AI-based damage mapping for urban infrastructure

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Abstract. Urban infrastructure damage assessment is essential for post-disaster recovery, resource allocation, and city resilience planning. Manual inspections are slow, subjective, and unsafe. This study presents an extended review of computer vision (CV) and geographic information system (GIS) approaches for automated multi-source damage detection. Methods for classification, detection, segmentation, and change detection are analyzed. An expanded AI→Damage Index→GIS pipeline is proposed. Challenges specific to Ukrainian cities are examined. The paper provides a comprehensive foundation for implementing automated damage-mapping systems.

Keywords: computer vision, GIS, damage assessment, segmentation, UAV imagery, reconstruction planning.

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INTRODUCTION

Urban environments are highly vulnerable to large-scale disasters, including earthquakes, industrial explosions, and, most notably for Ukraine, warfare-related destruction [12, 20]. Rapid evaluation of infrastructure damage is critical for emergency response, reconstruction scheduling, prioritization of repair budgets, and risk mitigation [7, 13].

Traditional manual inspections pose several problems: low scalability, dependence on expert availability, safety risks, subjective assessments, and delays in compiling city-wide reports [6, 12].

AI-based approaches can process thousands of images per hour and produce consistent, quantitative metrics. When combined with GIS layers such as building footprints, road networks, and population density, the results support municipal decision-making[15].

MODERN METHODS OF DAMAGE ASSESSMENT

In this section, we examine the primary computer vision techniques applied to infrastructure damage assessment. Each method offers distinct advantages depending on the specific requirements of the assessment task and available data sources.

Classification models assign a global severity category to an entire image. Typical labels include no damage, minor, moderate, severe, and destroyed. Common architectures such as ResNet, EfficientNet, and MobileNet [1, 8] offer fast processing and low resource usage. However, these models lack spatial understanding of damage distribution within the image, limiting their utility for detailed damage mapping.

Object detection models identify and localize specific damage components such as cracks, façade failures, debris piles, and roof collapse. Modern detectors like YOLOv8, YOLO-NAS, Faster R-CNN, and DETR [5, 16] provide bounding boxes and confidence scores for each detected element. While these models enable rapid localization of damaged areas within complex urban scenes, they do not provide precise geometric boundaries of the damaged regions.

Semantic segmentation provides pixel-level classification of damaged versus undamaged regions, which is essential for calculating exact damage area. Widely used architectures include U-Net, U-Net++ [3, 4, 9], DeepLabv3+, Mask R-CNN, and the recent Segment Anything Model (SAM). Segmentation forms the backbone of quantitative damage analysis by enabling precise measurement of affected surfaces and providing the foundational data for Damage Index calculation.

Change detection analyzes differences between pre-event and post-event images, making it particularly useful when baseline imagery exists from sources such as Google Street View or satellite archives. Common models include Siamese Networks, Transformer-based change detection architectures, and Temporal CNNs. This approach enables direct quantification of damage by comparing identical locations across time, eliminating ambiguity from pre-existing structural deterioration.

COMPUTER VISION TECHNIQUES

The evolution of deep learning architectures has significantly impacted damage assessment capabilities. Convolutional Neural Networks have dominated computer vision tasks for the past decade, establishing robust feature extraction methods for image analysis [3, 5]. However, Vision Transformers now provide superior contextual modeling through self-attention mechanisms and outperform CNNs on large-scale datasets [11]. Transformers can capture long-range dependencies in images, which proves valuable for understanding damage patterns across entire building facades or urban blocks.

Future damage assessment systems will increasingly rely on multimodal approaches that merge multiple data sources [17, 19]. These systems integrate visual imagery with metadata such as GPS coordinates and elevation data, GIS context layers providing urban infrastructure information, and text descriptions from field reports. This multimodal fusion enables more robust and comprehensive damage characterization by leveraging complementary information sources that individually may be incomplete or ambiguous.

A critical component of standardized damage assessment is the Damage Index, a scalar metric representing normalized severity on a scale of 0–1 or 0–100 [15]. The DI incorporates multiple factors: percentage of structural surface damaged, presence and volume of debris, façade deformation magnitude, roof penetration area, and contextual GIS-based weighting that accounts for building importance, location, and structural type. The Damage Index enables cross-regional comparison and objective prioritization of reconstruction efforts, transforming qualitative visual assessments into quantitative decision-making metrics.

ROLE OF GIS IN DAMAGE MAPPING

Geographic Information Systems provide the spatial intelligence infrastructure needed for effective reconstruction planning. The integration of computer vision outputs with GIS platforms transforms raw damage detections into actionable operational intelligence.

Georeferencing aligns computer vision outputs with authoritative building footprints and cadastral data, ensuring accurate spatial localization of damage assessments. This process requires careful coordinate transformation and quality control to maintain positional accuracy across different data sources and coordinate systems.

