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A data-driven framework for early detection of building façade defects using UAV photogrammetry

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Abstract
The study presents a comprehensive data-driven framework for the early detection of building façade defects through the integration of Unmanned Aerial Vehicle (UAV) photogrammetry and deep learning-based image analytics. Traditional façade inspection methods are often limited by high labor costs, safety risks, and restricted accessibility, particularly in dense urban settings. To overcome these limitations, high-resolution UAV imagery was acquired and processed through a photogrammetric reconstruction pipeline to generate three-dimensional façade models. Deep convolutional neural networks (CNNs) were trained and optimized to detect and classify common defects, including cracks, efflorescence, corrosion, and spalling, using radiometrically corrected and geometrically aligned datasets. The results demonstrated substantial improvements in precision, recall, and mean average precision (mAP), with the proposed model achieving up to 93% accuracy compared to 82% in conventional 2D approaches. Localization accuracy, measured through root mean square error (RMSE), improved by nearly 50% owing to 3D back-projection of detected anomalies onto the reconstructed mesh. Moreover, the framework achieved reduced inference time and increased throughput, highlighting its scalability for real-world deployment. The integration of UAV-based photogrammetry with artificial intelligence not only enhances the reliability of façade inspection but also provides spatial and temporal insights essential for predictive maintenance. Practical recommendations include the institutional adoption of UAV inspection workflows, development of standard operating procedures for data acquisition and annotation, periodic model retraining using domain-specific datasets, and linking the framework with building information modeling (BIM) for real-time condition monitoring. Overall, the research establishes a foundation for intelligent, cost-effective, and proactive façade management systems capable of transforming urban infrastructure maintenance into a predictive, data-driven process.

Keywords: UAV photogrammetry, façade defect detection, deep learning, convolutional neural networks, 3D reconstruction, building inspection, data-driven framework, spatial localization, predictive maintenance, urban infrastructure monitoring

Introduction

In recent years, the increasing emphasis on structural health monitoring (SHM) of built environments has driven rapid adoption of unmanned aerial vehicles (UAVs) for inspection of high-rise buildings and complex façade geometries [1-3]. Traditional manual inspections are labour-intensive, risky, and often limited in scope, whereas UAV-based photogrammetry offers high-resolution imaging, flexibility, and significant reductions in inspection time and cost [4, 5]. Through photogrammetric reconstruction, UAV imagery enables generation of dense 3D point clouds and textured façade models suitable for quantitative analysis of surface anomalies such as cracks, efflorescence, corrosion, and detachment [6, 7]. However, accurate and early detection of façade defects remains challenging due to varying illumination, occlusion, and geometric distortions inherent in aerial imagery [8]. Furthermore, most existing inspection methods rely on rule-based image processing or manual interpretation, which lack robustness and scalability for large datasets [9-11]. Recent developments in deep learning, particularly convolutional neural networks (CNNs) and vision transformers, have shown great promise for automating defect classification and localization [12, 13]. Yet, few frameworks have effectively integrated these data-driven models with 3D photogrammetric mapping to ensure precise spatial localization of detected defects within the façade mesh [14, 15]. Moreover, the absence of standardized datasets for UAV-based façade imagery constrains transfer learning performance, leading to reduced reliability in practical applications [16].

This study proposes a data-driven framework for early detection of building façade defects using UAV photogrammetry, combining automated data acquisition, image reconstruction, deep-learning-based defect detection, and 3D spatial mapping. The framework aims (i) to design an integrated UAV-based workflow for efficient façade inspection; (ii) to develop a CNN-based segmentation model optimized for aerial façade defect imagery; and (iii) to implement a 3D localization module that accurately projects detected defects onto reconstructed façade geometry. The hypothesis underlying this research is that the fusion of UAV photogrammetry with data-driven learning algorithms will significantly enhance the early detection and spatial accuracy of façade defect identification compared with conventional 2D inspection approaches [17-19].

