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Application of geospatial data and Artificial Intelligence in underground infrastructure development near existing structures

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ABSTRACT: As urban populations expand, especially in cities like Sydney, detailed engineering assessments are increasingly necessary to evaluate the impact of new developments near existing underground infrastructure. This is critical to ensure the structural integrity of these assets, as required by authorities. Conducting dilapidation surveys before and after construction is essential for detecting structural changes attributable to construction works. This paper discusses the application of advanced technologies, including laser scanning and 3D photorealistic imaging, to assess infrastructure conditions with millimetre precision. It also examines the integration of artificial intelligence (AI) for tunnel dilapidation surveys. These tools are pivotal in obtaining approvals from asset owners for proposed development. The case study demonstrates that 3D scanning offers greater efficiency and cost-effectiveness compared to traditional methods, while also addressing challenges related to access and operational constraints.

1 INTRODUCTION

Urban densification in cities like Sydney has increased the complexity of developments near existing underground infrastructure. These projects require detailed engineering analyses to evaluate potential structural impacts on adjacent tunnels, utilities, and subsurface structures. Dilapidation surveys are critical to documenting pre-existing infrastructure conditions to establish baselines for detecting construction-induced changes or damage. Regulatory authorities require comprehensive instrumentation and monitoring programs that compare actual construction effects with predicted impacts from engineering assessments (Pan et al., 2023). These programs should integrate with pre- and post-construction dilapidation surveys to provide complete infrastructure protection and liability management frameworks.

This study focuses on the application of advanced technologies to enhance infrastructure protection and the evaluation of new developments undertaken in an eastern suburb of Sydney, highlighting the use of high-precision geospatial data acquisition techniques, such as laser scanning and three-dimensional (3D) photorealistic imaging, to perform detailed condition assessments with millimetre-level accuracy. Additionally, AI-assisted tools such as the Dibit8 system are explored for their effectiveness in tunnel dilapidation surveys.

For rail infrastructure specifically, laser scanning facilitates precise geometry capture and lining thickness estimation, which is crucial for identifying potential conflicts and ensuring instrumentation placements do not interfere with rail or track alignment. The present case study underscores the benefits of 3D scanning technology for tunnel dilapidation surveys. Unlike traditional inspection methods, which are often constrained by limited access and operational downtime, 3D scanning offers a more efficient, comprehensive, and cost-effective alternative.

This study demonstrates how geospatial and AI-assisted technologies assist in overcoming access limitations, improve defect detection accuracy, and support structural assessment and regulatory approvals in an underground infrastructure-adjacent development. The application of deep learning-based frameworks in tunnel condition assessment, such as those demonstrated by Jiang et al. (2023), further illustrates the potential of AI-enhanced methods to improve decision accuracy and reliability.

This paper describes the case study site conditions, engineering assessment methodology, tunnel condition survey techniques, and instrumentation strategy, illustrating the practical implementation of these technologies to address specific challenges and support project objectives.

2 OVERVIEW OF CASE STUDY

2.1 *Project Site*

An underground development undertaken in this study, adjacent to the existing rail tunnels, is shown in Figure 1. The development involved the construction of a multistorey building with two basement levels located directly above existing rail tunnels. The works required additional excavation to a maximum depth of 2 m below the existing basement level.

Records indicate that this tunnel section was excavated in 1971 using a ~5 m diameter Tunnel Boring Machine (TBM), supplemented by drill-and-blast, ripping, and roadheader excavation to achieve the final profile. (Braybrooke, 1985). The cross-section comprises twin single-tracked inverted U-shapes, each measuring 5 m in width and 6.3 m in height, as shown in Figure 2.

Between October 2004 and April 2006, a rail crossover was constructed between the two tunnels, resulting in the expansion of the Down tunnel at the case study site, which creates additional structural considerations for the overlying development.

