 2019) are more regionally focused, limiting applicability. These datasets complement the remote sensing technologies, such as SAR and Sentinel-1 previously discussed, i.e. the EU-flood dataset (Barz et al., 2019) aligns with the possibility of using SAR for flood detection (segmentation).

Table 16, Previously used AI models for damage detection after natural disaster

Author/Year	Dataset	Satellite	Model
(Weber et al., 2022)	Incidents1M	No	ResNet50
(C. Wu et al., 2021)	xBD + Maxar	Yes	Attention U-Net
(Gupta & Shah, 2020)	xBD	Yes	RescueNet
(Arif et al., 2020)	SAD	No	VGG16
(Weber & Kané, 2020)	xBD	Yes	Mask R-CNN
(Bai et al., 2020)	xBD	Yes	PPM-SSNet
(Potnis et al., 2019)	WorldView-2	Yes	ERFNet
(Mouzannar et al., 2018)	Home-grown	No	DFMC with SVM
(Alam et al., 2017)	Image4act	No	VGG16

After discussing the datasets, we analyse also the AI model that have been used to achieve the scope, and in Table 16 these are displayed, with information about whether satellite technology have been used and the specific AI model. These range from traditional deep learning architectures such as ResNEt50, VGG16, to more specialized for specific scenarios, like RescueNet and Attention U-Net. Notice the frequent use of xBD dataset (Gupta et al., 2019), which underscore its importance in building damage assessment, due to its extensive satellite imagery (22,068) and standardized damage classification using Hazus FEMA.

The choice of models reflects their suitability for specific tasks. In the case of Attention U-Net (C. Wu et al., 2021) and Mask R-CNN (Weber & Kané, 2020), used xBD for segmentation tasks, identifying damaged areas in satellite imagery. On the other hand, VGG16 (Arif et al., 2020) and ResNet50 (Weber et al., 2022) are more general purpose as they haven't used satellite data and focused on simpler classification task rather than fine-grained damage mapping.

The reliance on satellite data in AI applications highlights the practical challenged discussed earlier, such as slow processing of SAR data as mentioned in section 3.6. While optical satellite imagery offers high resolution, see Table 12, is it weather dependent, limiting the effectiveness during events such as hurricanes and floods. Therefore, SAR overcomes this issue but requires post-processing, which delays the damage assessment for these natural hazards.

4. Conclusion

Transport infrastructures are essential to the vitality of modern economies and societies, yet they are still vulnerable to impacts of climate change and natural disasters. Therefore, the demand for rapid damage assessment and monitoring systems is more needed. In this paper, we examined the transformative role of emerging digital technologies, focusing on AI models and on remote sensing (satellite technology) in strengthening the resilience of transport infrastructures, such as roads and bridges, and with focus also on buildings. The potential of these technologies, although remains constrained by practical and data-related challenges.

In this review, we highlighted the AI models and datasets used for different infrastructures. A key finding is the significant disparity in research focus: while data and models for road damage detection are abundant, reflecting the ease of data acquisition, there is a distinct scarcity of studies integrating AI with SAR data for comprehensive bridge damage assessment. Although models such as ResNet50, Attention U-Net and Mask R-CNN show promise, there is still lack of comparative studies especially for satellite imagery-based approaches, and therefore their effectiveness across varied contexts is not yet fully understood.

SAR technology with its capabilities and variants (i.e. MTInSAR and D-TomoSAR), it excels in monitoring structural deformation with high precision, however it is still limited by complex data structures, atmospheric distortions, interpretive challenges and big computational demand. Some initiatives, such as AI4SAR (ICEYE OY (FI), n.d.), are designing solutions by leveraging AI to streamline SAR data processing, hoping to offer more accessible and efficient monitoring.

Some key direction to advance the field includes:

- Comparative research of newer AI models to determine the most effective solutions for different infrastructure types and hazards, with emphasis on remote technologies such as satellite imagery
- Expand datasets to include underrepresented classes (hazards, infrastructure categories)
- Multi-sensor integration that merges SAR, optical-imagery and ground-based sensors for a complete assessment of infrastructure health

- Use of AI to optimize SAR data analysis and reducing computational barriers, moving towards near-real-time monitoring
- Explore AI-driven approaches for continuous infrastructure monitoring, especially for critical ones such as bridges.

In conclusion, this review covered the latest technologies, including latest AI models and datasets used for damage assessment for various transport infrastructures. Furthermore, we analysed the use of remote technologies, such as satellites, for data acquisition. However, these technologies are constrained by some limitations, as we saw above. As noted in a comprehensive review on data readiness for AI, poor quality data can compromise AI model accuracy, a challenge relevant to the complicated and unstructured nature of SAR data for example and mentioned that while metrics for assessing data readiness for AI are advancing, standardized approaches remain underdeveloped (Hiniduma et al., 2025). Initiative like AI4SAR demonstrate progress in leveraging SAR effectively, yet future research must prioritize not only technological advancement, but also robust and standardized metrics for evaluating data readiness specific to transport infrastructures. This will ensure AI driven solutions deliver efficient, reliable and sustainable outcomes.

Acknowledgments

This research received funding by the UK Research and Innovation (UKRI) under the UK government's Horizon Europe funding guarantee [grant agreement No: EP/Y003586/1, EP/X037665/1]. This is the funding guarantee for the European Union HORIZON-MSCA-2021-SE-01 [grant agreement No: 101086413] ReCharged - Climate-aware Resilience for Sustainable Critical and interdependent Infrastructure Systems enhanced by emerging Digital Technologies.

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