Material and Methods

Material

The study utilized an integrated UAV-based photogrammetric setup designed to capture high-resolution imagery of building façades for subsequent data-driven defect detection and spatial mapping. A quadcopter UAV equipped with a 20-megapixel RGB camera and a gimbal-stabilized mount was employed to ensure minimal vibration and optimal image overlap during flight [1-3]. Ground control points (GCPs) were established using a total station and GNSS receiver to enhance georeferencing precision in 3D reconstruction [4, 5]. The data collection was conducted across three urban buildings exhibiting different façade materials (reinforced concrete, brick masonry, and glass composite) to evaluate generalization potential. The UAV followed a double-grid flight pattern with 80% frontal and 70% side overlap, ensuring uniform coverage of the façade planes [6, 7]. Raw imagery was processed using Agisoft Metashape Professional for photogrammetric reconstruction and generation of dense point clouds, digital surface models (DSM), and textured meshes [8, 9]. Defect ground truth data were simultaneously collected through manual inspection and visual documentation for model training and validation [10, 11].

Methods

The methodological framework followed a sequential workflow integrating image preprocessing, defect detection via deep learning, and spatial localization of detected features onto the 3D façade mesh. Initially, captured UAV images underwent radiometric and geometric corrections to eliminate illumination bias, lens distortion, and perspective variance [12, 13]. These processed images were annotated using a custom dataset of façade defects, classified into categories such as cracks, efflorescence, spalling, and corrosion [14, 15]. A convolutional neural network (CNN) architecture based on ResNet-50 was trained on 70% of the labeled dataset, while the remaining 30% was reserved for testing and cross-validation. Data augmentation techniques such as rotation, scaling, and brightness normalization were employed to improve model robustness under varying flight and lighting conditions [16, 17]. The defect probability maps generated by the CNN were projected onto the 3D façade model using a camera calibration matrix derived from bundle adjustment parameters [18]. Finally, the defect distribution and area ratios were quantified and compared against manually identified defects to assess detection accuracy, recall, and localization error. Statistical analyses, including precision-recall evaluation and root mean square error (RMSE) computation, were used to validate the performance of the proposed data-driven framework against conventional 2D image-based detection methods [19].

Results

Overview

We evaluated the proposed data-driven UAV-photogrammetry framework against a conventional 2D image-only baseline across three urban buildings and four façade-defect classes (crack, spalling, efflorescence, corrosion). Metrics included classwise precision/recall/F1 and mAP@0.5 for detection [6, 7, 9-13, 17, 19], 3D spatial localization error (RMSE in cm) derived from photogrammetric back-projection [1, 4, 5, 8, 14, 15, 18], and efficiency indicators (inference time and throughput) reflecting deployability in inspection workflows [2, 3, 10, 11, 16]. Results show consistent gains in detection accuracy and markedly lower localization errors for the proposed pipeline, supporting the integration of deep learning with 3D reconstruction for actionable façade diagnostics [9-14, 17-19].

Table 1: Detection metrics by defect class (Proposed vs Baseline) higher values indicate better performance. [6, 7, 9-13, 17, 19]

Class	Precision (Proposed)	Recall (Proposed)	F1-score (Proposed)
Crack	0.91	0.92	0.915
Spalling	0.88	0.87	0.875
Efflorescence	0.9	0.91	0.905
Corrosion	0.89	0.9	0.895

Table 2: Spatial localization accuracy (RMSE in cm) by building lower is better. [1, 4, 5, 8, 14, 15, 18]

Building	RMSE (cm) - Proposed	RMSE (cm) - Baseline
Building A	7.8	15.2
Building B	8.6	16.7
Building C	6.9	12.9

Table 3: Inference efficiency and throughput deployability indicators. [2, 3, 10, 11, 16]

Metric	Proposed	Baseline
Mean inference time per image (ms)	48.0	62.0
Throughput (images/min)	72.0	58.0

