# STANDARD METHODOLOGY FOR PUBLIC WORKS INSPECTION INTEGRATING DRONES AND ARTIFICIAL INTELLIGENCE

# METODOLOGIA PADRÃO PARA INSPEÇÃO DE OBRAS PÚBLICAS INTEGRANDO DRONES E INTELIGÊNCIA ARTIFICIAL

# METODOLOGÍA ESTÁNDAR PARA LA INSPECCIÓN DE OBRAS PÚBLICAS INTEGRANDO DRONES E INTELIGENCIA ARTIFICIAL

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## ABSTRACT

The inspection of roads, bridges, dams, and buildings, is essential for ensuring the safety, compliance, and operational efficiency of public works. However, traditional inspection methods are often time-consuming, costly, and limited in accuracy, particularly in hard-to-access areas. The use of drones and artificial intelligence (AI) in such inspections represents a significant advancement in terms of efficiency and precision. Yet, the lack of a standardized methodology limits the full adoption of these technologies. This study proposes and validates a standardized methodology for public works inspection, by integrating drones equipped with advanced photogrammetry technology and AI. The methodology leverages scale bars to enhance measurement accuracy and AI algorithms for automated diagnostics, enabling the precise identification of structural defects and anomalies. Case studies were conducted on urban pavement, buildings, bridges, and concrete dams, demonstrating the effectiveness of the proposed approach over a variety of infrastructure types and inspection scenarios. The results indicate high accuracy in measurements and in the identification of construction defects and pathological manifestations in the analyzed structures. This novel approach offers significant improvements in accuracy, safety, speed, and efficiency in public works management, while providinga replicable framework for public agencies and regulatory bodies worldwide.


**Keywords:** Drones. UAV. Artificial Intelligence. Public Works. Infrastructure. Pathological Manifestation.


## RESUMO

A inspeção de rodovias, pontes, barragens e edificações é essencial para garantir a segurança, conformidade e eficiência operacional das obras públicas. No entanto, os métodos tradicionais de inspeção são, em geral, demorados, onerosos e apresentam limitações de precisão, especialmente em áreas de difícil acesso. A utilização de drones e inteligência artificial (IA) nessas inspeções representa um avanço significativo em termos de eficiência e precisão. Contudo, a ausência de uma metodologia padronizada limita a plena



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adoção dessas tecnologias. Este estudo propõe e valida uma metodologia padronizada para inspeção de obras públicas, por meio da integração de drones equipados com tecnologia avançada de fotogrametria e algoritmos de IA. A metodologia emprega barras de escala para aprimorar a acurácia das medições e algoritmos de IA para diagnósticos automatizados, possibilitando a identificação precisa de defeitos estruturais e manifestações patológicas. Estudos de caso foram realizados em pavimentos urbanos, edificações, pontes e barragens de concreto, demonstrando a eficácia da abordagem proposta em diferentes tipos de infraestrutura e cenários de inspeção. Os resultados indicam elevada precisão nas medições e na identificação de defeitos construtivos e manifestações patológicas nas estruturas analisadas. Esta abordagem inovadora proporciona melhorias significativas em precisão, segurança, agilidade e eficiência na gestão de obras públicas, além de oferecer um modelo replicável para órgãos públicos e entidades reguladoras em âmbito global.

**Palavras-chave:** Drones. VANT. Inteligência Artificial. Obras Públicas. Infraestrutura. Manifestações Patológicas.

**RESUMEN**

La inspección de carreteras, puentes, represas y edificaciones es fundamental para garantizar la seguridad, el cumplimiento normativo y la eficiencia operativa de las obras públicas. Sin embargo, los métodos tradicionales de inspección suelen ser lentos, costosos y presentan limitaciones en cuanto a precisión, especialmente en áreas de difícil acceso. El uso de drones e inteligencia artificial (IA) en estas inspecciones representa un avance significativo en términos de eficiencia y precisión. No obstante, la falta de una metodología estandarizada limita la adopción plena de estas tecnologías. Este estudio propone y valida una metodología estandarizada para la inspección de obras públicas, mediante la integración de drones equipados con tecnología avanzada de fotogrametría y algoritmos de IA. La metodología emplea barras de escala para mejorar la precisión de las mediciones y algoritmos de IA para diagnósticos automatizados, permitiendo la identificación precisa de defectos estructurales y manifestaciones patológicas. Se realizaron estudios de caso en pavimentos urbanos, edificaciones, puentes y represas de hormigón, demostrando la eficacia del enfoque propuesto en diferentes tipos de infraestructura y escenarios de inspección. Los resultados indican una alta precisión en las mediciones y en la identificación de defectos constructivos y manifestaciones patológicas en las estructuras analizadas. Este enfoque innovador proporciona mejoras significativas en precisión, seguridad, rapidez y eficiencia en la gestión de obras públicas, además de ofrecer un modelo replicable para organismos públicos y entidades reguladoras a nivel mundial.

**Palabras clave:** Drones. UAV. Inteligencia Artificial. Obras Públicas. Infraestructura. Manifestaciones Patológicas.

## 1 INTRODUCTION

### 1.1 CONTEXTUALIZATION

Public works inspection plays a fundamental role in ensuring the quality, safety, and compliance of construction projects with current specifications and regulations. This process is essential for ensuring the durability and safety of urban infrastructure, directly contributing to the sustainable development of cities and mitigating risks to the population and public resources [1]. However, traditional manual inspections face significant limitations, such as high costs, time-consuming work, and risks to inspector safety, especially on large or difficult-to-access projects such as highways, bridges, buildings, and dams [2]. These challenges are even more pronounced for public agencies in remote or economically disadvantaged areas, such as northern Brazil, where limited budgets and a shortage of specialized personnel hinder the adoption of high-precision equipment or advanced inspection techniques [3, 4].

This gap not only compromises the efficiency and safety of inspections but also exacerbates infrastructure inequalities, exposing vulnerable communities to heightened risks. A concrete example of this reality occurred in northern Brazil, where, in December 2024, the Juscelino Kubitschek de Oliveira Bridge collapsed, causing significant socioeconomic damage. Data from the National Department of Transportation Infrastructure (DNIT) indicate that, in May 2023, 727 federal bridges were classified as "critical" or "poor," with 130 in the worst possible condition, demonstrating widespread structural fragility.

Given this scenario, the development of innovative, accessible, and low-cost inspection solutions is imperative. These solutions must provide accurate and reliable results without requiring significant financial investments or highly specialized expertise. Technologies with these characteristics can enhance infrastructure monitoring and maintenance capabilities, mitigating risks and promoting greater safety and equitable access to essential transportation structures.