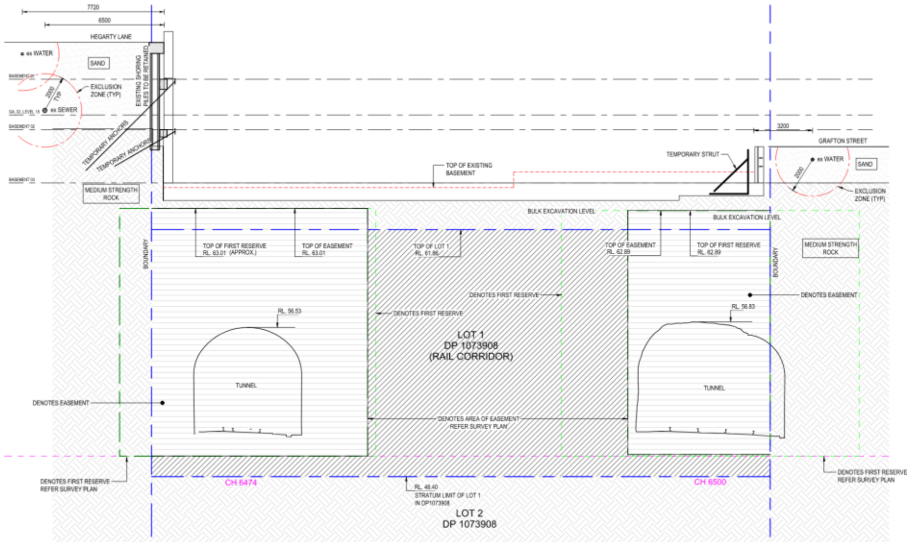


Figure 1. Development site layout showing proximity to existing underground rail tunnels and designated protection reserves.

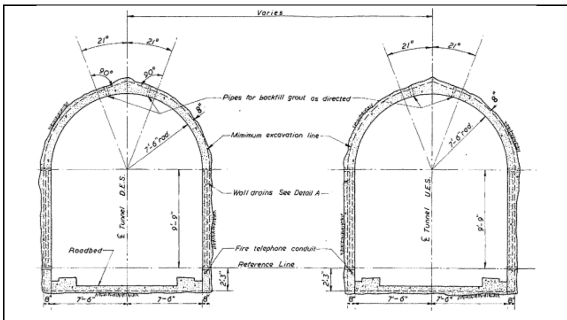
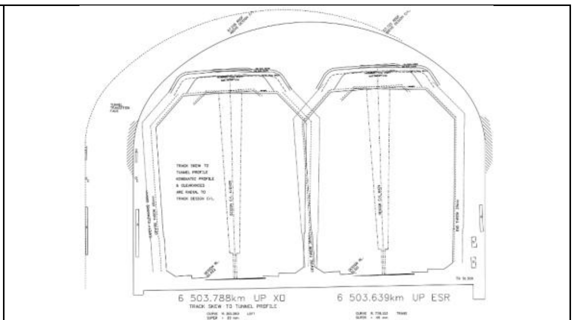
	
(Left)	(Right)

Figure 2. Twin single-track rail tunnels with inverted U-shaped profiles. (Left) View of tunnel cross-section. (Right) Up Track tunnel showing electrical clearance zones for pantographs and overhead wiring equipment.

2.2 *Site Geotechnical Profiles*

Site-specific geotechnical investigations, along with existing data, indicate a subsurface profile generally consisting of fill materials and residual soils overlying Hawkesbury Sandstone. The sandstone ranges from moderately to slightly weathered with medium to high strength. The Hawkesbury Sandstone typically contains two prominent sub-vertical joint sets: Set 1 trending approximately N-NE and Set 2 trending E-SE. The formation is generally thickly bedded, with east-west trending thrust faults present. Bedding planes observed in core samples are clay-coated and, above the tunnel crown, typically spaced at intervals of 1 to 2 m.

Numerical modelling was conducted to assess the impact of construction on the existing tunnels. The soil was modelled using the Mohr-Coulomb constitutive model, whereas the rock mass model utilised the Hoek-Brown failure criterion. Discontinuities were included explicitly, as illustrated in Figure 3. Given no groundwater encountered during the investigation, the tunnels were understood to be drained, with the water table likely drawn down to the invert level. These geotechnical characteristics informed the structural assessment, particularly concerning foundation loads, tunnel movement, and excavation effects, as discussed in the following section.

3 TUNNEL CONDITION ASSESSMENT

3.1 *General*

To establish a baseline record of tunnel conditions prior to construction, the dilapidation survey employed advanced scanning and AI-enabled tools for condition assessment. This method utilised 3D measurements and high-resolution imaging to document surface defects and structural damage, with modern scanning systems enabling 3D reconstruction, crack detection, and feature classification. Three primary approaches supported tunnel monitoring: Reality Capture, Terrestrial Laser Scanning (TLS), and 3D modelling. Reality Capture involved cameras, LiDAR, lighting systems, thermal cameras, and Unmanned Aerial Vehicles (UAVs) to gather extensive photographic and spatial data. These datasets were aligned using standard survey coordinate registration to maintain accuracy. TLS provided dense point cloud data from multiple angles, enabling the creation of precise 3D models of infrastructure, heritage sites, and complex environments.