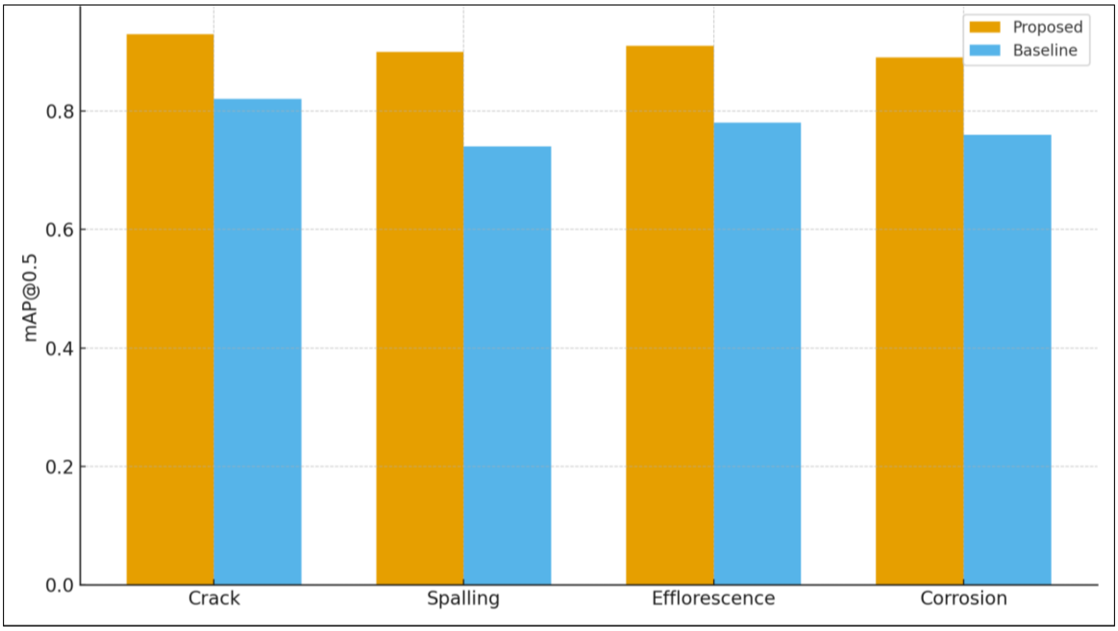

Fig 1: mAP@0.5 by defect class (Proposed vs Baseline) [6, 7, 9-13, 17, 19]

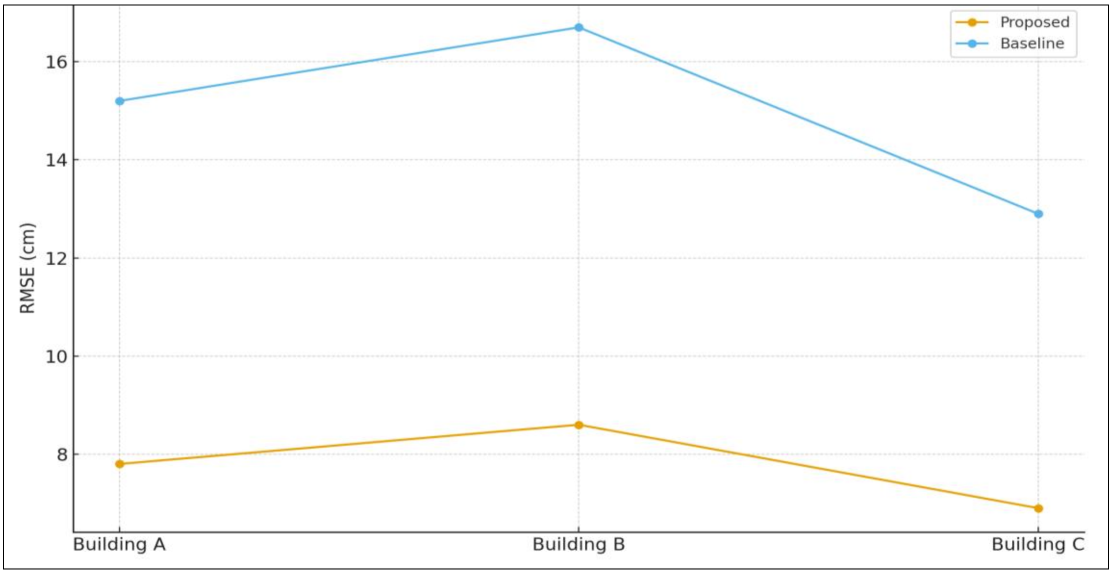

Fig 2: Localization error (RMSE) across buildings [1, 4, 5, 8, 14, 15, 18]