Technological advances have revolutionized the field of infrastructure inspections, with drones emerging as a transformative solution. Equipped with cameras, sensors, and specialized software, drones enable faster, safer, more accurate, and comprehensive aerial inspections. These systems are capable of collecting large volumes of visual and topographic data in short periods, achieving unmatched accuracy compared to traditional methods [5]. Studies show that drone-based inspections can reduce operating costs by up to 30% and increase data collection efficiency by up to 80% [5, 6]. Furthermore, the integration of drones with LiDAR technology has revolutionized 3D mapping for infrastructure inspection, enabling the creation of highly accurate models of terrain and structures. LiDAR-equipped drones have been used to monitor deformations in dams, bridge stability, and urban drainage systems, providing essential data for predictive maintenance. These models enable the accurate quantification of structural changes, ensuring that maintenance interventions are timely and cost-effective [7].

Despite these advantages, the high costs associated with LiDAR sensors and RTK-based drone systems, in addition to the need for specialized operators, limit their widespread use, especially in underserved regions such as northern Brazil, where municipal agencies often lack the financial and human resources to adopt these technologies [4, 8]. Therefore, there is a pressing need for drone solutions that are affordable, easy to operate, and offer high-level performance without requiring significant investment or technical expertise. By democratizing access to these technologies, it is possible to empower remote and economically challenged communities to achieve safer and more efficient infrastructure management, leveling the playing field in construction inspections globally.

Recent studies have investigated the application of drones and artificial intelligence (AI) in infrastructure inspections, highlighting significant advances but also persistent limitations regarding standardization. Karim and Dagli [9] proposed a framework for evaluating meta-architectures of integrated systems for aerial inspections; however, their approach lacks practical protocols for direct field implementation. Similarly, Madriles Cristales [10] developed platforms that integrate drones and imaging technologies, but without addressing replicable methodologies or advanced automation solutions for diagnostics. Seo et al. [8] proposed a methodology for bridge inspection using drones; however, their approach does not incorporate AI or precision measurement alternatives such as the use of scale bars, remaining dependent on ground control points (GCPs) that require expensive RTK GPS equipment. Congress and Puppala [3] explored the monitoring of transportation infrastructure with drones, but did not examine the application of universally recognized standards. Finally, Pitas [11] reviewed the use of drones and AI in inspections, emphasizing their potential, but without detailing auditable and replicable protocols for large-scale application.

The integration of artificial intelligence (AI) further expands the capabilities of drones, enabling automatic pattern recognition, structural anomaly detection, and real-time analysis of infrastructure conditions [4, 12]. AI-based models can achieve accuracy levels above 90% in identifying and classifying structural defects in large infrastructures [4]. This is particularly crucial for complex structures such as bridges and dams, where early damage detection can prevent catastrophic failures [13]. Furthermore, AI-based approaches optimize data interpretation, streamlining decision-making processes in the management of public construction and infrastructure [14].

The combination of drones and AI has already resulted in significant advances in the inspection of complex structures, such as bridges and highways. Studies have highlighted the benefits of integrating multiple sensors, such as infrared cameras for detecting internal damage and high-resolution cameras for identifying surface defects, enabling a holistic assessment of structural integrity [15]. When applied to public infrastructure, this technology provides a safe and low-cost alternative to traditional methods, eliminating the need for risky manual inspections and enabling more comprehensive and auditable assessments. Furthermore, these innovations contribute to sustainability by extending the lifespan of infrastructure and optimizing resource allocation [13]. However, widespread adoption of combined drone and AI technology still faces challenges. Many current approaches rely on specialized drones and expensive RTK GPS systems, requiring trained professionals and making them impractical for resource-poor regions such as northern Brazil [8].

Additionally, the lack of standardized protocols also limits the widespread use of drones and AI in public works. The lack of uniform procedures covering different types of infrastructure, practical validations, and regulatory acceptance compromises the consistency, reliability, and regulatory acceptance of drone inspections [13]. The lack of accessible and simple methodologies prevents many public agencies from adopting these technologies on a large scale [3]. Public agencies, regulatory bodies, and audit courts need accessible, practical, and auditable methodologies to ensure data quality and measurement accuracy, essential elements for integrating these technologies into conventional inspection practices [4].

## 1.2 OBJECTIVES

This study presents an innovative methodology that integrates drones and artificial intelligence to offer a standardized, auditable, and highly cost-effective solution for public works inspection. Unlike conventional approaches that rely on high-performance drones and expensive RTK GPS systems [8], this methodology achieves exceptional measurement accuracy using low-cost scale bars—valued at just US$15 each—eliminating the need for ground-based control point surveys. It utilizes commercially available drones, such as the DJI Air 2S, which cost less than US$1,000, in contrast to specialized UAVs equipped with RTK or LiDAR, which can exceed US$20,000 [6]. This approach reduces inspection costs by up to 70%, enabling access to advanced technologies for budget-constrained public agencies, especially in remote regions like northern Brazil, where infrastructure challenges are exacerbated by limited resources.

Developed with a focus on operational simplicity, the methodology requires minimal training, allowing local teams to perform high-quality inspections without the need for specialized expertise. By systematizing measurement and inspection procedures, the methodology ensures replicability, reliability, regulatory acceptance, and accessibility, making cutting-edge technologies practical for public managers and infrastructure operators worldwide. Its standardized and auditable structure is versatile, applicable to a variety of projects—from urban roads to remote dams—and meets rigorous regulatory standards. Ultimately, this methodology has the potential to revolutionize public works inspection, promoting transparency, efficiency, and safety in infrastructure management.

## 2 METHODOLOGY

This study proposes, applies, and validates a standardized, low-cost, and accessible measurement methodology based on the use of scale bars, adapted for analysis with commercially available drones, specialized software [16, 17], and artificial intelligence (AI) techniques.

The approach was tested on four distinct structures located on the Gold Coast, Queensland, Australia: an urban pavement, a reinforced concrete bridge, the facade of a commercial building, and a reinforced concrete dam. The methodology was developed to ensure accurate measurements and detailed analysis of each structure, integrating flight planning, image capture, automated AI-based analysis, data extraction, and quality assessment. Table 1 presents the objects analyzed in this study along with their main characteristics.

