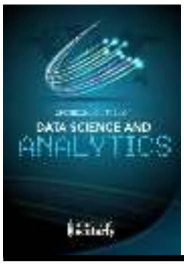

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A Systematic Review of GeoAI and Deep Learning for Automated Road Infrastructure Damage Detection Using Satellite Imagery

Kazi Mohammad Khalid Ahsan[1];

[1]. MS in Computer Science, San Francisco Bay University, CA,USA.
Email: khalid.grid@gmail.com

Doi: 10.63125/77cy0h19

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Abstract

This study addresses the problem that research on automated road infrastructure damage detection using satellite imagery remains fragmented across damage categories, data sources, model architectures, and evaluation practices, making it difficult to form unified evidence base for infrastructure monitoring and decision support. The purpose of the study was to systematically synthesize how GeoAI and deep learning have been applied to road damage detection between 2018 and 2026, identify dominant data and model trends, compare case-based findings, and evaluate recurring methodological challenges. Methodologically, the study used a cross-sectional, case-based systematic literature review design with light quantitative synthesis rather than primary field experimentation. The sample consisted of published multi-country, region-specific, and disaster-context studies treated as analytical cases. Key variables included road-damage detection outcomes, satellite imagery characteristics, preprocessing and data quality conditions, model architecture, spatial context, and damage-mapping outputs. The analysis plan combined structured screening, eligibility assessment, extraction and coding of study characteristics, and thematic narrative synthesis supported by descriptive quantitative summaries. Headline findings showed that deep learning-based GeoAI has become the dominant paradigm, with very strong support for H1 and H3 and strong support for H2 and H4. Quantitatively, the RDD2020 benchmark included 26,336 road images and more than 31,000 damage instances across India, Japan, and the Czech Republic; a pixel-level satellite road-damage model achieved an F1 score of 76.09%; a transfer-learning road-quality study using 53,686 images covering 2,400 km reported 80.0% accuracy and 99.4% predictions within the true or adjacent class, rising to 94.0% after adaptation; post-earthquake road-damage detection over more than 530 km of roads reported 87.1% accuracy; and a semi-supervised GAN approach achieved 81.540% mean IoU and 79.228% F1. Overall, the findings imply that high-resolution imagery, strong labels, and context-aware architectures improve performance, but standardization, cross-region transferability, and deployment readiness remain major limitations for real-world geospatial infrastructure intelligence.

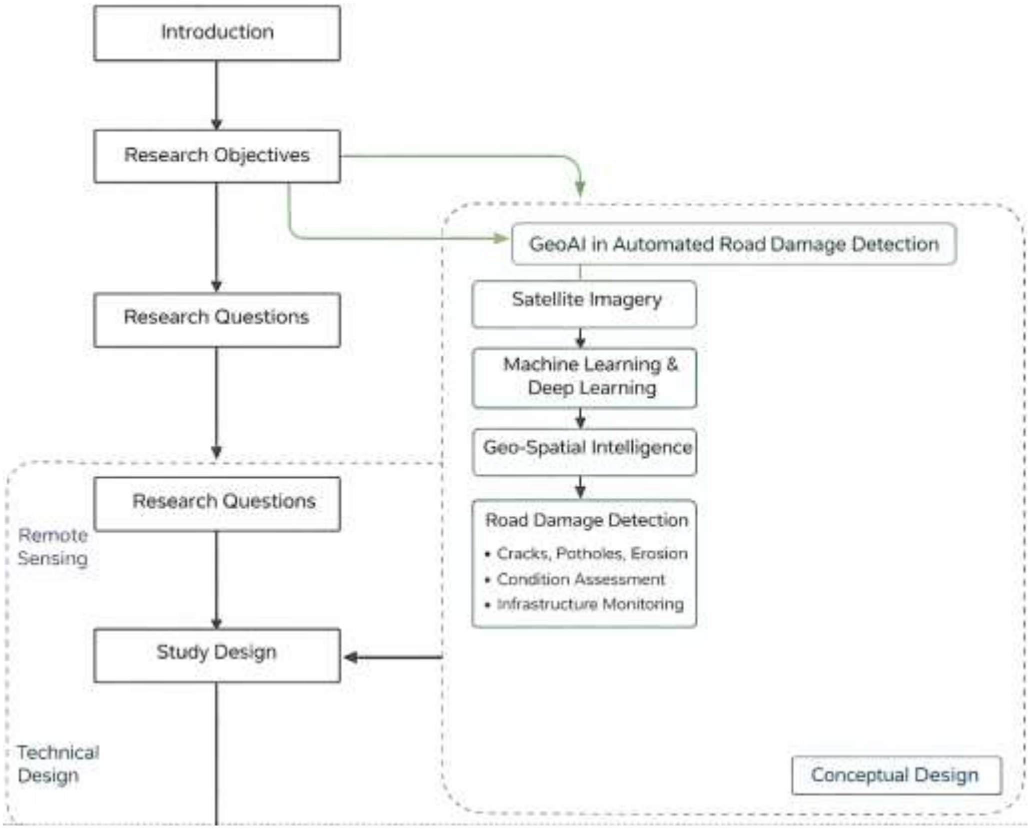
Keywords
GeoAI; Deep Learning; Road Infrastructure Damage Detection; Satellite Imagery; Remote Sensing.

INTRODUCTION

Road infrastructure damage detection refers to the identification, classification, and spatial interpretation of physical deterioration or disruption affecting roadway assets, including cracks, potholes, rutting, shoulder erosion, washouts, and post-disaster surface failures (Adegun et al., 2023). In transportation studies and geospatial science, this subject is closely tied to road extraction, surface condition assessment, and infrastructure monitoring from remotely sensed imagery. Satellite imagery, in turn, denotes Earth observation data captured by spaceborne sensors that record spatial, spectral, and temporal information over large territories (Arya, Maeda, Ghosh, Toshniwal, & Sekimoto, 2021). GeoAI is commonly understood as the integration of geographic information science, spatial big data analytics, machine learning, and artificial intelligence for place-based inference and decision support. Deep learning refers to representation-learning architectures, especially convolutional and encoder-decoder networks, that automatically learn hierarchical visual features from large datasets rather than relying primarily on hand-crafted rules (Badrinarayanan et al., 2017). When these concepts intersect, they produce a research field concerned with the automated recognition of road forms, road connectivity, and road condition states from remotely sensed imagery (Arya, Maeda, Ghosh, Toshniwal, Mraz, et al., 2021). The international significance of this topic is substantial because roads organize mobility, supply chains, emergency response, agricultural-market access, and regional integration across both highly urbanized and geographically remote settings. Accurate road information supports mapping, navigation, maintenance scheduling, and disaster logistics, while road damage information supports transportation safety, continuity of commerce, and post-event accessibility assessment. In the remote sensing literature, road-related geospatial intelligence has been treated as a foundational task because linear infrastructure networks structure the movement of people, goods, and services at local, national, and transnational scales. A road segment that is disconnected, inundated, eroded, or structurally degraded can reshape travel time, emergency reach, and economic productivity far beyond the damaged location itself (Blaschke, 2010). For that reason, road damage detection using satellite imagery is not only a technical image-analysis problem; it is also a spatial infrastructure problem with wide relevance to humanitarian operations, smart transportation management, environmental hazard response, and public works governance. The scholarship between 2005 and 2023 shows a sustained effort to formalize roads as geospatial objects, define road signatures in complex imagery, and improve the accuracy with which infrastructure conditions can be interpreted through computational methods.

The earlier road-monitoring literature established that manual inspection and conventional field surveys provide useful localized evidence, yet they are labor-intensive, time-consuming, and difficult to scale across large territories or rapidly changing conditions (Cao & Sun, 2014). Within remote sensing, the problem of road identification initially emerged as a feature-extraction challenge in which roads had to be distinguished from roofs, bare soil, parking lots, rivers, shadows, and vegetation through combinations of spectral, geometric, and contextual cues. Early work on automatic road extraction from high-resolution satellite imagery relied on image processing, neural-network-aided pixel discrimination, fuzzy optimization, shape rules, and CAD-assisted vector reconstruction (Chen et al., 2018). These studies established the practical value of transforming raw imagery into road centerlines, road polygons, and connected networks usable in GIS workflows. As object-based image analysis developed, remote sensing researchers increasingly moved from pixel-only interpretation toward object, segment, and context-aware reasoning, recognizing that roads are elongated, topologically connected, and spatially dependent features rather than isolated spectral patches. The shift mattered because roads often share color and texture properties with other urban surfaces, which makes purely local classification unstable under shadows, occlusion, seasonal variation, and material heterogeneity. Work on machine learning for high-resolution aerial imagery demonstrated that computational models could learn road appearance directly from image data, marking a methodological turning point for linear-feature extraction. Subsequent studies expanded this problem setting into high-resolution satellite imagery and GPS-supported workflows, centering on centerline extraction, completeness, and network continuity (Jiang et al., 2019). Review studies later classified the field into knowledge-based, classification-based, morphology-based, contour-based, and optimization-based approaches, showing that road extraction had already become a mature remote sensing subdomain before the acceleration of deep learning. This earlier body of work is important for the present topic because road damage detection inherits many of the same representational challenges as road extraction itself: road adjacency, contextual ambiguity, incomplete visibility, variable width, and the need to preserve topological continuity in the output map (He et al., 2016). In other words, before damage can be interpreted, roads must first be located, delineated, and differentiated from visually similar background classes across heterogeneous landscapes.