3.2 *Tunnel Scan Data/System*

The tunnel scanning system shown in Figure 5 collected LiDAR and photogrammetry data at a spatial resolution of 1 mm × 1 mm, with colour imagery captured via digital single-lens reflex (DSLR) cameras at up to 50 megapixels. Point cloud registration to survey control utilised iterative closest point (ICP) algorithms, achieving sub-centimetre alignment accuracy. Data acquisition was completed during two tunnel access windows of approximately 2.5 hours. Raw point clouds were denoised, segmented, and meshed to create high-fidelity 3D models, consistent with methods applied in recent mobile laser scanning frameworks for tunnel environments (Liu et al., 2024). These datasets were then converted to .las, .obj, and .shp formats for integration with Computer-Aided Design (CAD) objects or Building Information Modelling (BIM) software and asset management databases. Geospatial metadata, including tunnel chainage, invert level, and station location, were tagged to each segment, enabling spatial filtering and time-based defect tracking during future inspections.

Figure 3. Vehicle-mounted tunnel scanning system equipped with laser profiler and DSLR cameras for 360° image and geometry capture.

3.3 *Data Processing and 3D Modelling*

Data is processed in phases. Initially, scans and photos are registered to survey control to produce 3D mesh models, point clouds, and high-resolution images. Defects such as cracks, spalling, delamination, water leaks, joint misalignment, and corrosion are identified through manual inspection, semi-automated tools, and machine learning techniques based on predefined defect libraries. This integrated workflow aligns with current research combining point cloud geometry and photographic imagery for accurate and automated tunnel defect classification (Huang et al., 2025).

Traditional survey methods supported and verified digital data capture. Survey control was established along the tunnel alignment using conventional total station methods, with surveyed targets positioned for accurate LiDAR and photogrammetric data georeferencing. Point cloud registration utilised iterative closest point (ICP) algorithms aligned to this established control network, ensuring spatial accuracy to sub-centimetre levels. Table 1 summarises the geospatial data workflow, digital deliverables and their source data.

Table 1. Summary of Digital Deliverables and Source Devices.

Digital Product/Deliverable	Description/Use	Primary Data Source(s)
3D Point Cloud (.las format)	High-resolution spatial dataset used for tunnel geometry modelling and measurement	LiDAR (Laser Profiler)
Textured 3D Mesh (.obj format)	Visual model of tunnel surfaces used for virtual inspection and defect review	Photogrammetry (DSLR Cameras)
High-Resolution Imagery	Still images used for manual review and input to AI-based defect detection	DSLR Cameras
Defect Mapping & Classification	Annotated records of cracks, spalling, leakage, etc., for reporting and monitoring	Combined Photogrammetry + AI Software (Dibit8)
Georeferenced CAD/BIM Layers (.shp, .dxf)	Spatially tagged infrastructure elements (e.g., lighting, services, emergency doors)	Combined LiDAR and Photogrammetry

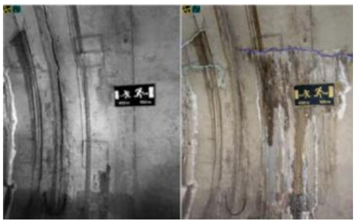
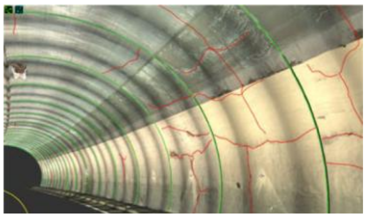
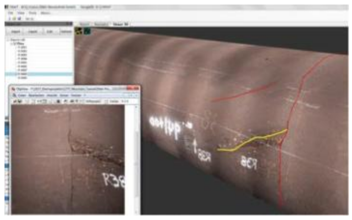
Total processing time for the tunnel scanning dataset was approximately four working days. Automated processing entailing point cloud registration, meshing, and initial AI-based defect detection required two days, while human verification, manual refinement of defect classification, and preparation of final deliverables consumed the remaining 2 days. The AI-assisted workflow significantly reduced manual interpretation time, particularly for defect identification, compared to traditional methods, typically requiring 1 to 2 weeks for comparable tunnel lengths.