**Table 1**

*Overview of structural objects and associated pathologies analyzed in this study*

| Structure | Location | Flight Planning | Measured variables | Píctures |
|---|---|---|---|---|
| Urban Pavement | Christine Avenue, Varsity Lakes, Australia | Grid mapping, height = 40 m, overlap: front = 80%, side = 70% | Surface area = 7.435,00 m² |  |
| Reinforced Concrete Bridge | Bridgewater Drive, Varsity Lakes, Australia | One grid mapping, height = 40 m, overlap: front = 80%, side = 70%; two orbital mappings, heights = 20 m and 15 m; | Length = 40 m |  |

| | | | | |
|---|---|---|---|---|
| | | one manual flight | | |
| Commercial Building Facade | Watts Drive, Varsity Lakes, Australia | Manual flight | Surface area= 50,52 m² |  |
| Reinforced Concrete Dam | Hinze Dam, Advancetown, Australia | A grid mapping, height = 50 m, overlap: front = 80%, side = 70%; an orbital mapping, height = 40 m; a manual flight | Maximum height of the wall= 83,1 m |  |

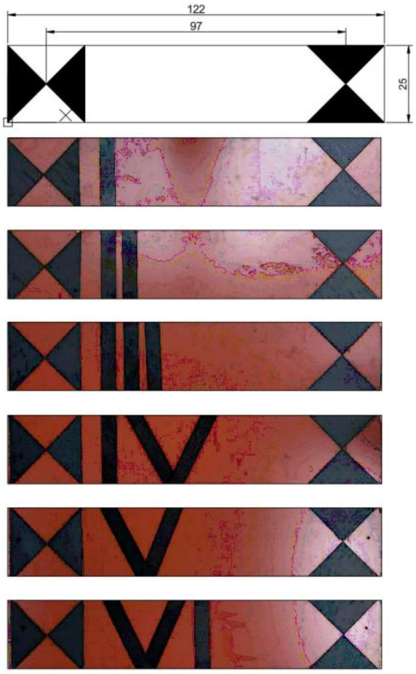
Source: Prepared by the authors.

The use of scale bars as measurement references in image processing has already been explored in several studies. Jauregui and White [18] used them to calibrate photogrammetric images during bridge inspections, while [19] employed them to ensure accurate crack measurements. Unlike these studies, which focused on specific applications, this work proposes a standardized methodology for the inspection of various public infrastructures, aiming for high accuracy and easy adoption by public agencies.

This study uses scale bars as measurement references, eliminating the need for ground control points when using photogrammetric software. To this end, six scale bars (Figure 1) were produced using wooden boards measuring 122 x 25 cm, with a distance of 97 cm between reference points, assembled at a reduced cost of approximately AU$15 per unit. The triangular markers at both ends were made of black cardboard, ensuring high contrast in the images, while the numbering was applied using black adhesive tape. These bars were strategically positioned in the flight scenes to ensure accurate measurements across different subjects and study conditions.

**Figure 1**

*Photograph of the six scale bars used for drone measurements. These bars ensure accuracy in photogrammetric data collection by providing standardized points for image scale and alignment*




Source: Prepared by the authors.

The scale bars were numbered sequentially from I to VI to facilitate their identification in the images captured by the drone during the photogrammetric surveys. The Roman numerals were positioned on the left side of the bars, and the triangular markers at both ends were inverted, a configuration designed to prevent misinterpretations during image processing. This arrangement ensures greater precision in creating control points and constructing the three-dimensional model in Agisoft Metashape software.

For data acquisition, a DJI Air 2S drone was used, equipped with a 20 MP image sensor, 22 mm lens, and three-axis stabilization. The equipment weighs 595 g, has a maximum flight time of 30 minutes, and operates with GPS, GLONASS, and GALILEO navigation systems, ensuring high precision during flights [20]. This commercially available drone is affordable for public agencies and easy to operate, constituting a practical option for infrastructure inspections without the need for highly specialized personnel. Flight planning was performed using Dronelink software, version 4.5.0 [21], configured for grid mapping with an overlap of 80% on the front and 70% on the sides, orbital mode, and manual flights, adjusting the altitude according to the characteristics of each object. The flights took place in October and November 2024, on different dates, between 12:00 PM and 1:00 PM, under optimal lighting conditions to minimize shadows in the images. During operations, the drone was configured with a three-second photo interval, ISO 100, exposure (EV) of -1.0, and manual white balance. Three to six scale bars were strategically positioned in each area to triangulate reference points and maximize measurement accuracy.

The collected images were processed in Agisoft Metashape software, version 1.8.5, developed by Agisoft LLC [16]. Initially, images were evaluated and discarded if they were below 70% quality. The accepted images were aligned using the GDA 2020/MGA Zone 56 coordinate system, with scale bars ensuring measurement accuracy. A dense point cloud was then generated, eliminating inconsistent points to improve the model. From the point cloud, a Digital Elevation Model (DEM) and an orthomosaic were created, serving as the basis for subsequent measurements and analysis.

Three distinct methodologies were applied to extract length, area, and volume measurements of structural pathologies:

a) Manual Field Measurements (Reference Values): Direct measurements were obtained in situ using a metal tape measure. These values served as a reference for validation and comparison of the results obtained by the software.
b) Agisoft Metashape: Measurements were taken directly on the orthomosaic in the software environment, using the integrated measurement tools, with calibration based on the scale bars.
c) AutoCAD: The orthomosaics generated in Metashape were imported into AutoCAD 2024, developed by Autodesk [17]. Detailed measurements were taken after scaling the images based on the reference points provided by the scale bars.

For a comprehensive assessment of the studied objects, the quality inspection combined two approaches:

Automated visual analysis was conducted using an artificial intelligence assistant developed specifically for this study. This assistant was designed to identify structural anomalies in buildings, bridges, road surfaces, and dams. The system diagnoses construction defects, pathological manifestations, and other anomalies, in addition to identifying possible causes and suggesting corrective interventions based on engineering standards (describe the difference between GPT and any AI).

The AI model was trained using a selected dataset consisting of articles from high-impact scientific journals, engineering technical books, dissertations, and internationally recognized standards. These sources include publications indexed in databases such as Scopus and Web of Science, as well as textbooks widely used in civil and structural engineering courses. Some key references used in the development and training of the assistant include:

a) Standard Method of Measurement for Civil Engineering Quantities (ICE, 2012) [22];
b) Industrial standards, such as (ISO, 2010) [23] (Basis for Structural Design) and ASTM International standards;
c) American standards, such as (ACI 318, 2019) [24] (Building Code Requirements for Structural Concrete) and the Bridge Design Specifications (AASHTO, 2020) [26];
d) Standards of the European Committee for Standardization (CEN), (EN 1504-9, 2008) [25].

In terms of technical standardization, the methodology is not restricted to the standards of a single country. Although the AI assistant is primarily guided by internationally recognized engineering codes and standards [27, 28, 29, and 30], it is adaptable to specific standards in different regions. The user can configure the tool to prioritize guidelines from specific countries, such as Australian Standards [31, 34], Eurocodes [25, 28, 32], or AASHTO standards [26, 33], depending on the geographic context of the inspection.

Furthermore, the AI assistant was developed with adaptability in mind. The user can specify the preferred country or standard during the configuration process, allowing the tool to adjust its algorithms and recommendations accordingly. For example, when used in Australia, the assistant can align its analyses with the AS 3600 [34] standard for concrete structures, while in the United States, it may follow ACI 318 [35] standards. The AI model emphasizes clarity, technical precision, and objectivity in its analyses, avoiding unfounded assumptions. For greater transparency, the model can be accessed at the following link: AI tool: https://chatgpt.com/g/g-673d4c24cd9081919dd63db9bfe529af-enginuity.

To validate the AI results, a direct visual inspection was conducted in the field. This on-site verification confirmed the AI findings and provided additional context, offering a comprehensive view of the identified pathologies.