Figure 1: Framework Linking Satellite Imagery, Deep Learning, and GeoAI for Road Infrastructure Damage Detection



A major methodological transformation occurred when deep learning architectures began to redefine visual recognition and semantic segmentation across computer vision. Convolutional neural networks showed that feature hierarchies could be learned directly from large labeled corpora, reducing reliance on manually designed descriptors and opening new possibilities for dense prediction tasks. In semantic segmentation research, fully convolutional networks introduced end-to-end pixelwise prediction, making it possible to generate spatially explicit class maps from entire images rather than from isolated image patches (Mohammadzadeh et al., 2008). U-Net extended this encoder-decoder logic by coupling multiscale representation learning with skip connections that preserve fine spatial detail, and it quickly became one of the most influential architectures for image segmentation problems where object boundaries and local continuity are important (Li et al., 2021). ResNet further deepened representational capacity through residual learning, and that advance influenced many subsequent remote sensing models designed for complex scene parsing and elongated-feature recognition. Dense object detection was also reshaped by methods such as Faster R-CNN, focal loss, Mask R-CNN, SegNet, and DeepLab, all of which contributed conceptual building blocks for later road-related applications involving segmentation, detection, edge preservation, class imbalance management, and contextual reasoning. In satellite-image analysis, these advances were especially relevant because road and road-damage tasks require the simultaneous handling of fine-grained texture, broad scene context, and strong foreground-background asymmetry (W. Chen et al., 2022). A narrow road fragment, a faint crack pattern, or a washed-out segment occupies relatively few pixels compared with the non-road background, which creates a demanding class distribution for learning systems (Li, Zhong, et al., 2018). Deep architectures helped address this by combining multiscale features, contextual aggregation, and trainable loss design. As a result, the conceptual move from hand-crafted feature engineering to learned feature hierarchies changed how geospatial researchers approached roads in imagery: roads were no longer treated simply as bright lines, elongated edges, or geometric primitives, but as semantically meaningful spatial objects that could be inferred from neighborhood structure, texture variation, and scene-level organization. This transition underlies the later emergence of automated road infrastructure damage detection from satellite images (Li, Zhang, et al., 2018).

The diffusion of deep learning into remote sensing was accompanied by a rich body of review and tutorial literature that clarified why Earth observation posed a distinctive computational environment. Remote sensing images differ from conventional natural-image benchmarks in their spatial resolution, spectral variability, acquisition geometry, scale diversity, and geographic heterogeneity, which means that methods successful in mainstream computer vision often require adaptation before they can achieve stable geospatial performance (Lin et al., 2017). Tutorials and surveys published during this period documented how CNNs, residual networks, transfer learning, attention mechanisms, and segmentation architectures were being used for land-cover mapping, scene classification, object detection, and change detection across optical and multisensor imagery (Krizhevsky et al., 2017; Li et al., 2020). These syntheses emphasized that spatial context, label scarcity, class imbalance, and domain shift are recurring constraints in remote sensing applications (Ma et al., 2019). Object detection studies in optical remote sensing further showed that targets in Earth observation data often appear small, sparsely distributed, and heavily affected by background clutter, all of which complicates localization and class assignment. Geographic scene understanding research added that high-spatial-resolution imagery demands models capable of integrating local textural detail with broader environmental context, because roads, buildings, vegetation, and exposed surfaces are rarely interpretable from isolated pixels alone (Zhu et al., 2017). The literature also documented the rapid expansion of deep-learning-based satellite image classification and comparative evaluation, demonstrating that remote sensing had become a major application domain for AI research by the early 2020s. This accumulated scholarship matters for a systematic review of road infrastructure damage detection because it situates roads within the broader transformation of geospatial image understanding. Damage detection is rarely a standalone task; it is a composite problem that depends on reliable scene understanding, road segmentation, object delineation, and contextual discrimination within complex landscapes. Studies on remote sensing image classification, scene interpretation, and geospatial object detection provide the methodological language through which road damage becomes machine-readable (Long et al., 2015). They also clarify why performance cannot be interpreted apart from resolution, annotation design, and environmental diversity. The road-damage literature emerged from this larger epistemic shift in which Earth observation moved from rule-based interpretation toward data-driven, representation-learning-centered analysis (Zhang et al., 2018; Zhu et al., 2021).

Within that broader methodological transition, GeoAI gained a distinct identity as a framework for combining geographic reasoning, spatial analytics, and AI-driven inference over Earth observation data. GeoAI has been described as an emerging field at the intersection of spatial science, data science, and artificial intelligence, and this framing has proven especially useful for infrastructure analysis because road systems are inherently geographic, relational, and context dependent. A road is meaningful not only as an image object but also as part of a network that connects settlements, production zones, ports, health facilities, and emergency corridors (Liu et al., 2022). From a GeoAI perspective, automated road damage detection involves more than labeling visual anomalies; it entails spatially grounded interpretation of where a damaged segment lies, how it interacts with surrounding land uses and hazards, and what forms of network disruption it may generate (Gu et al., 2019; He et al., 2017). Benchmark initiatives helped accelerate this development by creating shared datasets and evaluation environments for road extraction and related Earth observation tasks, allowing researchers to compare models on common satellite-image benchmarks (Wang et al., 2016). Concurrent work in disaster-damage interpretation from satellite imagery showed that deep learning could support damage magnitude inference and spatial change analysis, broadening the conceptual bridge between infrastructure mapping and infrastructure condition assessment. This bridge is central to the present topic because road damage often manifests through partial disappearance, fragmentation, displacement, flooding-related obscuration, or abrupt surface change rather than through simple geometric absence (Ronneberger et al., 2015). GeoAI provides a conceptual space in which segmentation, detection, change analysis, and geospatial reasoning can be integrated within one analytical pipeline. In such pipelines, road damage becomes an interpretable geospatial phenomenon through the interaction of input imagery, spatial context, learned features, and map-oriented output products. The international significance of that integration is clear in contexts where roads support evacuation, relief distribution, agricultural transport, and access to public services across vast territories. GeoAI-oriented road monitoring is thus aligned with cross-border concerns in infrastructure resilience, disaster logistics, and territorial governance. It brings together the representational strengths of deep learning and the locational intelligence of geographic analysis, forming the analytical foundation from which satellite-based road damage detection has increasingly been studied (Ren et al., 2017).

Road-focused satellite-image studies between 2018 and 2023 illustrate how rapidly methodological sophistication increased once deep learning became standard in remote sensing. Deep residual U-Net models, refined residual convolutional networks, DenseUNet variants, boundary-enhanced extraction models, and context-aware segmentation frameworks all sought to address persistent challenges such as occlusion, boundary blurring, road interruption, and the preservation of topological continuity (Ye et al., 2022). In very-high-resolution imagery, roads are often partially hidden by tree canopies, shadows, overpasses, buildings, or adjacent impervious surfaces, and the literature repeatedly identified these conditions as a source of fragmented or incomplete predictions (Ranyal et al., 2022). Attention-based and context-aware approaches were introduced to improve global-local reasoning and continuity restoration, as shown in cascaded attention DenseUNet and related work that explicitly targeted occluded roads and connected road-network representation. Studies also expanded into specialized terrain contexts such as mountainous roads, where steep topography, complex land cover, and narrow alignments complicate extraction, prompting generative-adversarial and neighborhood-probability strategies. Review work published in 2022 further consolidated this body of knowledge by organizing deep-learning-based road extraction methods around supervision modes, architecture families, feature-fusion designs, and performance criteria. Collectively, these studies reveal that the analytical core of road infrastructure interpretation lies in how models learn continuity, context, scale, and boundary precision from satellite images (Mnih & Hinton, 2010). These concerns are directly relevant to damage detection because deterioration and disruption often appear as local interruptions in surfaces or as topological irregularities in otherwise continuous road segments. The extraction literature thus provides both methodological tools and problem definitions for a road-damage review. It shows that performance is shaped by image resolution, class definitions, training labels, regional complexity, and the way architectures encode contextual dependencies. It also shows that road intelligence from satellite imagery has evolved from generic segmentation toward more targeted handling of road-specific difficulties, including small-width representation, connectivity preservation, and visually ambiguous surroundings. Those developments form the immediate technical backdrop against which automated damage detection studies can be understood (Wang et al., 2020).