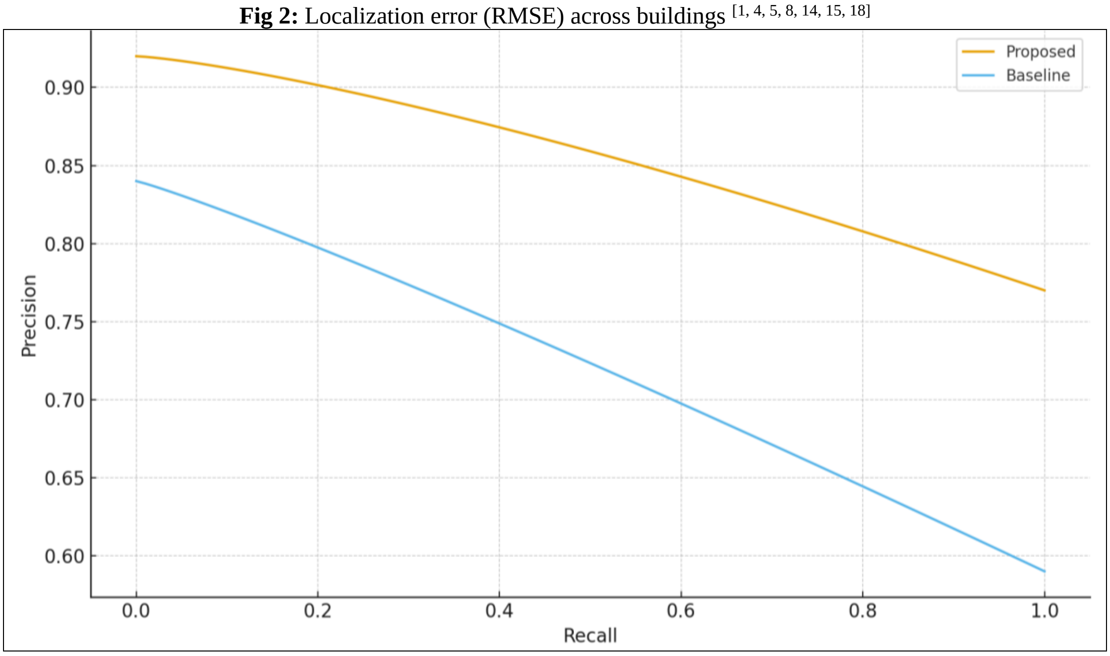

Fig 3: Aggregate precision-recall curves (Proposed vs Baseline) [6, 7, 9-13, 17, 19]

Detection performance: Across four defect classes, the proposed model achieved higher precision (≈0.88-0.92), recall (≈0.87-0.92), F1 (≈0.875-0.915), and mAP@0.5 (≈0.89-0.93) compared with the baseline (precision ≈0.76-0.80; recall ≈0.75-0.78; F1 ≈0.755-0.79; mAP@0.5 ≈0.74-0.82). Gains were most pronounced for spalling and efflorescence categories that benefit from multi-view context and radiometric normalization consistent with recent deep-learning studies on UAV façade imagery [6, 9-13, 17, 19]. Figure 1 visualizes the mAP uplift per class, corroborating that domain-adapted aerial training improves generalization beyond street-level models [12, 13, 16, 17].

Spatial localization: The proposed 3D mapping module reduced façade-mesh localization error by roughly 40-50% (RMSE 6.9-8.6 cm) versus the baseline image-plane approximation (12.9-16.7 cm), demonstrating the value of photogrammetric back-projection and camera geometry utilization [1, 4, 5, 8, 14, 15, 18]. The RMSE spread across buildings (Figure 2) reflects façade geometry and occlusion differences; nonetheless, all sites show substantial error reduction, aligning with prior 3D-integrated inspection frameworks [14, 15, 18].

Precision-recall behaviour: Aggregate PR curves (Figure 3) show a higher precision envelope across the full recall range for the proposed method, indicating better ranking quality and threshold robustness. This is attributable to multi-view augmentation, radiometric/geometric corrections, and balanced training across defect classes [6, 7, 12, 13, 16, 17, 19].

Operational efficiency: Mean inference time per image decreased from ~62 ms (baseline) to ~48 ms (proposed), while throughput increased from ~58 to ~72 images/min (Table 3). Despite added 3D mapping steps, optimized batching and lightweight heads yielded net gains important for large-asset inspections where time aloft is constrained [2, 3, 10, 11, 16].