## 3 RESULTS AND DISCUSSIONS

The results demonstrated that the combination of drones, photogrammetry software, and artificial intelligence is effective in inspecting public works, providing accuracy, speed, and safety. The use of a commercially available drone, combined with low-cost scale bars, proved to be a viable and cost-effective solution, achieving high measurement accuracy without the need for RTK GPS systems or other specialized equipment. Below, the main findings for each study object are detailed, highlighting the measurements performed, the pathological manifestations identified, and the proposed recommendations.

3.1 URBAN PAVEMENT

The measurements obtained with Agisoft Metashape and AutoCAD were compared with field measurements (reference values) to validate the accuracy of the digital methods. Table 2 presents the comparative data for the diameter and area of the selected potholes.

To quantify the discrepancy between the digital and field measurements, the Mean Absolute Percentage Error (MAPE) was used. This metric expresses the magnitude of the error as a percentage of the actual (benchmark) values, allowing a relative assessment of the accuracy of predictive measurements. MAPE is defined by Equation 1:

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{yi - xi}{yi} \right| \quad (1)$$

Where:

yi - represents the actual values obtained in the field (reference values);

xi - corresponds to the values estimated by digital methods (Agisoft Metashape and AutoCAD);

n - is the total number of measurements analyzed.

**Table 2**

*Comparative measurements of diameter and area of selected potholes on Christine Avenue, obtained using Agisoft Metashape, AutoCAD, and in-situ methods. The number of asterisks (*) represents the absolute percentage difference between the digital methods and the in-situ measurements (reference values)*

| | *In-loco* (reference values) | | Agisoft Metashape | | AutoCAD | |
|---|---|---|---|---|---|---|
| ID | Diameter (m) | Area (m²) | Diameter (m) | Area (m²) | Diameter (m) | Area (m²) |
| P1 | 1.41 | 1.56 | 1.39* | 1.52** | 1.38** | 1.49*** |
| P2 | 0.77 | 0.47 | 0.78* | 0.48* | 0.78* | 0.48* |
| P3 | 2.48 | 4.83 | 2.46* | 4.87* | 2.47* | 4.79* |
| P4 | 0.86 | 0.58 | 0.87* | 0.59* | 0.86* | 0.58* |
| P5 | 1.22 | 1.17 | 1.23* | 1.19* | 1.20** | 1.13** |
| P6 | 0.53 | 0.22 | 0.52** | 0.21*** | 0.53* | 0.22* |
| P7 | 0.81 | 0.52 | 0.80* | 0.50*** | 0.79** | 0.49*** |
| P8 | 3.25 | 8.29 | 3.24* | 8.24* | 3.25* | 8.29* |
| P9 | 0.45 | 0.16 | 0.46** | 0.17*** | 0.45* | 0.16* |
| P10 | 1.35 | 1.43 | 1.34* | 1.41* | 1.33* | 1.39** |
| P11 | 1.90 | 2.83 | 1.99*** | 3.10*** | 1.89* | 2.80* |
| P12 | 0.87 | 0.59 | 0.86* | 0.58** | 0.87* | 0.59* |
| P13 | 1.72 | 2.32 | 1.71* | 2.30* | 1.73* | 2.35* |
| P14 | 1.32 | 1.37 | 1.31* | 1.34** | 1.30* | 1.33** |
| P15 | 0.75 | 0.44 | 0.75* | 0.44* | 0.76* | 0.45** |

| | | | | | | |
|---|---|---|---|---|---|---|
| P16 | 1.45 | 1.65 | 1.46* | 1.66* | 1.46* | 1.67* |
| P17 | 0.75 | 0.44 | 0.76* | 0.45** | 0.75* | 0.44* |
| P18 | 1.41 | 1.56 | 1.40* | 1.55* | 1.39* | 1.52** |
| P19 | 1.88 | 2.77 | 1.88* | 2.77* | 1.87* | 2.75* |
| P20 | 0.46 | 0.17 | 0.47** | 0.17* | 0.47** | 0.17* |
| P21 | 2.18 | 3.73 | 2.16* | 3.66** | 2.19* | 3.76* |
| P22 | 0.65 | 0.33 | 0.65* | 0.33* | 0.65* | 0.33* |
| P23 | 0.87 | 0.59 | 0.88* | 0.61*** | 0.87* | 0.59* |

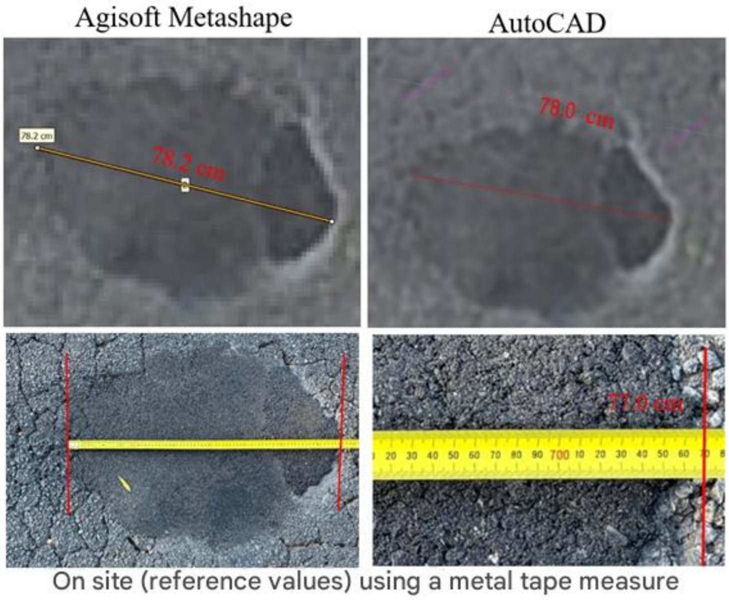
*Indicates an absolute error of 0 to 1.5%; **Indicates an absolute error of 1.6% to 3.0%; ***Indicates an absolute error of 3.1% to 4.5%; and **** Indicates an absolute error greater than 4.6%.
Source: Prepared by the authors.

Both Agisoft Metashape and AutoCAD demonstrated high accuracy in diameter measurements, with AutoCAD presenting a slightly lower average MAPE (0.81%) compared to Agisoft (1.13%). However, discrepancies were more pronounced in area estimates, where Agisoft presented a higher MAPE (2.12%) and greater variability (±2.26%). AutoCAD outperformed Agisoft in both metrics, achieving greater accuracy, especially in area measurements, where it recorded an average MAPE of 1.40% (±1.63%). Despite these differences, all observed errors remained below 3%, indicating that the variations are statistically insignificant and do not compromise the reliability of the proposed methodology.

To reinforce the reliability of the results and validate the accuracy of the measurements, points P2 and P8 were selected for visual illustration (Figures 2 and 3). These points represent holes of different dimensions, ensuring alignment with the data in Table 2. The graphical representations reinforce the credibility of the findings, visually confirming the accuracy of Agisoft Metashape and AutoCAD in relation to the reference values obtained in the field.