Aggregation capabilities summarize Damage Index values at multiple spatial scales, from individual buildings to grid cells, neighborhoods, districts, and entire municipalities. This multi-scale analysis enables decision-makers to understand damage patterns at the appropriate level of detail for their specific planning needs.

Heatmap generation creates intuitive visual representations of damage density, allowing rapid identification of the most severely affected areas for priority response and resource allocation [12, 13]. These visualizations communicate complex spatial patterns effectively to stakeholders who may lack technical expertise in geospatial analysis.

Urban analytics functions leverage the integrated damage and GIS data to support advanced decision-making. Applications include population exposure estimation by overlaying damage maps with residential density data, road blockage assessment for emergency vehicle routing, proximity analysis identifying damage near critical facilities such as hospitals and schools, and multi-criteria prioritization of infrastructure repair based on structural importance, population served, and economic impact.

KEY CHALLENGES

Despite significant advances in AI-based damage mapping, several challenges must be addressed for successful implementation in Ukrainian cities.

Dataset scarcity remains a fundamental obstacle [8, 20]. Limited training data exists for Ukrainian architectural styles, particularly Soviet-era panel buildings with unique structural characteristics that respond differently to damage compared to Western construction types. Developing representative training datasets requires extensive field documentation and expert annotation.

Image source variability creates technical challenges for model generalization. Inputs range from high-altitude satellite imagery to low-altitude UAV footage and ground-level photographs, each exhibiting different resolutions, viewing angles, lighting conditions, and atmospheric effects. Models must maintain consistent performance across this heterogeneous input space.

Ambiguous damage signatures complicate automated classification. Weathering, shadows, architectural features, and pre-existing deterioration can be misclassified as disaster damage. Distinguishing recent damage from historical deterioration requires temporal context that may not always be available.

Coordinate system mismatches require careful geometric processing. Transforming between WGS84, UTM, and local coordinate systems while maintaining spatial accuracy demands robust geodetic procedures and quality control workflows.

Lack of standardized Damage Index methodologies across organizations and countries makes it difficult to compare assessments and integrate data from multiple sources. International collaboration is needed to establish consistent calculation frameworks and validation protocols.

The structural uniqueness of Soviet-era panel buildings presents a specialized challenge. These prefabricated concrete structures exhibit failure modes distinct from cast-in-place or masonry construction, requiring dedicated training data and potentially specialized model architectures.

PROPOSED PIPELINE

We propose an integrated processing pipeline that transforms raw imagery into actionable damage intelligence through sequential processing stages [6, 12].

The input stage accepts data from multiple sources: satellite imagery providing pre-event and post-event coverage at medium to high resolution, UAV imagery captured at low altitude delivering detailed building-level data with oblique viewing angles, ground photographs from first responders and civilians offering close-range damage documentation, and archived baseline imagery from Google Street View enabling temporal change detection.

The computer vision module processes these diverse inputs through multiple analysis pathways. Semantic segmentation generates pixel-level damage masks quantifying affected surface area. Object detection identifies and localizes specific damage features such as façade collapse, debris accumulation, and structural deformation. Classification assigns overall severity levels to entire structures or image regions. Change detection performs temporal comparison between pre-event and post-event imagery to isolate damage from pre-existing conditions.

Damage Index calculation integrates outputs from the computer vision module with contextual information. Weighted area ratio scoring quantifies the proportion of structural surface exhibiting damage. Structural failure metrics assess the severity of detected damage features. GIS-based contextual factors adjust the base damage score based on building importance, population served, and criticality to urban infrastructure networks.

The GIS integration layer performs geospatial mapping to associate damage assessments with specific structures in the urban cadastre. Heatmap generation visualizes damage density at multiple spatial scales. Reconstruction priority zoning identifies areas requiring immediate intervention based on damage severity, population exposure, and infrastructure criticality.

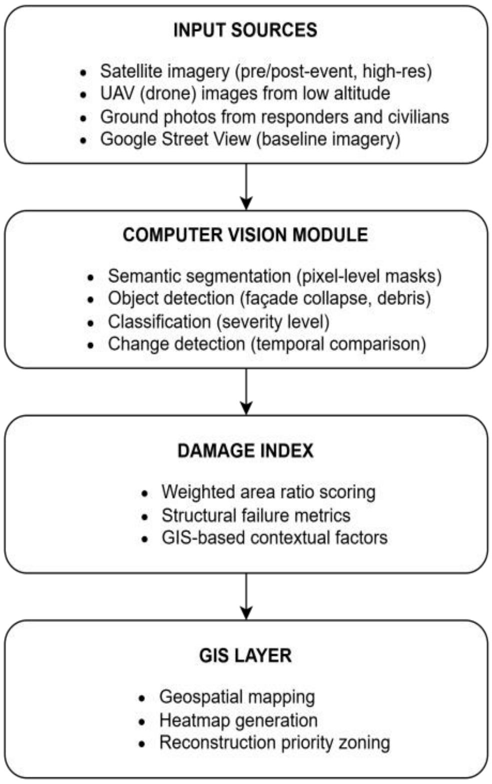

Fig. 1. AI-based damage assessment pipeline showing integration of multiple data sources

VISUAL EXAMPLES OF URBAN DAMAGE

To illustrate the practical application of the proposed damage assessment pipeline, we present representative examples of infrastructure damage from Ukrainian cities affected by recent military operations.