The literature on road damage and road condition monitoring adds another layer to this progression by focusing attention on distress categories, annotated datasets, comparative evaluation, and the translation of image analysis into maintenance-relevant information. A notable characteristic of this body of work is that road damage has frequently been studied through ground-level or mobile imagery, while satellite-based damage assessment remains comparatively scattered across road extraction, disaster mapping, condition inference, and change-detection studies (Subramanyam, 2008). Multi-country work on deep-learning-based road damage detection and classification illustrated the importance of geographic diversity, annotation consistency, and shared benchmarks for comparing methods across real-world contexts (Yu et al., 2017; Zhang et al., 2016). The RDD2020 dataset contributed to this momentum by providing structured annotations for automated road damage detection, strengthening reproducibility and comparative learning in this research area. Review scholarship on smart sensing and AI for road condition monitoring further showed that infrastructure condition assessment has become an interdisciplinary domain involving sensing technologies, computer vision, remote sensing, and maintenance analytics rather than a single-method field (Gao et al., 2019). At the same time, adjacent work in change detection from satellite imagery emphasized the relevance of difference-aware representation learning for identifying spatial disruption and surface transformation, which is conceptually aligned with road damage recognition in post-event and temporally varying settings (Demir et al., 2018). Broader reviews of deep learning in satellite-image classification and geospatial scene understanding reinforce that the interpretation of road distress from spaceborne imagery depends on the same foundational issues that govern remote sensing AI more generally: high-quality labels, robust generalization, sensitivity to scene complexity, and careful metric interpretation. This combination of road extraction, damage classification, condition monitoring, and geospatial change analysis defines the scholarly setting for the present review (Mei et al., 2023). The introduction to this study is located within that setting, where road infrastructure damage detection using satellite imagery is approached as a GeoAI problem shaped by deep learning, spatial context, benchmark development, and the international need for scalable roadway intelligence across heterogeneous geographic environments (Wheeler & Karimi, 2020).

Background of the Study

Road infrastructure is one of the most essential foundations of national and regional development because it supports the movement of people, goods, emergency services, and economic activity across urban, peri-urban, and rural environments. The condition of roads directly affects transportation efficiency, public safety, logistics performance, market accessibility, and the continuity of social services. When roads experience physical deterioration such as cracks, potholes, rutting, edge collapse, washouts, or other surface and structural defects, the consequences can extend beyond localized transport inconvenience to broader disruptions in trade, mobility, disaster response, and infrastructure planning. In many parts of the world, especially in rapidly urbanizing regions and hazard-prone areas, the frequency and intensity of road damage have become more visible due to aging infrastructure, growing traffic demand, extreme weather events, flooding, erosion, and limited maintenance capacity. This has created a strong need for faster, broader, and more reliable methods of monitoring road conditions. Conventional inspection methods, which often depend on manual surveys, field crews, or vehicle-based observation, are valuable for detailed engineering assessment, yet they are often expensive, slow, spatially limited, and difficult to apply consistently across large or inaccessible territories. As a result, researchers and infrastructure agencies have increasingly turned toward remote sensing and geospatial technologies as scalable alternatives for road monitoring. Among these technologies, satellite imagery offers a particularly important advantage because it enables repeated observation over extensive geographic areas, including locations that are difficult to reach on the ground. At the same time, the growing availability of artificial intelligence techniques, especially GeoAI and deep learning, has transformed the way geospatial data can be processed and interpreted. These methods allow complex visual patterns in satellite imagery to be identified, classified, and mapped with greater automation than traditional image analysis techniques. In the context of road infrastructure, this development has opened a new research space focused on automated detection of damaged or disrupted road segments from spaceborne imagery. The background of this study is therefore rooted in the intersection of transportation infrastructure management, remote sensing, geospatial intelligence, and deep learning-based automation. It emerges from the need to understand how the existing body of knowledge has developed, what methods have been applied, what kinds of road damage have been studied, and how satellite-based GeoAI systems are being positioned as tools for large-scale infrastructure condition assessment.

Problem Statement

The growing dependence of societies on road networks for transportation, trade, service delivery, emergency mobility, and regional integration has made road infrastructure condition assessment an increasingly important area of research and practice. Roads are continuously exposed to heavy traffic loads, environmental stress, water intrusion, temperature variation, construction weaknesses, and disaster-related impacts, all of which contribute to different forms of physical deterioration and structural disruption. When these damages are not detected and addressed in a timely manner, they can reduce road safety, interrupt connectivity, increase maintenance costs, and weaken the efficiency of broader transport systems. Although conventional inspection methods remain useful for detailed engineering evaluation, they are often limited by cost, labor requirements, time consumption, and restricted spatial coverage, especially when road networks extend across large, remote, or difficult-to-access areas. For this reason, satellite imagery has gained importance as a scalable source of spatial information for infrastructure monitoring. At the same time, GeoAI and deep learning have emerged as promising tools for automating the interpretation of geospatial imagery and detecting patterns that would otherwise require extensive manual observation. Even with this progress, the body of literature on automated road infrastructure damage detection using satellite imagery remains fragmented across different study contexts, methodological designs, damage categories, and analytical objectives. Many published studies focus on road extraction, general infrastructure mapping, or disaster damage assessment without fully centering on road surface deterioration and infrastructure damage as a distinct research domain. In addition, the reviewed literature varies greatly in terms of data sources, image resolution, annotation practices, evaluation metrics, and model architectures, making it difficult to build a unified understanding of what methods are most frequently used, what forms of road damage are most commonly examined, and what methodological challenges continue to affect accuracy and generalizability. This creates a clear research problem: there is insufficient systematic synthesis of the literature specifically addressing how GeoAI and deep learning have been used for automated road infrastructure damage detection from satellite imagery between 2018 and 2026. Without such synthesis, the field lacks a consolidated view of its conceptual foundations, technical progress, recurring limitations, and case-based evidence. The present study addresses this problem by organizing, reviewing, and critically synthesizing the existing literature in order to clarify the current state of knowledge and support a more coherent understanding of this emerging research area.

This study is designed to achieve a set of interconnected objectives that collectively establish the direction and analytical scope of the research. The first objective is to examine the evolution of GeoAI and deep learning approaches used for automated road infrastructure damage detection through satellite imagery within the 2018–2026 review period. This objective is important because it enables the study to trace how the field has developed in response to advances in geospatial data availability, satellite image resolution, and deep learning model design. The second objective is to identify and classify the major satellite data sources, damage categories, and computational methods that have been reported across the literature. Through this objective, the study seeks to determine which kinds of imagery, analytical workflows, and model families have been most commonly employed in the detection of road deterioration and disruption. The third objective is to compare the findings of selected studies from a case-based perspective in order to reveal similarities and differences across geographic regions, infrastructure environments, and research applications. This cross-case orientation supports a more structured understanding of how context shapes methodological decisions and reported performance. The fourth objective is to analyze the key challenges repeatedly identified in the literature, including issues related to image quality, annotation inconsistency, class imbalance, environmental complexity, limited transferability, and practical deployment constraints. Addressing this objective allows the study to move beyond a descriptive summary and toward a more critical synthesis of the barriers affecting the maturity of this field. The fifth objective is to assess the reviewed evidence in relation to the study's hypotheses and research questions so that the findings are organized around clear analytical propositions rather than broad thematic observation alone. This objective-based structure helps ensure that the review remains focused, coherent, and aligned with the broader purpose of understanding how satellite-based GeoAI and deep learning are being used to interpret road infrastructure damage. In this way, the study does not merely collect prior works; it systematically evaluates them in relation to defined goals that guide the interpretation of methods, findings, and recurring patterns across the literature.

Research Hypotheses

The hypotheses of this study are formulated as literature-based analytical propositions that guide the review and provide a structured basis for interpreting the evidence gathered from prior studies. Since the research is systematic review–based and qualitative in orientation, the hypotheses are not intended for statistical testing through primary field data, but rather for structured assessment through comparative synthesis of published findings. The first hypothesis proposes that deep learning–based GeoAI approaches have become the dominant methodological trend in satellite-based road infrastructure damage detection studies during the review period. This proposition reflects the assumption that recent studies increasingly rely on advanced learning architectures rather than conventional image-processing and rule-based techniques. The second hypothesis proposes that studies using high-resolution satellite imagery and more sophisticated deep learning architectures tend to report stronger detection performance than studies relying on lower-resolution imagery or less advanced methods. This proposition is grounded in the expectation that model effectiveness is closely linked to the quality and interpretability of input data as well as the representational strength of the algorithm. The third hypothesis proposes that the accuracy and reliability of automated road damage detection are strongly shaped by annotation quality, geographic context, and the complexity of the visual environment in which roads are located. This means that performance is not determined by model architecture alone, but also by the quality of labeling, the diversity of landscapes, and the spatial conditions surrounding road segments. The fourth hypothesis proposes that, while the literature shows methodological progress, it also reveals persistent limitations in benchmark standardization, cross-regional generalizability, and real-world implementation. This proposition allows the study to examine whether technical success reported in isolated case studies translates into broader methodological consistency and practical usability. Together, these hypotheses provide an analytical framework for organizing the review findings and linking the results to the study's research questions and objectives. They also help transform the literature review from a purely descriptive exercise into a more focused and interpretive scholarly investigation centered on identifiable patterns, recurring evidence, and structured assessment of the field.