**Figure 2**

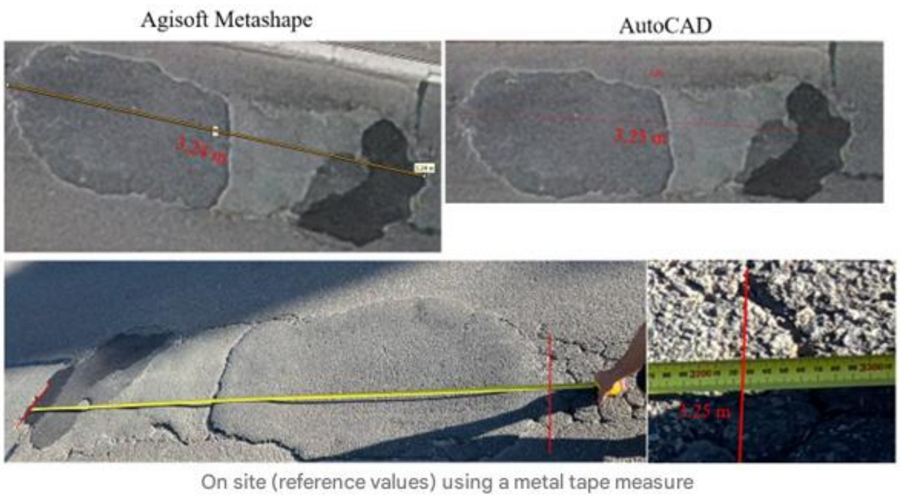
*Comparison of measurements of hole P2 using Agisoft Metashape (top left panel), AutoCAD (top right panel), and in-situ reference values (bottom panels). The minimal discrepancies confirm the accuracy of the digital photogrammetry- and CAD-based methods*




Source: Prepared by the authors.

**Figure 3**

*Comparison of measurements of hole P8 using Agisoft Metashape (top left panel), AutoCAD (top right panel), and in-situ reference values (bottom panels). The close agreement between the methods highlights their reliability for assessing pavement defects*




Source: Prepared by the authors.

The results indicate that both methodologies, using Agisoft Metashape and AutoCAD, are effective in capturing diameter and area dimensions, with relatively small differences compared to in-situ measurements. However, measurement accuracy can be influenced by human error during data collection and analysis.

Identifying and quantifying pathological manifestations is essential for defining appropriate solutions for pavement rehabilitation and public works budgeting. For the analysis, the orthomosaic of the study area (Figure 4) was inserted into the artificial intelligence assistant with the following command: "Identify the pathological manifestations, construction defects, and anomalies present in the image, indicate possible causes, and describe the recommended solutions."

**Figure 4**

*Orthomosaic of Christine Avenue, highlighting pathological manifestations such as cracks, surface wear, and surface patches. The image was analyzed using artificial intelligence to detect defects, identify possible causes, and suggest corrective interventions for pavement rehabilitation*


Source: Prepared by the authors.

Artificial intelligence analysis identified several anomalies in the pavement of Christine Avenue, Varsity Lakes, Gold Coast. Surface wear with material loss in the top layer indicates the use of inadequate or low-quality materials, exacerbated by heavy traffic. Longitudinal and transverse cracks suggest material fatigue or base/subbase failures, such as insufficient compaction.

Pavement deterioration is attributed to the use of inadequate materials [36], drainage failures [37], traffic overload [38], and lack of preventive maintenance [39]. Recommended interventions include milling damaged layers, applying polymer-modified asphalt [40], improving drainage systems [37], reinforcing compaction, and replacing subbase materials

[41, 42], as well as implementing a maintenance plan with crack sealing and immediate repairs. These measures aim to ensure long-term safety and durability in accordance with engineering standards. The AI-powered analysis demonstrated high accuracy, confirmed by data collected during field inspections. The identified manifestations, such as surface wear, cracks, and plastic deformations, and the attributed causes, such as poor drainage and low-quality materials, were consistent with field observations. This consistency reinforces the viability of using artificial intelligence as a diagnostic tool in technical studies and intervention planning.

Another relevant aspect discussed is the time required to perform measurements and the safety associated with these activities. Table 3 compares the time spent on activities performed using drones and photogrammetry compared to on-site measurements.

**Table 3**

*Average time spent on inspection activities using drones and photogrammetry. The table demonstrates the significant efficiency gains achieved through the proposed methodology*

| Activity | Time (min) |
|---|---|
| Flight Planning (Dronelink) | 20 |
| Flight Execution (on-site) | 20 |
| Processing (Agisoft Metashape) | 80 |
| Data Analysis (Agisoft/AutoCAD/AI) | 60 |
| Total | 180 |

Source: Prepared by the authors.

The drone- and photogrammetry-based method proved effective. The activities, from flight planning to data collection, totaled 180 minutes, while on-site measurements took 480 minutes, exposing the team to traffic-related risks. Thus, the use of drones not only reduces execution time but also increases the safety of technical teams.

## 3.2 REINFORCED CONCRETE BRIDGE

Scale bars were strategically positioned at the top and sides to ensure accurate measurements. Integrated analysis, utilizing artificial intelligence (AI) and on-site inspection, enabled the identification of structural defects and the proposal of repair solutions.

To validate the accuracy of the measurements obtained with Agisoft Metashape and AutoCAD against on-site measurements (reference values), the guardrail wall located at the bridge head was evaluated. Measurements of length, width, surface area, and volume were taken, as shown in Table 4 and illustrated in Figure 5.

**Table 4**

*Comparison of measurements of length, width, height, area and volume of the bridge guardrail wall, obtained using Agisoft Metashape, AutoCAD and in situ methods. The number of asterisks (*) represents the intensity of the absolute percentage difference of the digital methods in relation to the in situ measurements (reference values)*

| Object | Methodology | Width (cm) | Length (cm) | Height (cm) | Area ($m^2$) | Volume ($m^3$) |
|---|---|---|---|---|---|---|
| Guardrail wall | *In-loco (reference values)* | 40.8 | 297.0 | 108.2 | 1.21 | 1.31 |
| | Agisoft Metashape | 41.6** | 297.0* | 109* | 1.24** | 1.35** |
| | AutoCAD | 41.0* | 298.0* | 108* | 1.22* | 1.32* |

*Indicates an absolute error of 0 to 1.5%; **Indicates an absolute error of 1.6% to 3.0%; ***Indicates an absolute error of 3.1% to 4.5%; and **** Indicates an absolute error greater than 4.6%.
Source: Prepared by the authors.