3.4 *Defect Identification*

The tunnel scan system data were then analysed using dedicated software tools for defect classification and mapping. Dibit8 software enables operators to map, classify, and analyse defects through a semi-automated detection system driven by artificial intelligence and machine learning algorithms. The software employs a convolutional neural network (CNN) framework trained on a curated dataset of tunnel defect images, including cracking, corrosion, water ingress, and spalling. The trained model can detect linear and non-linear features such as cracks down to a resolution of 0.3 mm, classify them by geometry and orientation, and automatically generate geometry attributes, including crack length, width, and position. Anomaly detection using unsupervised learning identifies unfamiliar or unexpected features. AI-based techniques employed in Dibit8 and similar frameworks for real-time tunnel defect detection (Zhao et al., 2024; Fang et al., 2025) significantly reduce interpretation subjectivity and enable rapid re-analysis of updated scans, improving the accuracy and repeatability of condition assessments.

This approach significantly improves efficiency and consistency over traditional manual methods. All identified defects are stored in a database using spatial positioning and condition assessment criteria, as demonstrated in Table 2.

Table 2. Defect identification.

Data Visualisation	Defect Management	Data Management
– View and navigate large datasets – Epoch to epoch comparison – Custom visual reports	– Identify defects – Semi-automated/AI detection – Imagery overlay and digitisation	– Unique identifiers for observations – Georeferencing metadata – Open source data sharing
		

3.5 *Measuring change of condition over time*

The tunnel scanning enables side-by-side comparison of spatial data captured at different stages, facilitating detection of deformations, evolving damage patterns, crack growth, and newly formed defects. Only the pre-construction dilapidation scan has been completed at the time of writing. Planned scans during and after construction will enable direct comparisons with the baseline dataset to support comprehensive dilapidation surveys throughout construction.

3.6 Advantages of tunnel scanning and monitoring

The tunnel condition assessment demonstrated several practical benefits for infrastructure monitoring and dilapidation surveys. Approximately 190 m of rail tunnels were scanned, capturing geometric details and spatial data, as depicted in Figure 4.

(Left) (Right)

Figure 4. 3D reconstruction of tunnel lining using Dibit8 software. (Left) Colour-mapped mesh of the Down Track tunnel surface. (Right) Crown region showing darker-coloured 2004 shotcrete overlay compared to the original 1971 lining.

Photogrammetric models provided accurate visual representations of tunnel surfaces, while defect mapping for corrosion, leakage, and cracking was carried out using Dibit8 software. The software also mapped tunnel features, including emergency doors, lights, and service cables. The Down Track tunnel exhibited localised expansion and crown deformation. Figure 4 (Right) illustrates the darker coloured shotcrete applied in 2004, distinguishable from the original 1971 lining through AI-assisted 3D scanning and analysis. This diagnostic capability demonstrates enhanced accuracy compared to conventional inspection methods.

3.6.1 Technical Integration

The Dibit8 software processed the tunnel data into true-colour 3D point clouds and textured 3D mesh models exported in various data formats (e.g., .las for LiDAR point cloud, .obj for the photogrammetric model, .shp for integration with CAD and BIM software. Bentley OpenRail software was subsequently used to import point cloud files, generate a 3D track alignment model, produce 3D track alignment models and cross-sections, and export tunnel geometries for instrumentation planning (Figure 5). The tunnel dilapidation survey is shown in Figure 6, with Down Track and Up Track tunnels demonstrated in the left and right layouts.