Significance of the Research

The significance of this research can be explained as follows:

i. **Academic significance**: This study contributes to the academic literature by providing a focused and systematic synthesis of research on GeoAI and deep learning for automated road infrastructure damage detection using satellite imagery. It helps organize an emerging field that is currently dispersed across remote sensing, transportation engineering, geospatial intelligence, and computer vision studies.

ii. **Theoretical significance**: The study strengthens the theoretical understanding of how pattern recognition, geospatial intelligence, and deep learning-based feature learning intersect in infrastructure monitoring. It also supports the use of a theory-based lens for interpreting how automated systems identify road damage patterns from complex satellite imagery.

iii. **Methodological significance**: This research is significant because it compares different methodological approaches, including imagery sources, model architectures, damage categories, and evaluation practices. By doing so, it identifies how different research designs shape findings and where inconsistencies exist across the literature.

iv. **Practical significance for infrastructure management**: The study is valuable to road agencies, transportation planners, and maintenance authorities because it synthesizes evidence on automated monitoring approaches that can support broader and more efficient road condition assessment across large geographic areas.

v. **Significance for disaster and emergency response**: Since damaged roads affect evacuation, relief delivery, and accessibility during crises, this review is important for understanding how satellite-based damage detection can support spatial awareness in hazard-prone and post-disaster contexts.

vi. **Technological significance**: The study highlights the role of GeoAI and deep learning as transformative tools in modern infrastructure analytics. It clarifies how automation is changing the interpretation of road conditions and how geospatial technologies are becoming central to large-scale monitoring systems.

vii. **Policy and planning significance**: This research is important for policy discussions related to digital infrastructure governance, smart transportation systems, and resilient development planning. It provides a knowledge base that can inform infrastructure monitoring strategies and institutional adoption of geospatial AI systems.

viii. **Significance for future scholarly synthesis**: The study creates a structured reference point for later researchers by identifying key trends, gaps, and recurring challenges in the literature. In this way, it serves as a scholarly foundation for more specialized studies on datasets, algorithms, regional applications, and operational deployment.

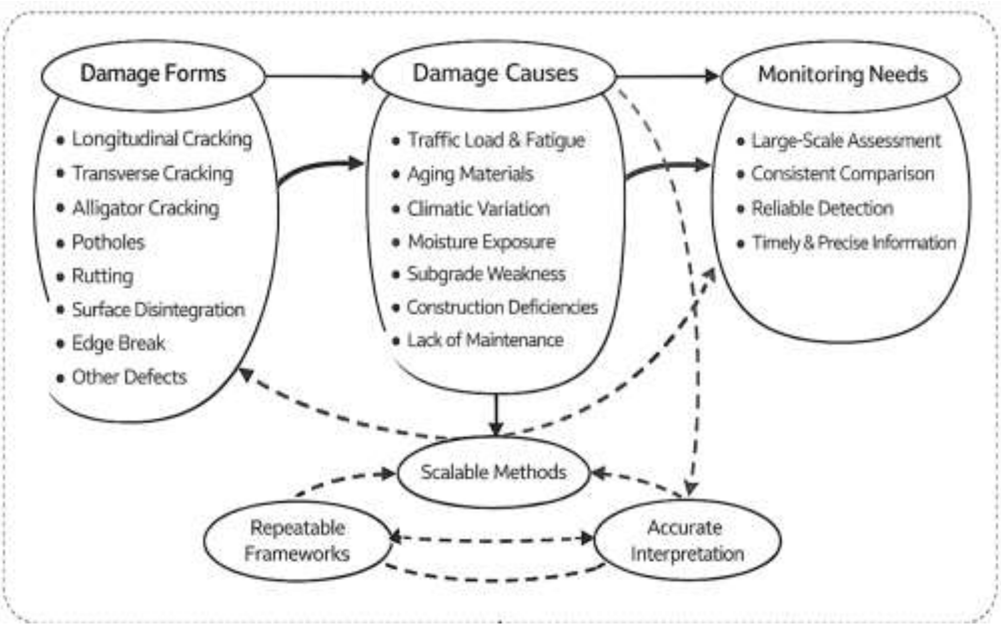
LITERATURE REVIEW

The literature on automated road infrastructure damage detection using satellite imagery is situated at the intersection of transportation infrastructure assessment, remote sensing, geospatial intelligence, and artificial intelligence–driven image analysis. Road infrastructure has long been recognized as a critical physical system supporting mobility, trade, public service access, emergency response, and territorial integration, which has made the monitoring of road conditions an essential concern in both developed and developing contexts. Within the broader transportation and geospatial literature, road damage has been studied as a form of physical deterioration or disruption that affects the functionality, safety, and continuity of roadway systems. Traditional approaches to road condition assessment have commonly relied on manual inspection, field surveys, and vehicle-based monitoring, which provide detailed localized information but are often constrained by time, labor, cost, and limited spatial reach. The growth of remote sensing technologies introduced a broader observational capacity, enabling researchers and institutions to monitor surface conditions over extensive regions using imagery acquired from aerial and satellite platforms. As satellite imagery became more detailed and increasingly accessible, researchers began to examine how roads and their changing physical conditions could be interpreted from spaceborne data. At the same time, advances in GeoAI and deep learning transformed the methodological landscape of geospatial analysis by allowing complex image patterns to be learned automatically from data rather than being defined solely through manual rules or handcrafted features. This shift created new opportunities for road-related applications such as road extraction, road network mapping, disaster damage detection, and infrastructure condition assessment. The literature review in this study is therefore grounded in a body of scholarship that has evolved from conventional image-processing and classification techniques toward more advanced segmentation, object detection, and context-aware deep learning models. It also reflects a growing recognition that road infrastructure damage detection is not merely a technical classification task, but a spatially embedded analytical problem influenced by image resolution, annotation quality, damage typology, geographic variability, and the practical demands of infrastructure management. In this research, the literature review serves to establish the conceptual and methodological foundation of the study by examining the key themes, theories, frameworks, methods, and empirical patterns that define the field. It provides the basis for identifying what is already known, what remains insufficiently understood, and how the present review is positioned within the broader scholarly conversation on GeoAI-enabled road infrastructure analysis.

Road Infrastructure Damage: Forms, Causes, and Monitoring Needs

Road infrastructure damage is generally understood as the physical deterioration, deformation, or disruption of pavement surfaces and associated roadway elements that reduces serviceability, safety, structural quality, and user comfort. In the literature, this damage is commonly represented through observable defect classes such as longitudinal cracking, transverse cracking, alligator cracking, potholes, rutting, patching failure, ravelling, edge break, and surface disintegration, all of which indicate that a road segment is losing its functional and engineering integrity. The significance of these defects is not limited to their visible appearance; rather, each defect reflects a deeper interaction among material fatigue, traffic stress, environmental exposure, water infiltration, thermal variation, and maintenance history. This is why pavement damage has long been treated as a central indicator in pavement management systems, where condition monitoring is necessary for maintenance prioritization, budget allocation, and service-life preservation. Early work in automated distress inspection already showed that road surface damage could be treated as a measurable visual phenomenon rather than only a field-observed engineering issue, thereby opening the possibility of replacing purely manual inspection with image-driven computational analysis (Huang & Xu, 2005). Later review scholarship organized this broader area by showing that pavement distress detection includes not only the recognition of cracks and potholes, but also the classification, quantification, and updating of damage information for network-level management. That body of work also clarified that agencies need distress information that is repeatable, scalable, and sufficiently objective to support maintenance planning across extensive road systems rather than isolated sections (Ragnoli et al., 2018). In this sense, the study of road infrastructure damage begins with the recognition that roads are dynamic assets whose condition changes over time under cumulative loading and environmental stress. The literature therefore frames road damage as both an engineering problem and an information problem: engineering, because damage emerges from physical processes of deterioration; and informational, because authorities must identify, interpret, and record these defects accurately if road performance is to be maintained in a systematic and timely manner.

Figure 2: Framework Linking Road Defects, Damage Causes, and Monitoring Priorities



The causes of road infrastructure damage are presented in the literature as multidimensional and cumulative rather than singular or isolated. Surface defects emerge through interactions among axle loading, aging materials, climatic variation, subgrade weakness, drainage failure, repetitive moisture exposure, construction deficiencies, and the absence or delay of preventive maintenance. Because these factors rarely act alone, the visual manifestation of road damage often differs across pavement types, traffic conditions, and geographic settings. This complexity makes monitoring a central concern in transport infrastructure management, since identifying the type, severity, and spatial spread of defects is necessary before any rational intervention can be planned. Review studies on pavement monitoring systems have shown that both paved and unpaved roads require structured assessment regimes, and that monitoring technologies have expanded from static visual surveys toward dynamic and sensor-supported systems capable of supporting larger-area evaluations with greater consistency and speed (Shtayat et al., 2020). This shift in monitoring logic is important because the need is no longer limited to documenting whether a road has failed; it is also concerned with detecting deterioration early enough to avoid higher rehabilitation costs, rising accident exposure, reduced ride quality, and disruptions to mobility. The literature also shows that image-based technologies have become increasingly relevant in this context because pavement defects are highly visual in nature and can often be captured, enhanced, segmented, and classified through digital imagery. A review of image technology in pavement distress detection explains that image acquisition, preprocessing, recognition, and feature interpretation together form a coherent analytical chain for translating visible pavement defects into usable condition information (Du et al., 2021). From this perspective, monitoring needs are shaped by scale, repeatability, and precision. Road agencies need methods that can observe large networks, distinguish between defect classes, and support consistent comparison over time. The importance of automated approaches therefore comes from their ability to respond to growing road networks and increasingly complex maintenance environments, where manual inspection alone cannot easily satisfy expectations of speed, cost efficiency, and spatial coverage.