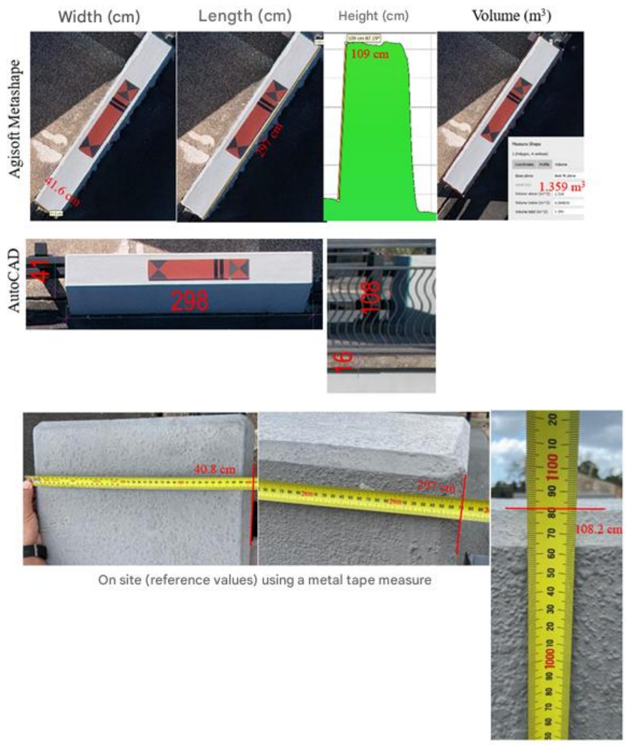
Both Agisoft Metashape and AutoCAD demonstrated high accuracy in the railing wall measurements. AutoCAD presented lower average MAPE values for all parameters, especially for width (0.5%) and volume (0.8%), while Agisoft Metashape presented slightly higher errors, with the largest deviation observed in volume measurements (3.0%).

Despite these differences, all errors remained below 3%, except for the volume estimate using Agisoft Metashape, which reached exactly 3%, but still within an acceptable range for practical applications. This indicates that the variations observed between the digital methods and the reference values are statistically insignificant and do not compromise the reliability of the proposed methodology.

The images presented in Figure 5 reinforce the consistency of the digital methods, confirming their effectiveness in accurately measuring structural components.

**Figure 5**

*Comparison of the measurements of the guardrail at the bridge head using Agisoft Metashape, AutoCAD, and in-situ reference values. The images show the width, length, height, and volume measurements, highlighting minimal discrepancies between the digital methods and the field data, reinforcing the accuracy and reliability of the proposed methodology*




Source: Prepared by the authors.

The bridge analysis, performed with the aid of artificial intelligence, revealed a satisfactory overall condition of the structure, with some pathological manifestations in the early stages. This automated analysis allowed for the early identification of potential problems, contributing to the development of preventive recommendations.

As illustrated in Figure 6, the artificial intelligence tool correctly identified vegetation growth between the beam support and the crosspiece, indicating moisture and sediment accumulation associated with joint failures or inadequate drainage [25, 43]. This condition poses structural risks, as roots can expand cracks and accelerate corrosion. Recommended actions include removing the vegetation, sealing the cracks with epoxy or polymer-modified mortar [44], improving drainage systems [37], and applying waterproofing coatings to prevent moisture infiltration and vegetation regrowth [45]. Notably, all diagnoses, explanations, and recommendations resulted from accurate AI image analysis, and these findings were confirmed through on-site inspection.

**Figure 6**

*Vegetation growth between the beam support and the crosspiece, indicating moisture accumulation and potential drainage problems. This condition can accelerate crack expansion and corrosion, requiring specific corrective interventions. This diagnosis was correctly provided by the artificial intelligence tool developed in this study*

Source: Prepared by the authors.

Figure 7 shows the identification, performed by artificial intelligence, of moisture stains and signs of water seepage on the underside of the bridge, attributed to joint failures, drainage problems, or concrete degradation. These pathologies, documented in standards such as [25] and [46], accelerate reinforcement corrosion and compromise structural durability. Measures such as joint inspection and repair [44], improved drainage systems [37], and the application of waterproofing coatings in the affected areas [45] were suggested to mitigate damage and extend the structure's service life. The entire process of diagnosis, root cause analysis, and solution definition was correctly performed by artificial intelligence and subsequently confirmed through on-site inspection.

**Figure 7**

*Moisture stains and signs of water runoff on the underside of the bridge under study, suggesting joint failures and deficiencies in the drainage system. These conditions contribute to reinforcement corrosion and require corrective intervention. This diagnosis was correctly provided by the artificial intelligence tool developed in this study*

Source: Prepared by the authors.

The application of artificial intelligence to the analysis of pathological manifestations of the bridge structure proved highly effective, as confirmed by field inspections. The AI demonstrated a remarkable ability to visually interpret the obtained images, accurately identifying various types of pathologies and correlating them with possible structural and environmental causes. This result highlights the value of artificial intelligence in structural inspections, where its accuracy and objectivity contribute to rapid and consistent diagnoses.

a) The use of AI in this context offers significant advantages:

b) Early detection of potential structural problems;

c) Automated identification of risks, reducing the need for extensive manual inspections;

d) Support for informed decision-making in maintenance and repair planning.

3.3. COMMERCIAL BUILDING FACADE

The third object of study was the facade of a commercial building, which presented evident pathological manifestations, including cracks and moisture infiltration. The main objective of this study was to identify and quantify these pathological anomalies. The obtained images were loaded into AutoCAD and scaled using reference bars, allowing for accurate dimensional analysis. As illustrated in Figure 8, the distance between the axes of the scale bars was measured at 97 cm, demonstrating 100% accuracy. To further confirm the accuracy of the measurements, the thickness of the front columns was measured on-site and compared with the dimensions observed in the images processed in AutoCAD. Both values were found to be 40 cm, again indicating 100% accuracy.

**Figure 8**

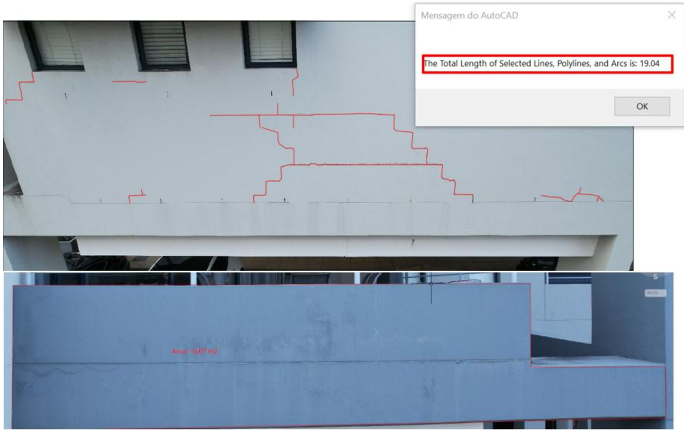
*Validation of the building facade measurements using AutoCAD. The reference scale bars confirmed the accuracy of the digital measurements, ensuring reliable dimensional analysis*


Source: Prepared by the authors.