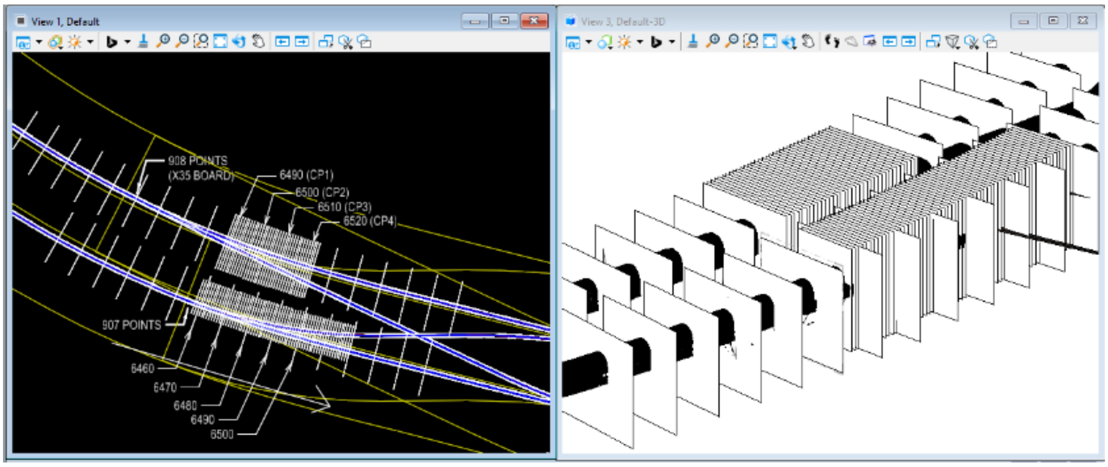
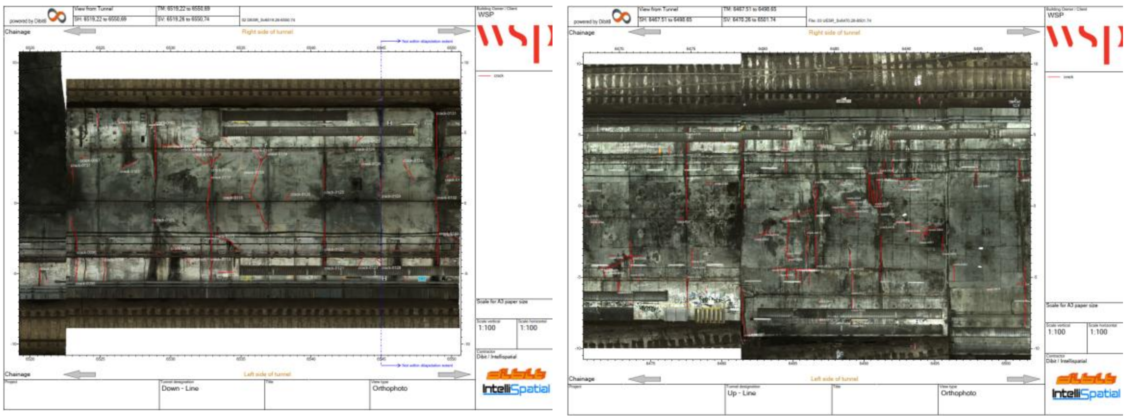


Figure 5. Bentley OpenRail software showing tunnel cross-sections, track alignments, and kinematic envelopes used for instrumentation planning.



(Left) (Right)

Figure 6. Plan layout of tunnel dilapidation survey results. (Left) Down Track tunnel. (Right) Up Track tunnel. Annotated defects mapped using AI-assisted 3D scanning.

3.6.2 Operational Advantages

The 3D scanning approach provided significant operational benefits:

- Traditional dilapidation surveys in confined tunnel environments often require multiple site visits and repeated tunnel shutdowns, typically scheduled during limited night-time access windows of approximately two hours. Conventional surveys for this project would have required eight nights of tunnel access compared to only two nights needed for 3D scanning.
- Conventional inspections struggle with crown defect identification due to obstructions and poor lighting. 3D scanning with AI-based techniques provides superior defect detection capabilities. The 1971 tunnel contained over 600 cracks, which were semi-automatically identified and classified using Dibit8 within two days, compared to the estimated two weeks required for traditional methods.

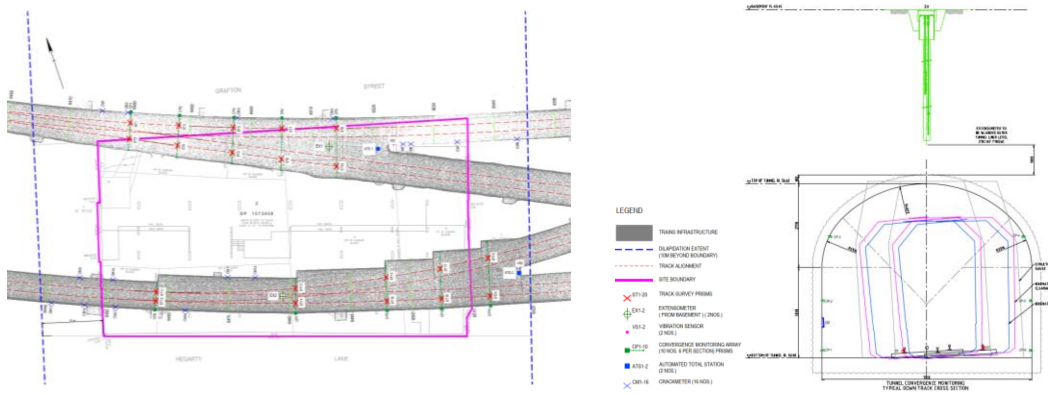
– 3D scanning enables precise kinematic assessments at any cross-section, facilitating optimal monitoring equipment placement and reducing operational risks through virtual inspection capabilities.