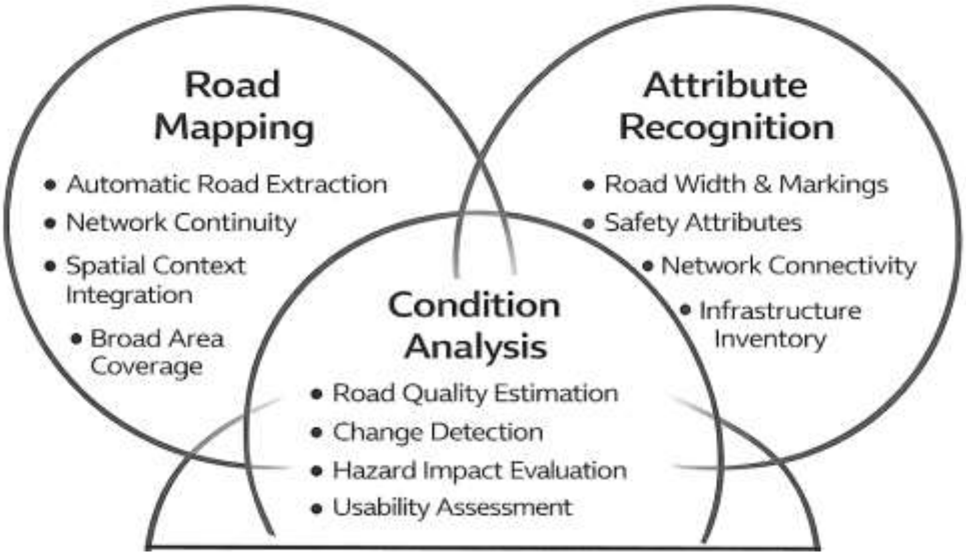
The monitoring needs identified in recent scholarship also reveal why road infrastructure damage has become a major analytical domain for artificial intelligence and computer vision. As road agencies and researchers moved from simple defect spotting toward automated condition intelligence, the emphasis increasingly shifted to how damage information is generated, compared, and interpreted across datasets and operational environments. This raised a new set of concerns regarding benchmark reliability, variation in performance measures, differences in annotation practices, and the gap between reported model accuracy and independent real-world applicability. A 2023 synthesis of deep learning performance in vision-based pavement distress detection showed that the field has generated a substantial volume of research, yet the reported success of automated systems is shaped by methodological inconsistencies in dataset composition, evaluation design, and performance reporting (Amena Begum & Md. Nazmul, 2021; Zihan et al., 2023). This is highly relevant to the present research because road infrastructure damage is not simply a visible surface event; it is a condition state that must be detected under changing illumination, texture diversity, defect scale variation, background complexity, and context-specific pavement conditions (Ferdous Ara, 2021; Mahfuj Ahmed & Md. Hasan Or, 2021). In practical terms, this means that the need for monitoring is inseparable from the need for dependable interpretation (Aditya & Mohammad Robel, 2022; Mohammad Robel & Md. Morshedul, 2021). A system that detects cracks in one dataset but performs weakly across another setting does not fully satisfy the operational demands of infrastructure management. For that reason, the literature frames road damage monitoring as an issue of both technical capability and decision quality. Maintenance authorities require information that is timely, spatially extensive, interpretable, and sufficiently robust to support intervention decisions without producing misleading classifications or incomplete damage records. The conceptual importance of road damage monitoring therefore lies in its role as the bridge between visible physical deterioration and maintenance action. In literature-review terms, this makes road infrastructure damage a foundational theme for the present study, because the later discussion of GeoAI, deep learning, satellite imagery, and automated detection methods all depend on a clear understanding of what road damage represents, why it occurs, and why large-scale monitoring of that damage has become an essential research and operational priority.

Satellite Imagery in Road Infrastructure Assessment

Satellite imagery has become an increasingly important source of information in road infrastructure assessment because it enables repeated, large-area observation of transport corridors without requiring continuous field presence. In infrastructure studies, the value of satellite imagery lies in its capacity to capture spatial patterns across urban, peri-urban, rural, and remote settings where conventional inspection methods are often constrained by time, labor, cost, and accessibility. Road systems are long, geographically distributed assets, which means that any monitoring approach limited to localized surveys can leave major information gaps across broader networks (Istiaq & Nusrat, 2022; Mahfuj Ahmed & Rajib, 2022). Satellite-based observation addresses this challenge by allowing analysts to evaluate road presence, continuity, surrounding land cover, and visible surface characteristics within a spatially integrated framework (Md Khaled & Hisham, 2022; Md Mehedi & Md, 2022). Earlier research on road extraction from high-resolution satellite imagery already demonstrated that roads could be treated as machine-interpretable features whose spectral, geometric, and contextual properties support automated detection and mapping. In that foundational stage, satellite imagery was used primarily to distinguish roads from adjacent land cover and to translate image features into GIS-compatible road representations, establishing the basis for later infrastructure-oriented applications that extend beyond simple road presence toward surface condition and damage interpretation (Md. Mainuddin & Palash Chandra, 2022; Md. Morshedul et al., 2022; Mena & Malpica, 2005). This progression is significant because road infrastructure assessment depends first on reliable road delineation before any meaningful interpretation of quality, safety, or damage can be attempted. The use of satellite imagery therefore entered the road-assessment literature not merely as a substitute for visual observation, but as a scalable analytic resource through which road networks could be studied as spatial systems. In more recent work, high-resolution imagery has also been used to infer road quality directly, showing that satellite-based learning approaches can move from binary road extraction toward condition-sensitive analysis of roadway segments (Brewer et al., 2021; Md. Nazmul & Amena Begum, 2022; Md. Shahinur & Md. Sultan, 2022). This has broadened the conceptual role of satellite imagery in road infrastructure studies from mapping where roads are to assessing how roads are performing, what features they exhibit, and how their condition varies across space. In this sense, satellite imagery has become central to the transition from static road inventory toward dynamic, image-based road intelligence within geospatial infrastructure assessment.

A major reason for the growing relevance of satellite imagery in road infrastructure assessment is the improvement in spatial resolution and the associated capacity to identify smaller and more complex roadway attributes. As image resolution improved and very-high-resolution imagery became more accessible, researchers gained the ability to study roads not only as broad linear objects but also as corridors containing distinct structural and operational characteristics.

Figure 3: Satellite Imagery Framework For Road Mapping, Attribute Recognition, And Damage Detection



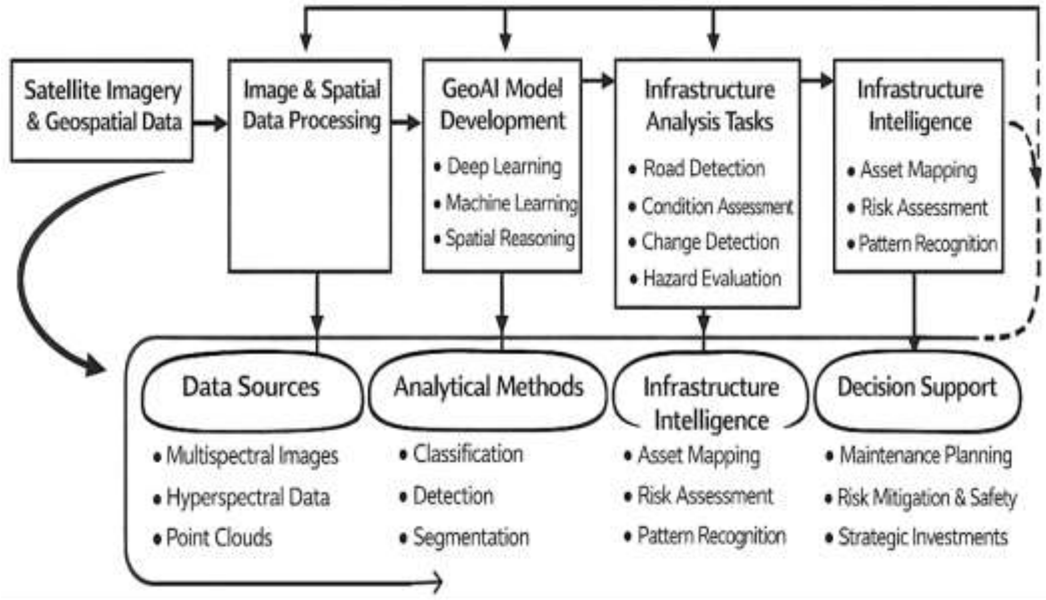
This change expanded the analytical use of satellite imagery from centerline extraction and road mapping toward more detailed forms of assessment, including road width interpretation, lane separation, markings, crossings, divided carriageways, and selected safety-related elements. Such developments are important because infrastructure assessment is rarely limited to the question of whether a road exists; it also concerns the condition, configuration, usability, and safety context of road segments within larger transport systems. Recent studies have shown that high-resolution satellite imagery can support automated identification of road-related safety attributes when coupled with advanced object detection methods, indicating that satellite data can function as a practical source for road inventory enhancement and safety screening over large territories (Šiljeg et al., 2023). In a similar way, newer road-extraction studies using deep learning have emphasized the role of remotely sensed imagery in maintaining updated and connected road information under conditions of shadow, occlusion, and background confusion, all of which are critical obstacles in infrastructure interpretation from space (Das et al., 2023). These contributions show that satellite imagery is not only useful when roads are clearly visible under ideal conditions; it is also valuable because it allows the development of computational strategies for handling the ambiguity that commonly characterizes real-world road scenes. For infrastructure assessment, this is particularly important because roads often pass through environments where vegetation cover, urban materials, topographic variation, and adjacent impervious surfaces make interpretation difficult. The literature therefore treats satellite imagery as both a data source and a testing ground for analytical robustness. It enables researchers to assess how well models can preserve road continuity, detect fine-scale roadway features, and generate outputs that are meaningful for transport agencies responsible for monitoring geographically dispersed infrastructure assets.