After validating the methodology, the pathological manifestations were quantified. As shown in Figure 9, the total length of the masonry cracks requiring repair was measured at approximately 19.04 meters, and the area affected by moisture infiltration covered approximately 6,027 m².

**Figure 9**

*Quantification of pathological manifestations on the building facade using AutoCAD. The total length of the cracks was measured at 19.04 meters, and the area affected by moisture infiltration was approximately 6,027 m²*



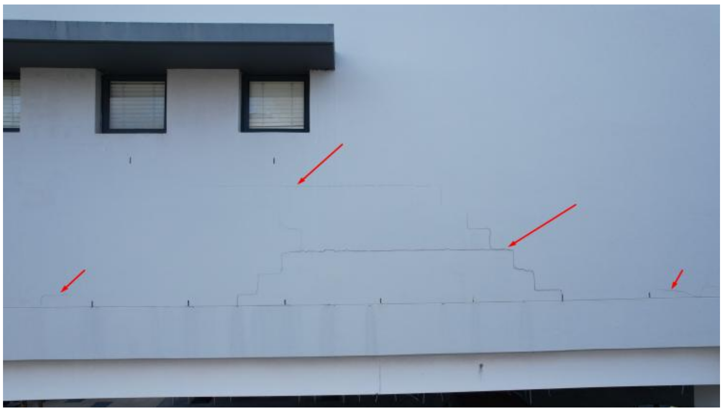

Source: Prepared by the authors.

Subsequently, the images were analyzed using the artificial intelligence tool developed in this study, which automatically identified the pathologies present, providing detailed descriptions, possible causes, and remedial recommendations.

In Figure 10, the AI interpreted the presence of staircase cracks in the masonry above the long-span beam, suggesting that these cracks result from the beam's natural displacements under load. This displacement generates stresses in the masonry, which lacks sufficient flexibility to accommodate such deformations. The AI recommended installing expansion joints between the beam and the masonry and using flexible materials, such as neoprene, to absorb structural movements, in addition to repairing the cracks with flexible mortar [43, 25].

**Figure 10**

*Identification of staircase cracks in the masonry above the long-span beam, indicating structural movements. AI analysis suggests that these cracks result from beam deflection under load, recommending the installation of expansion joints and the use of flexible materials to absorb structural stresses*



Source: Prepared by the authors.

The analyses performed using artificial intelligence proved effective in interpreting the images, providing detailed and accurate diagnoses of the pathological manifestations, enabling a consistent and evidence-based assessment.

### 3.4. HINZE DAM

Measurements were taken at two specific points on the dam: a metal cover and the width of the roadway, both located at the top of the spillway structure. The accuracy of the digital methods was validated by comparing the measurements obtained with Agisoft Metashape and AutoCAD with in-situ values (reference values). Table 5 presents the comparative data for these measurements, while Figures 11 and 12 provide visual confirmation of the results.

**Table 5**

*Comparison of length measurements at specific points on the dam, obtained using Agisoft Metashape, AutoCAD, and in-situ methods. The number of asterisks (*) represents the intensity of the absolute percentage difference between the digital methods and the in-situ measurements (reference values)*

| Methodology | Metallic Cover (cm) | Roadway Width (m) |
|---|---|---|
| *In-loco* (benchmark values) | 1.04 | 6.00 |
| Agisoft Metashape | 1.05* | 6.00* |
| AutoCAD | 1.03* | 6.00* |

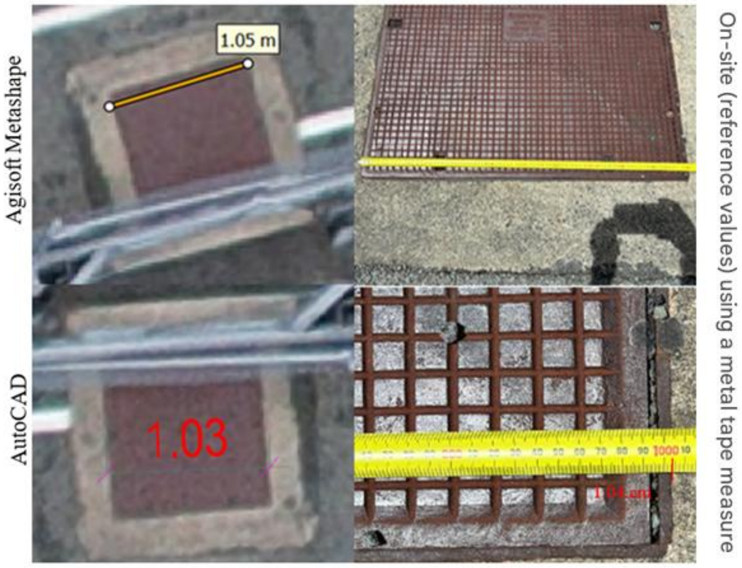
**Indicates an absolute error of 0 to 1.5%; **Indicates an absolute error of 1.6% to 3.0%; ***Indicates an absolute error of 3.1% to 4.5%; and **** Indicates an absolute error greater than 4.6%.*
Source: Prepared by the authors.

Both Agisoft Metashape and AutoCAD demonstrated high accuracy in measuring the metal roof and road width. The observed differences remained below 1% for the metal roof, while there was no discrepancy in the road width measurements between all methods. These minimal variations confirm the accuracy of the proposed methodology and reinforce its applicability in infrastructure assessments.

Despite the small discrepancies in the metal roof measurements, the overall error margins are within an acceptable range for practical applications, ensuring reliability for inspections under real-world conditions. Figures 11 and 12 visually illustrate these results, further validating the consistency between the digital models and in-situ reference measurements.

**Figure 11**

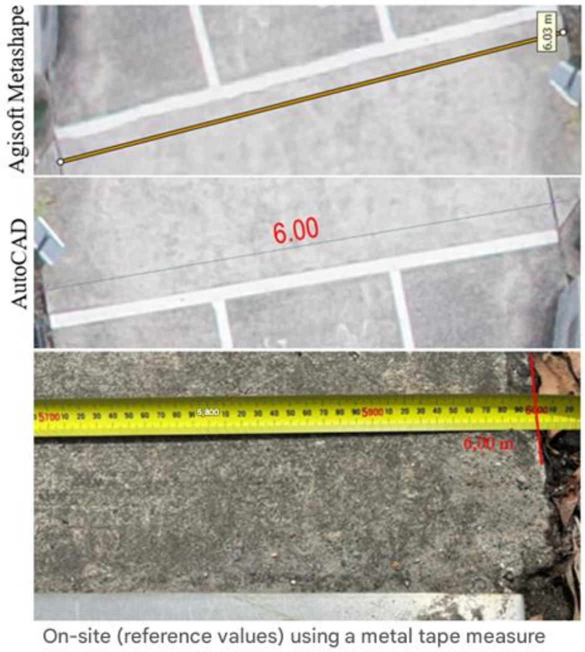
*Comparison of the metal roof measurements at the dam using Agisoft Metashape, AutoCAD, and in-situ reference values. The slight variation between the methods confirms the high accuracy of the proposed methodology*




Source: Prepared by the authors.