3.6.3 *Data Delivery and Stakeholder Engagement*

Outputs were delivered in multiple formats to accommodate varying technical expertise levels. 3D point clouds and mesh models were shared in open formats and integrated into BIM platforms. Annotated defect maps were provided as layered PDF reports and georeferenced CAD files. A web-accessible 3D viewer enabled non-technical stakeholders to visualise tunnel conditions without specialised software. Annotated PDFs and interactive 3D viewers, which provided clarity and accessibility for technical and non-technical project participants, proved most effective for stakeholder communication, enabling improved collaboration, decision-making, and alignment with asset owner requirements.

4 INSTRUMENTATION AND MONITORING

Beyond condition assessment, instrumentation and monitoring (I&M) are essential for verifying engineering predictions and ensuring infrastructure protection during construction activities near existing structures. The proposed I&M plan complies with the requirements outlined in Transport for New South Wales (TfNSW) Standard TS 01717 - Development Near Rail Tunnels (TfNSW, 2020), ensuring adequate clearances for the tunnel kinematic envelope, pantographs, and overhead wiring systems. Figure 7 illustrates the I&M implementation plan and instrumentation cross-section for this case study.



(Left) (Right)

Figure 7. (Left) I&M implementation plan. (Right) Cross section showing the instrumentation details with kinematic envelope.

4.1 *Kinematic Envelope*

Kinematic envelopes define rolling stock boundaries by incorporating static vehicle outlines, dynamic tolerances, and applied safety margins. LiDAR point clouds and alignment data were used to generate 3D kinematic envelopes at defined intervals, determining optimal instrument placement. Figure 7 (Right) illustrates the kinematic envelope (KE) and KE+200 envelope for authorised rolling stock operations. All monitoring instruments are positioned outside KE+200, with the highest prisms placed at a maximum height of 4 m from the tunnel invert level to prevent interference with overhead lines and pantographs.

5 CONCLUSION AND RECOMMENDATIONS

This study presents a methodological approach to underground development near existing infrastructure, demonstrating the application of advanced geospatial technologies and AI-assisted systems for comprehensive condition assessment in Sydney's urban environment.

The findings demonstrate that tunnel defects can be analysed in virtual 3D environments, providing high-quality data to support tunnel condition assessments. This approach delivered several tangible benefits: 3D scanning and AI-assisted detection identified and measured over 600 cracks within two days, significantly reducing time, access constraints, and resource requirements compared to traditional dilapidation surveys. High-resolution digital models facilitated coordination with rail authorities, enabling instrumentation design that complied with the kinematic envelope and clearance requirements, streamlining the approval process.

While 3D scanning and AI-assisted defect detection offer substantial advantages in efficiency, coverage, and repeatability, certain limitations warrant consideration. AI-based detection reliability depends on training dataset quality and diversity, with rare or novel defects potentially requiring manual verification. Environmental factors, including lighting conditions, surface texture, and tunnel obstructions, can affect data quality and processing accuracy, emphasising the continued importance of engineering judgment and validation alongside digital tools.

The technologies and workflows demonstrated, i.e., terrestrial laser scanning, photogrammetry, AI-based defect classification, and CAD/BIM integration, are broadly transferable across infrastructure types and operating conditions, particularly where access limitations make conventional inspections impractical. Future research should explore long-term performance implications, scalability across different infrastructure types, and effectiveness under varied site conditions.

This work contributes to the evolving field of infrastructure protection in urban development, highlighting the critical role of digital technologies in addressing complex engineering challenges. As urban densification continues, such methodologies will become increasingly critical for delivering safe, efficient, and sustainable infrastructure outcomes.

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