Satellite imagery has also become highly relevant in road infrastructure assessment because it supports condition-oriented analysis in contexts where roads are damaged, degraded, or affected by hazardous events. This aspect moves the discussion beyond road extraction and attribute recognition toward the broader question of how satellite-based evidence can inform the evaluation of road usability and infrastructure vulnerability. One important stream of research has explored whether satellite imagery can be used to estimate pavement quality and travel-related conditions through machine learning, thereby showing that the visual properties captured from above are associated with differences in road surface quality and functional performance (Amena Begum & Mst Kaniz, 2023; Brewer et al., 2021; Tanjina Binte & Md. Hasan Or, 2022). Another important stream has focused on damaged road detection after disasters, particularly in contexts where rapid situational awareness is needed and field inspection is difficult or delayed. In such cases, remotely sensed imagery becomes an operationally valuable source of evidence because it can capture post-event surface changes across wide areas and support damage assessment under urgent conditions. Research using synthetic aperture radar and field datasets has shown that satellite-based deep learning approaches can identify road damage following earthquakes, extending road infrastructure assessment into disaster-response settings where optical visibility, field accessibility, and time constraints can all limit conventional inspection methods (Ferdous Ara & Beatrice Onyinyechi, 2023; Islam & Aditya, 2023; Karimzadeh et al., 2022). The significance of this development lies in the fact that infrastructure assessment is no longer confined to routine maintenance monitoring; it also includes emergency evaluation of transport connectivity and disruption. Satellite imagery is particularly suitable for this role because it combines broad spatial reach with the capacity for repeated acquisition, allowing road condition evidence to be interpreted within a wider environmental and regional context. Across the literature, satellite imagery therefore appears as a multi-purpose infrastructure assessment resource: it supports road extraction, road attribute interpretation, quality estimation, and damage recognition under both routine and disrupted conditions. This makes it a central component in modern road infrastructure research, where the objective is not only to observe roads from space, but to transform imagery into actionable knowledge about the state, safety, and continuity of transport networks across diverse geographic settings.

GeoAI for Geospatial Infrastructure Intelligence

Geospatial artificial intelligence has emerged as a specialized analytical domain that combines geographic information science, remote sensing, machine learning, deep learning, and spatial reasoning for the interpretation of complex Earth-related phenomena. In the literature, GeoAI is not treated as a simple extension of conventional artificial intelligence into mapped data; rather, it is presented as a spatially explicit form of intelligence in which location, scale, topology, spatial dependence, and contextual relationships are integral to how models learn, infer, and generate knowledge from georeferenced information. This distinction is important for infrastructure studies because infrastructure systems such as roads, bridges, corridors, and utility networks are inherently spatial objects embedded within physical, social, and environmental environments. Their meaning is shaped not only by visual appearance but also by connectivity, adjacency, hierarchical network position, land-use context, and exposure to environmental stressors. Foundational GeoAI scholarship has therefore emphasized that geographic knowledge discovery requires analytical frameworks able to account for the unique properties of geospatial data rather than applying artificial intelligence in a purely generic manner (Janowicz et al., 2020; Mahfuj Ahmed & Md. Mehedi, 2023; Md. Hasan Or et al., 2023). Related review work has reinforced this view by describing GeoAI as an interdisciplinary direction that integrates geography, earth science, and artificial intelligence in order to improve dynamic perception, intelligent reasoning, and knowledge discovery about geographic phenomena and spatial processes (Gao, 2020; Md. Mainuddin & Palash Chandra, 2023; Md. Mehedi & Khairum Nahar, 2023). Within this conceptualization, geospatial infrastructure intelligence refers to the ability to transform heterogeneous spatial data into interpretable, decision-supportive knowledge about infrastructure location, condition, functionality, risk, and change. GeoAI provides the methodological means for doing so because it can process imagery, trajectories, point clouds, mapped features, and spatiotemporal observations within a unified computational framework(Mostafa, 2023; Palash Chandra, 2023). The significance of this transition for infrastructure research is substantial. Traditional geospatial analysis often depended on manual feature engineering, rule-based modeling, or descriptive GIS operations, while GeoAI introduces automated representation learning and scalable pattern recognition that can identify infrastructure-related signatures across large and diverse territories (Amena Begum & Mst Kaniz, 2024; Rukaiya Khatun & Zakia, 2023). As a result, GeoAI is increasingly positioned in the literature as the intellectual and methodological foundation for the next stage of spatial infrastructure analysis, where interpretation extends beyond mapping static assets toward understanding how infrastructure behaves, deteriorates, interacts with surrounding conditions, and supports geographic systems of mobility and service provision (Janowicz et al., 2020; Md Khaled & Md. Morshedul, 2024; Md. Mehedi & Khairum Nahar, 2024).

Figure 4: GeoAI Framework For Infrastructure Analysis And Decision Support



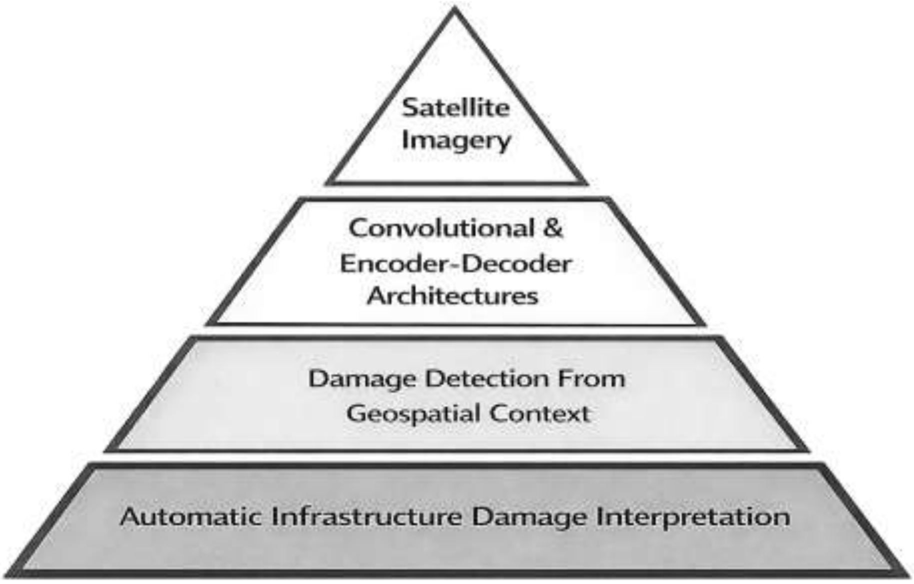
The application value of GeoAI for geospatial infrastructure intelligence becomes clearer when viewed through the types of data and analytical tasks addressed in recent research (Md. Towhidul & Uddin, 2024; Mohammad Robel & Md. Morshedul, 2024). Reviews of the field show that GeoAI is especially powerful in large-scale image analysis and machine vision because it can automate classification, object detection, segmentation, feature extraction, and pattern recognition over very large geospatial datasets that would be difficult to process through manual interpretation alone. In this context, roads, buildings, corridors, and other infrastructure objects become machine-readable through architectures that combine visual learning with spatial context, allowing models to move from simple recognition toward richer forms of geospatial understanding (Li & Hsu, 2022; Rajib, 2024; Zakia & Rukaiya Khatun, 2024). GeoAI has also been characterized as a broader framework for the interpretation of complex geomatics data, including RGB imagery, thermal data, trajectories, hyperspectral imagery, and three-dimensional point clouds, thereby showing that spatial intelligence is not limited to one sensor or one application domain but is instead a cross-cutting computational strategy for georeferenced knowledge production (Albert, 2025; Ishtiaque & Rajib, 2025; Pierdicca & Paolanti, 2022). This is highly relevant to infrastructure intelligence because road systems, transport facilities, and related assets are monitored through multiple forms of geospatial evidence, each contributing complementary information about visibility, structure, material condition, surface variation, or change over time. The literature increasingly recognizes that infrastructure analysis requires integrated interpretation rather than isolated image reading. A road, for example, may need to be understood as a segmented visual feature, a connected network element, a transport corridor, and a risk-sensitive asset exposed to terrain instability, flooding, or wear (Kazi Rakib Hasan, 2025; Md. Ashfaq & Ashraful, 2025). GeoAI supports this layered interpretation by making it possible to combine pattern learning with geographic relations and mapping objectives. This is why the field is frequently associated with knowledge discovery rather than only prediction. In infrastructure contexts, the goal is not simply to classify pixels correctly but to create spatially meaningful outputs that can guide inventory management, safety screening, maintenance prioritization, accessibility evaluation, and network resilience analysis. As the literature suggests, GeoAI gains its strength from this ability to bridge advanced computation with the geographic logic required to analyze built environments in a way that is both technically robust and operationally relevant (Mohammad Robel, 2025; Murad, 2025).