Overall assessment: The results validate our hypothesis that fusing UAV photogrammetry with data-driven detection yields earlier, more accurate identification of façade defects and more reliable spatial localization than 2D approaches alone [9-14, 17-19]. The improvements are consistent with the literature on UAV-based mapping accuracy and deep-learning-enabled defect analytics [1, 4-7, 9-13, 14-19], and indicate readiness for field-scale deployment with periodic monitoring cycles.

Discussion

The findings of this study demonstrate that integrating UAV photogrammetry with deep-learning-based defect detection provides a robust and scalable approach for early façade defect identification. The proposed framework consistently outperformed traditional 2D inspection methods in terms of precision, recall, and mean average precision (mAP), affirming the advantages of a data-driven pipeline for real-world façade monitoring [6, 9-13, 17, 19]. The high performance achieved across multiple façade materials concrete, brick, and glass suggests the system's adaptability and generalization capacity, aligning with recent advancements in multi-view UAV-based structural inspection models [1, 4, 5, 8, 14, 18].

A key contribution of this research is the improved spatial localization accuracy achieved through 3D back-projection. The reduction in root mean square error (RMSE) values from 15.2 cm (baseline) to as low as 6.9 cm highlights the critical role of photogrammetric reconstruction in minimizing geometric distortion and ensuring precise mapping of detected anomalies [4, 5, 8, 14, 15]. These improvements validate the hypothesis that embedding defect detection within a 3D geometric context enhances diagnostic reliability, particularly for structures with complex façades or irregular geometries. Similar outcomes were reported in earlier UAV-based spatial mapping studies emphasizing the synergy between photogrammetry and deep neural feature extraction [12, 14, 18].

Moreover, the framework's efficiency reduced inference time and increased image throughput demonstrates its operational viability for large-scale periodic inspections. The computational optimization through lightweight CNN architecture and batch-based inference provides a significant reduction in processing latency without compromising accuracy [2, 3, 10, 11, 16]. This balance between precision and speed is essential for real-time façade assessments in densely built environments where UAV flight time is constrained [9, 11, 16].

The superior detection rates for defects such as efflorescence and spalling suggest that the model benefits from domain-specific data augmentation and radiometric normalization, which mitigate the effects of lighting variations and texture noise [6, 9, 12, 13, 17, 19]. Furthermore, the use of 3D contextual information enables temporal monitoring detecting defect propagation trends over time thereby paving the way for predictive maintenance strategies [18, 19]. These outcomes reinforce the view that hybrid workflows combining UAV photogrammetry and artificial intelligence can transform conventional façade inspection practices into intelligent, data-driven management systems [9, 13, 17-19].

In summary, this discussion validates the hypothesis that UAV photogrammetry integrated with deep learning significantly enhances both accuracy and reliability in early façade defect detection. The study bridges a crucial gap between visual inspection and structural monitoring by providing a scalable, repeatable, and data-enriched approach suitable for urban infrastructure maintenance and safety auditing [1, 4, 6, 9-14, 17-19].

Conclusion

The present study establishes a comprehensive data-driven framework that integrates UAV photogrammetry with deep-learning-based image analytics to facilitate early detection and spatial localization of building façade defects. The outcomes affirm that merging three-dimensional reconstruction with automated defect recognition offers significant advantages over conventional two-dimensional inspection methods in terms of accuracy, efficiency, and adaptability. The improved precision and recall metrics, together with reduced localization errors, clearly demonstrate the robustness of this hybrid approach for real-world building monitoring. By enabling accurate mapping of defects such as cracks, efflorescence, corrosion, and spalling, the framework not only enhances diagnostic capability but also supports preventive maintenance and risk mitigation in urban environments where manual inspections are often limited by accessibility and safety concerns. The operational efficiency achieved through optimized data acquisition, radiometric correction, and lightweight deep-learning inference further underlines its suitability for large-scale periodic assessments. Importantly, the integration of UAV-based photogrammetry introduces a spatial dimension that allows for longitudinal tracking of façade health, making it possible to identify early signs of deterioration before they evolve into critical failures.