Figure 1 presents a schematic representation of the complete damage assessment pipeline, showing the flow from multiple input sources through computer vision processing, Damage Index calculation, and final GIS integration stages.

Figure 2 demonstrates typical façade damage patterns observed in residential buildings in Kyiv. The image shows characteristic destruction including broken windows, partial wall collapse, and exposed reinforcement structures resulting from explosive impact. This type of damage is particularly common in multi-story panel buildings constructed during the Soviet era.

Fig. 2. Facade destruction in residential building, Kyiv (example of moderate to severe damage classification)

Figure 3 illustrates more severe structural failures documented in Kharkiv, including partial collapse of load-bearing panel walls, destroyed floor sections, and extensive structural cracking. These damage patterns represent the most severe category in classification systems and require immediate structural stabilization interventions.

Fig. 3. Severe structural damage with partial collapse, Kharkiv (example of severe to destroyed classification)

These visual examples demonstrate the range of damage severity levels that the proposed AI-based assessment system must accurately classify and quantify. The variability in damage patterns, viewing angles, lighting conditions, and surrounding context illustrates the technical challenges discussed in the previous sections.

IMPLEMENTATION CONSIDERATIONS

Successful deployment of AI-based damage mapping systems requires addressing several practical considerations beyond algorithm development.

Computing infrastructure must support efficient processing of large image datasets. Cloud-based GPU resources can provide scalable computation for initial processing, while edge computing on UAV platforms enables real-time damage assessment during reconnaissance missions.

Model training requires diverse datasets representing the full range of Ukrainian architectural styles and damage patterns. Transfer learning from existing damage datasets can accelerate development, but domain-specific fine-tuning remains essential for optimal performance.

Validation procedures must compare automated assessments against expert ground-truth data collected through traditional field surveys. Establishing quality metrics and acceptable error thresholds requires collaboration between computer scientists and structural engineering experts.

Integration with existing municipal GIS systems ensures compatibility with local planning workflows and data standards. APIs and data exchange formats must accommodate the technical constraints of legacy systems while enabling modern spatial analysis capabilities.

User interface design must present complex spatial analysis results clearly to decision-makers who may lack technical expertise in remote sensing or geospatial analysis. Interactive web-based dashboards with intuitive visualization and filtering capabilities facilitate effective use of damage intelligence.

CONCLUSIONS

AI-based approaches offer unprecedented opportunities to automate infrastructure damage assessment at city scale. When integrated with Geographic Information Systems, these technologies enable rapid, objective, and data-driven reconstruction planning that would be impossible through traditional manual inspection methods.

The current situation in Ukraine provides a unique real-world environment for developing and validating damage mapping methodologies that will have global applicability. The large scale of infrastructure damage, availability of multi-temporal imagery, and urgent need for effective reconstruction planning create conditions conducive to innovation in this field.

Key contributions of this paper include a comprehensive review of computer vision models applicable to damage assessment, expanded analysis of GIS integration workflows that transform raw detections into actionable intelligence, identification of research gaps and challenges specific to Ukrainian architectural contexts, and proposal of a complete AI→Damage Index→GIS [12, 18] operational pipeline suitable for practical implementation.

Future research should focus on developing open-source training datasets documenting Ukrainian building types and damage patterns, standardizing Damage Index calculation methodologies to enable cross-regional comparison and data integration, validating automated assessment accuracy through systematic comparison with expert field surveys, and integrating multiple complementary data sources including satellite imagery, UAV reconnaissance, ground photography, and social media reports into unified operational systems supporting reconstruction planning and resource allocation.

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Картографування пошкоджень міської інфраструктури на основі штучного інтелекту

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Анотація. Оцінка пошкоджень міської інфраструктури є критично важливою для поставарійного відновлення, розподілу ресурсів та планування міської стійкості. Ручні інспекції є повільними, суб'єктивними та небезпечними. Дане дослідження представляє розширений огляд підходів комп'ютерного зору (CV) та геоінформаційних систем (ГІС) для автоматизованого виявлення пошкоджень з кількох джерел. Проаналізовано методи класифікації, детекції, сегментації та виявлення змін. Запропоновано розширений конвеєр ШІ→Індекс Пошкоджень→ГІС. Розглянуто виклики, специфічні для українських міст. Стаття надає комплексну основу для впровадження автоматизованих систем картографування пошкоджень.

Ключові слова: комп'ютерний зір, ГІС, оцінка пошкоджень, сегментація, БПЛА-зображення, планування реконструкції.