Recent scholarship further shows that GeoAI has matured into an influential framework for mapping applications across buildings and infrastructure, land systems, hazards, and human activity, indicating that geospatial infrastructure intelligence is part of a wider transformation in how Earth observation and geographic data are used for applied analysis. Editorial and review studies published in 2023 describe GeoAI as enhancing traditional geospatial analysis and mapping by altering the methods through which complex human–natural systems are understood and managed, with buildings and infrastructure explicitly identified as one of its major application domains (Md Khaled, 2026; Y. Song et al., 2023). This characterization is especially relevant for road infrastructure research because it locates roads within a broader set of built-environment applications where geospatial intelligence is expected to support not only recognition but also management, monitoring, and analytical integration. GeoAI contributes to this by enabling the extraction of infrastructure patterns from large geospatial datasets, the classification of infrastructure-related features across different environments, and the creation of mapped outputs that can be linked directly to planning and operational decision processes. In the context of this study, that means GeoAI provides the conceptual bridge between satellite imagery and actionable infrastructure assessment. It allows imagery to be interpreted as a source of evidence about road presence, continuity, condition, and disruption, rather than as a passive visual record. The importance of this for geospatial infrastructure intelligence lies in the fact that roads are not isolated objects; they are system components whose condition affects network performance, emergency access, trade corridors, and regional connectivity. GeoAI-oriented analysis can therefore support infrastructure intelligence by making roadway information more timely, more spatially extensive, and more analytically consistent across large territories. This growing body of literature positions GeoAI as an enabling framework for modern infrastructure studies because it integrates geospatial data, computational learning, and spatial reasoning into workflows capable of generating interpretable knowledge about built systems. Within the present research, this framework is central because automated road infrastructure damage detection using satellite imagery depends on exactly this form of geospatial intelligence: the capacity to detect, classify, and spatially interpret road-related conditions in a way that is meaningful for infrastructure assessment and geographic decision support (Janowicz et al., 2020).

Deep Learning Architectures for Satellite-Based Damage Detection

Deep learning architectures have become central to satellite-based damage detection because they allow image features to be learned automatically from complex geospatial data rather than being specified through fixed handcrafted rules. In conventional image analysis, the identification of damaged infrastructure often depended on manually designed texture descriptors, thresholding strategies, edge-detection routines, or object-based classification schemes that required substantial expert intervention and struggled under changing lighting, surface variation, and heterogeneous landscape conditions. Deep learning altered this analytical logic by enabling multilayer computational models to learn hierarchical representations of imagery, beginning with low-level visual cues and progressing toward more abstract semantic structures. This capacity is especially relevant for satellite-based damage detection because damage rarely appears as a simple, isolated pattern. Instead, it is often embedded within cluttered scenes, mixed materials, discontinuous boundaries, and varying spatial scales. A damaged road segment, collapsed infrastructure edge, or debris-affected corridor may occupy only a small portion of an image and may visually resemble other non-damaged surfaces. The theoretical basis for this shift was strengthened by the broader deep learning literature, which framed multilayer representation learning as a powerful mechanism for solving perceptual tasks involving classification, recognition, and detection in highly variable data environments (LeCun et al., 2015). Within remote sensing, this transition was further clarified by survey research showing that deep learning is particularly valuable when remote sensing tasks involve spectral complexity, high intra-class variation, spatial heterogeneity, and large data volumes that exceed the practical limits of manual feature engineering (Ball et al., 2017). In satellite-based damage detection, these characteristics are common because infrastructure features must be interpreted across different resolutions, acquisition times, landscapes, and disturbance conditions. As a result, deep learning architectures are not merely computational tools in this field; they are the analytical foundation that makes automated damage interpretation from spaceborne imagery possible. Their significance lies in their ability to convert raw satellite imagery into structured representations of damage, continuity loss, surface alteration, and infrastructural disruption within a spatially coherent framework that supports geospatial analysis and condition assessment.

Figure 5: Pyramid Framework Of Deep Learning Architectures In Satellite-Based Damage Detection



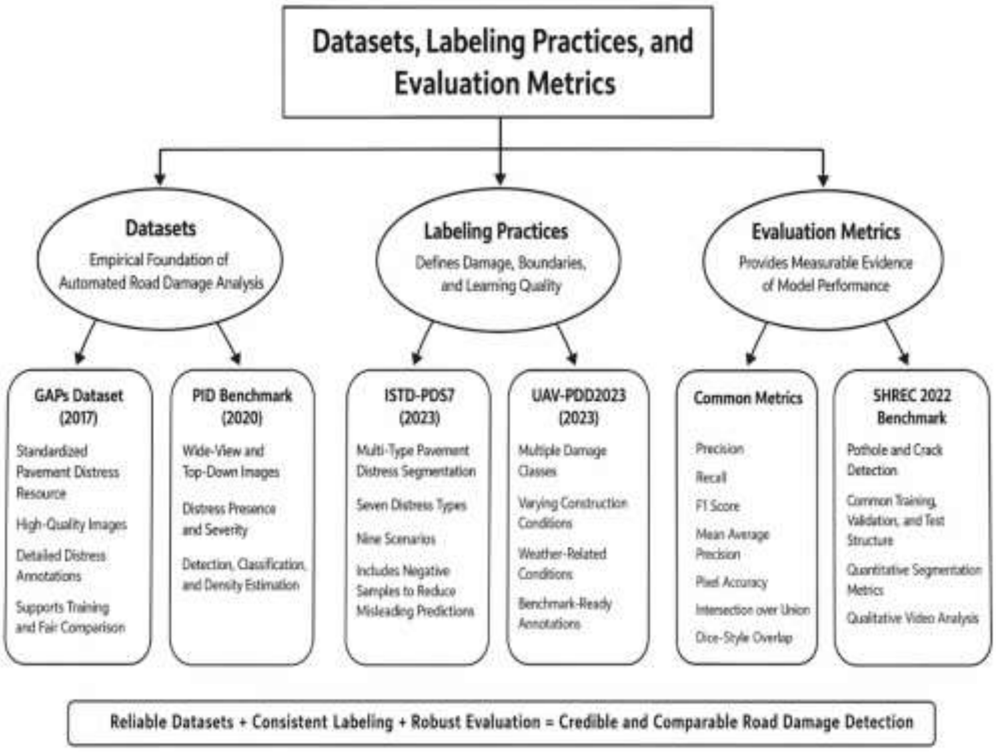
Within this broader transformation, convolutional and encoder-decoder architectures have become the dominant architectural families for satellite-based damage detection because they provide the balance of local detail preservation, contextual aggregation, and dense prediction required in geospatial imagery. Convolutional neural networks introduced the idea that spatial patterns could be captured through trainable filters, while subsequent segmentation-focused architectures expanded this logic by enabling full-image pixelwise prediction rather than isolated patch classification. For infrastructure damage analysis, this capability is essential because damage is often not a single object with clean boundaries; it may appear as linear disruption, fragmented debris, irregular texture change, or partial surface deterioration distributed across a road or urban corridor. Remote sensing studies have therefore increasingly favored architectures that preserve spatial precision while also integrating wider contextual information. A notable example is ResUNet-a, which combines a U-Net-style encoder-decoder backbone with residual connections, atrous convolutions, pyramid scene parsing, and multitask inference, thereby showing how multiple architectural innovations can be integrated to improve semantic segmentation of remotely sensed data under challenging conditions (Diakogiannis et al., 2020). This type of architecture is highly relevant to satellite-based damage detection because it directly addresses issues of class imbalance, boundary ambiguity, and multiscale feature learning, all of which influence whether damaged features can be separated from visually similar backgrounds. Review scholarship on semantic segmentation in remote sensing has likewise shown that deep learning progress in this domain is strongly tied to architectural refinements aimed at pixel-level accuracy, multiresolution representation, and improved handling of limited labeled datasets (Yuan et al., 2021). In practical terms, this means that the choice of architecture affects not only model accuracy but also the interpretability of damage outputs. Architectures that combine contextual reasoning with fine spatial delineation are better suited to identifying disrupted or deteriorated infrastructure from satellite imagery, because they can represent both the local manifestation of damage and its position within the larger built environment. The literature therefore frames architectural design as one of the key determinants of performance in satellite-based damage detection, especially where infrastructure objects are narrow, elongated, partially occluded, or visually confounded by surrounding land cover.