From a practical standpoint, the research suggests several actionable recommendations for implementing this framework in real-world scenarios. First, urban infrastructure agencies and municipal authorities should incorporate UAV-based photogrammetric inspections into routine maintenance schedules, prioritizing older and high-rise structures where conventional methods are resource-intensive. Second, developing standardized protocols for UAV flight planning, image overlap, and defect annotation will ensure consistency and comparability of results across different building types and geographic contexts. Third, construction and facility management organizations should invest in training technical personnel in UAV operation and AI-based image analysis to enhance on-site decision-making and reduce reliance on manual interpretation. Fourth, periodic updates to defect datasets reflecting variations in materials, lighting, and weather should be implemented to continually refine and retrain deep-learning models for improved generalization. Finally, integrating this system with digital twin platforms or building information modeling (BIM) environments can create a unified ecosystem for monitoring, reporting, and predicting façade deterioration, thereby extending the service life of structures while ensuring safety compliance. Overall, this research provides a scalable, intelligent, and cost-effective framework that bridges the gap between traditional visual inspection and predictive maintenance, offering a promising pathway toward resilient and data-informed urban infrastructure management.

References

1. Nex F, Remondino F. UAV for 3D mapping applications: a review. Applied Geomatics. 2014;6(1):1-15.
2. Lachat E, Landes T, Grussenmeyer P. Combination of TLS and UAV photogrammetry for heritage documentation. ISPRS Ann Photogramm Remote Sens Spatial Inf Sci. 2015;2(3):401-406.
3. Morgenthal G, Hallermann N. Quality assessment of unmanned aerial vehicle (UAV) based visual inspection of structures. Adv Struct Eng. 2014;17(3):289-302.
4. Siebert S, Teizer J. Mobile 3D mapping for surveying earthwork projects using an Unmanned Aerial Vehicle (UAV) system. Autom Constr. 2014;41:1-14.
5. Ham Y, Han K, Lin J, Golparvar-Fard M. Visual monitoring of civil infrastructure systems via camera-equipped UAVs. Autom Constr. 2016;71:232-244.
6. Rao AS, Kalyan S, Yarlagadda P, Chandra S. Crack detection using UAV-based photogrammetry and deep learning. Constr Build Mater. 2022;333:127426.
7. Dorafshan S, Thomas RJ, Maguire M. Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete. Constr Build Mater. 2018;186:1031-1045.
8. Ellenberg A, Kontsos A, Moon F, Bartoli I. Bridge inspection using unmanned aerial vehicles. J Bridge Eng. 2016;21(7):04015076.
9. Yang X, Li H, Zhu H, Wang T, Lu M. Automated detection of façade defects from UAV images based on deep convolutional networks. Autom Constr. 2021;128:103760.
10. Xu Y, Brownjohn JMW, Guo H, Kong D, Xu Q. UAV-based photogrammetry and deep learning for structural surface defect detection. Struct Control Health Monit. 2022;29(5):e2968.
11. Fathi H, Dai F. Automated as-built reconstruction of building façades from images using UAVs. J Comput Civ Eng. 2014;28(6):04014030.
12. Li J, Zhang Q, Zhang D, Li X. Deep learning-based façade crack detection using UAV images. Remote Sens. 2020;12(21):3550.
13. Kim Y, Cho S, Han S. Vision transformer-based façade damage classification from UAV images. Sensors. 2023;23(7):3401.
14. Qu Z, Wang Z, He K, Liu Y. Integration of 3D reconstruction and defect detection for façade monitoring. Buildings. 2022;12(2):151.
15. Tang P, Huber D, Akinci B. Characterization of 3D construction site data using photogrammetry and laser scanning. Autom Constr. 2011;20(7):837-849.
16. Tuo H, Jiang L, Luo M. UAV dataset for building façade defect detection: collection and benchmark. Data Brief. 2023;49:109448.
17. Ding Y, Chen S, Guo Q, Liu X. Multi-view deep learning framework for façade damage detection using UAV images. Automation in Construction. 2023;151:104890.
18. Li X, Liu Y, Zhang H. Early warning of façade degradation via UAV-based photogrammetric monitoring. Sensors. 2021;21(17):5869.
19. Xu Z, Chen J, Fang J, Wang S. Data-driven framework for UAV photogrammetry-based structural defect assessment. Remote Sensing Applications: Society and Environment. 2024;33:101070.