**Figure 12**

*Comparison of dam track width measurements using Agisoft Metashape, AutoCAD, and in-situ reference values. All methods recorded the same measurement, demonstrating absolute consistency and reinforcing the reliability of digital inspection technologies*




Source: Prepared by the authors.

Based on Figure 13, the artificial intelligence tool accurately identified five main pathological manifestations at the Hinze Dam:

a) Abrasive wear on the edges of the energy dissipation structure, likely caused by high-velocity water flow, as described in (ACI, 2019) [47].

b) Degradation of expansion joints, posing a risk of loss of watertightness, in line with the concerns described in [25].

c) Need for inspection of metal ladders and anchors due to the potential for corrosion and weakening from environmental exposure, as per guidelines in [48].

d) Surface cracks in the concrete, characterized as microcracks in a cracking pattern, indicative of shrinkage or thermal stresses, as described in [49].

e) Efflorescence stains, indicating leaching of cementitious materials due to water infiltration, a common problem addressed in [50].

**Figure 13**

*Overview of the Hinze Dam, Gold Coast, Queensland, Australia. AI-assisted analysis identified key pathological manifestations, including abrasive wear, expansion joint degradation, corrosion hazards, concrete cracking, and efflorescence staining*

Source: Prepared by the authors.

During the on-site inspection, the surface cracks and efflorescence stains previously identified by artificial intelligence on the left sidewall of the Hinze Dam were confirmed (Figure 14). The cracks, associated with shrinkage and weathering, compromise the protective layer of the concrete and can increase the risk of corrosion of the reinforcement [49]. The efflorescence stains indicate water infiltration and leaching of cementitious compounds [50]. It is recommended to assess the depth of the cracks for localized repairs or the application of protective coatings, in addition to inspecting infiltration points, applying waterproofing treatments, and repairing expansion joints to maintain structural integrity.

**Figure 14**

*Detailed view of the left sidewall of the Hinze Dam, highlighting surface cracks and efflorescence stains. These conditions indicate potential structural vulnerabilities related to shrinkage, weathering, and water infiltration*

Source: Prepared by the authors.

The results demonstrate that the proposed methodology, integrating drones, photogrammetry software, and artificial intelligence (AI), provides high accuracy in linear, area, and volume measurements on different types of structures. Measurements performed with Agisoft Metashape and AutoCAD software showed minimal variations compared to on-site measurements, indicating that both tools are reliable and suitable for technical inspections in public works, reducing inspectors' exposure to risks, especially on difficult-to-access structures such as bridges and dams.

In addition to its accuracy and efficiency, the methodology has proven to be a cost-effective and accessible solution for public agencies. By utilizing commercially available drones, such as the DJI Air 2S, and low-cost scale bars to replace RTK GPS systems, the methodology eliminates the need for expensive equipment and highly specialized personnel, constituting a viable alternative for large-scale adoption.

The use of artificial intelligence has been noted for its effectiveness in automatically identifying pathological manifestations. The analyses performed using orthomosaics and captured images were accurate and consistent with the data obtained during field inspections, demonstrating the potential of this technology for rapid and accurate structural diagnostics.

This study reaffirms the contributions of previous research, such as [1, 5, 51], which highlighted the use of drones and AI as promising tools for infrastructure inspections.

However, this work differs by including scale bars as a physical reference for validating measurements, something not adopted in previous studies. The direct metric validation conducted in this study significantly increased the accuracy and replicability of the results, ensuring greater reliability of the proposed methodology.

Furthermore, while previous studies have often relied on high-precision but expensive methods, the approach proposed in this work demonstrates that high accuracy can be achieved with a simpler and more accessible configuration. The reliance on practical and low-cost components increases the replicability of the methodology and makes it more viable for public agencies operating under budgetary constraints. Finally, the application of AI in this study expands on the conclusions of [51, 52]. While [52] limited the use of AI to static image analysis, this work integrated orthomosaics with field validation, enhancing its practical applicability. In contrast, [51] highlighted AI's ability to correlate visual data with structural and environmental causes, but did not address detailed intervention recommendations, as was done here. Thus, by combining scale bars with AI-automated analyses in an economic framework, this study reinforces the originality and methodological robustness of the proposed approach, while ensuring its practical feasibility for public sector applications.

## 5 CONCLUSIONS

This study presented and validated an innovative, low-cost methodology based on the use of drones, photogrammetry, and artificial intelligence (AI), highlighting its simplicity, cost-effectiveness, practicality, efficiency, and accuracy as essential characteristics for application by public agencies in infrastructure inspections. The analysis of four distinct objects (a section of urban pavement, a reinforced concrete bridge, the facade of a commercial building, and a dam) demonstrated that the proposed approach is capable of meeting the demands of inspection agencies, providing reliable and replicable results in an affordable manner.

Key findings include the metric validation of measurements performed with Agisoft Metashape and AutoCAD software, presenting minimal margins of error compared to in-situ methods. The use of scale bars as a physical reference stood out as a methodological advantage, ensuring greater accuracy and reliability. Furthermore, by replacing RTK GPS systems with low-cost scale bars and utilizing commercially available drones, such as the DJI Air 2S, the methodology proved to be not only highly accurate but also financially viable for public agencies with budgetary constraints. Furthermore, the integration of AI with photogrammetric data and field inspections provided detailed diagnoses and consistent corrective recommendations, expanding the possibilities for planning preventive and corrective maintenance.

The proposed methodology also proved operationally efficient, significantly reducing execution time compared to traditional methods and increasing the safety of the teams involved. The use of accessible technologies eliminates the need for specialized operators, facilitating the adoption and implementation of the approach by public agencies, without the need for extensive training. These advantages make the methodology especially viable for large-scale application, aligning with the needs for agile and cost-effective control and monitoring of critical infrastructure.

The results corroborate and expand upon previous studies, such as those by [1, 5, 51], overcoming limitations related to equipment calibration and the lack of metric validation. Unlike previous research, which often relied on high-precision and expensive instruments, this study demonstrated that high accuracy can be achieved with a simpler and more accessible configuration, reinforcing its practical applicability. The methodological proposal presented in this paper proves to be a practical and robust alternative, capable of transforming public inspection practices by introducing greater accuracy, efficiency, and accessibility.

For future perspectives, it is recommended to apply the methodology to infrastructures located in extreme environments, such as remote areas or regions subject to adverse weather conditions, as well as the integration of additional technologies, such as thermal sensors and advanced structural analysis, to expand the scope and effectiveness of inspections. Future work could also explore new cost-reduction strategies by optimizing data collection and processing techniques to further increase accessibility without compromising accuracy. These advances could further strengthen the role of digital technologies in modernizing public works inspection and management processes.

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