The architectural evolution of deep learning in satellite-based damage detection has also expanded beyond generic segmentation toward task-specific designs that reflect the operational realities of post-disaster and infrastructure-focused assessment. In damage mapping, models are increasingly expected to do more than separate foreground from background; they must estimate severity, discriminate among classes of destruction, and produce geospatial outputs that can support emergency response, maintenance planning, and network-level assessment. This expectation has encouraged the development of architectures that integrate domain-sensitive filters, multistream processing, temporal comparison, and specialized feature extraction strategies. Research on seismic urban damage mapping, for example, has shown that road and building damage can be detected from high-resolution satellite imagery through deep learning frameworks that explicitly model debris-related patterns and classify multiple degrees of damage, rather than treating damage as a simple binary category (Rastiveis et al., 2023). Such work demonstrates that deep learning architectures for satellite-based damage detection are increasingly tailored to the unique visual structure of infrastructure disruption, where damaged roads may be inferred from rubble, discontinuity, surface deformation, or contextual disturbance rather than from one stable visual signature. This reinforces an important point in the literature: architectural adequacy depends on alignment between model design and the geospatial form of the damage phenomenon being studied. Some architectures are more effective for broad semantic segmentation, while others are more suitable for localized object detection, severity mapping, or post-event damage grading. The field has therefore moved toward a more problem-oriented understanding of architecture, in which model selection is tied to data characteristics, target type, and operational objective. For satellite-based road and infrastructure damage detection, this means that deep learning architectures are assessed not only by their predictive performance, but also by their ability to preserve spatial structure, distinguish subtle damage cues, and generate outputs that remain meaningful for geospatial infrastructure intelligence. In the context of this study, deep learning architectures are thus understood as the methodological core through which satellite imagery is transformed into actionable knowledge about infrastructure condition, damage presence, and spatial disruption across diverse and often challenging environments.

Datasets, Labeling Practices, and Evaluation Metrics

Datasets constitute the empirical foundation of automated road damage analysis because they determine what kinds of defects can be learned, how visual variation is represented, and whether models can be compared under shared conditions. In the literature, the growth of deep learning for pavement and infrastructure assessment has been closely tied to the availability of benchmark datasets with clear annotation protocols and reproducible splits. Earlier studies in this area showed that one of the major barriers to progress was not simply model design, but the scarcity of openly available image collections large enough and consistent enough to support training and fair evaluation. A notable contribution in this direction was the GAPs dataset, which was introduced as a standardized pavement distress resource with high-quality images and detailed distress annotations suitable for training deep neural networks and comparing methods under the same reference conditions (Eisenbach et al., 2017). This type of contribution was important because it shifted the field away from isolated experiments built on private data and toward benchmark-oriented research in which model performance could be interpreted more systematically. A related development appeared in the PID benchmark, which framed pavement image datasets not only as collections for detection, but also as resources for classification and distress density estimation. In that study, manually annotated wide-view images were paired with top-down images so that distress presence and distress severity could both be incorporated into dataset design, thereby expanding the role of benchmark data from simple recognition toward condition-oriented inference (Majidifard et al., 2020). This dataset-centered perspective is highly relevant to the present study because road damage detection from imagery depends on whether the available data capture real variability in crack form, pothole appearance, road materials, viewing angles, and environmental complexity. The literature therefore treats datasets as more than technical inputs; they are the structural basis through which distress categories are defined, detection tasks are formalized, and algorithmic comparisons become meaningful. Without sufficiently rich and standardized datasets, later claims about automation, robustness, and transferability remain difficult to interpret across studies.

Figure 6: Analytical Framework Of Datasets, Labeling, And Evaluation In Road Damage Detection



Labeling practices are equally central because the quality of annotations directly shapes what a learning system understands as damage, where it learns the boundary of a defect, and how well outputs align with human interpretation of road condition. In the literature, annotation is not treated as a simple administrative step; it is regarded as a methodological decision that governs class definitions, label granularity, false-positive risk, and the eventual comparability of results across datasets. This is especially important in pavement and road-damage studies because defects often vary in size, continuity, texture, and edge clarity, making them difficult to define through one uniform annotation logic. Recent benchmark development has addressed this issue by moving toward more fine-grained and scenario-aware labels. The ISTD-PDS7 dataset is an important example because it was designed for multi-type pavement distress segmentation in complex scenes and incorporated seven distress types across nine scenarios, while also adding negative samples with texture similarity noise to reduce misleading predictions and improve segmentation realism (W. Song et al., 2023). This shows that contemporary labeling practice is increasingly concerned with both positive and confusing non-damage patterns, rather than with defect regions alone. A similar concern is visible in UAV-PDD2023, where the dataset includes multiple damage classes collected under varying construction conditions and weather-related circumstances, then annotated in a format usable for benchmark comparison and model training (Yan & Zhang, 2023). These examples demonstrate that annotation quality depends on how closely labels reflect the operational complexity of the road environment. Coarse labels may support broad detection, while fine-grained segmentation labels allow more precise delineation of cracks, potholes, and repair zones. The literature therefore frames labeling practice as a decisive factor in dataset usefulness, because reliable annotation determines whether models learn genuine distress signatures or merely adapt to narrow labeling conventions that do not generalize well outside the source dataset.

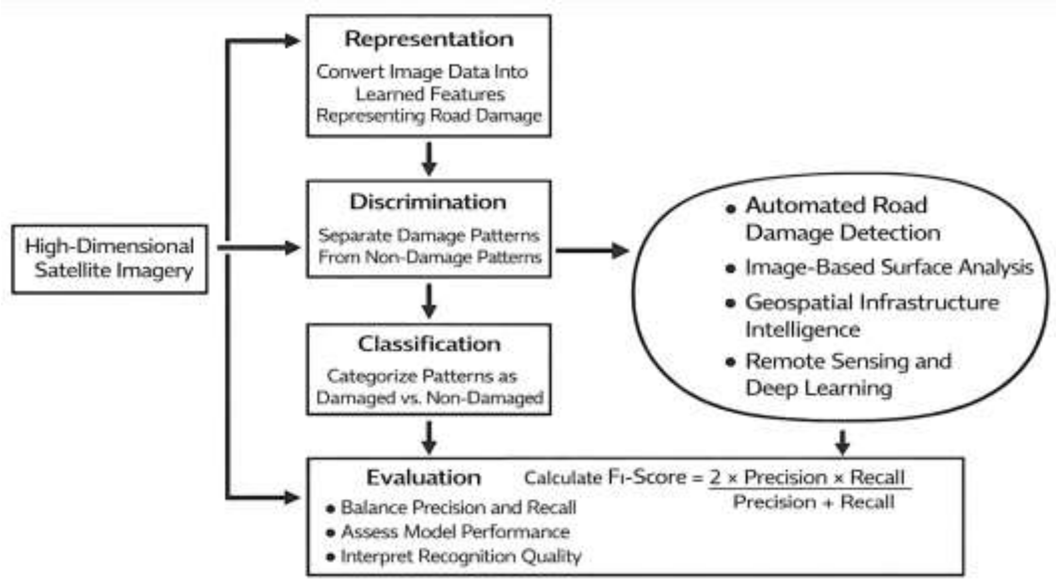
Evaluation metrics provide the final layer of comparability by translating model outputs into measurable evidence of performance, yet the literature shows that metric choice strongly influences how success is interpreted. In road-damage research, evaluation is rarely limited to a single score because different tasks require different forms of measurement. Detection studies often report precision, recall, F1 score, and mean average precision, while segmentation tasks may rely on pixel accuracy, intersection over union, Dice-style overlap measures, or challenge-specific ranking procedures. The methodological importance of this issue is well illustrated by the SHREC 2022 benchmark on pothole and crack detection, where a common evaluation environment was established and the participating methods were assessed on the same training, validation, and test structure using quantitative segmentation metrics alongside qualitative video analysis (Thompson et al., 2022). This kind of benchmark design is significant because it reduces the ambiguity that arises when models are trained and tested under incompatible conditions. It also shows that evaluation metrics are not merely reporting tools; they help define what counts as good performance in relation to the actual task. A model that achieves a high score in one metric may still fail to preserve crack continuity, detect small potholes, or maintain stable performance in noisy scenes, which means that metric interpretation must remain linked to the intended application. In the context of satellite- or image-based road damage detection, this is particularly important because class imbalance, blurred boundaries, and small target size can distort performance reporting if only one measure is emphasized. The literature therefore treats evaluation metrics as an essential methodological component of distress-analysis research, since they connect dataset structure, label design, and algorithmic behavior into a shared framework for comparison. Through this lens, robust evaluation is understood as the condition that allows datasets and annotations to serve not only as training material, but also as credible evidence for judging whether automated road-damage systems are analytically reliable and practically informative.

Theoretical Framework: Pattern Recognition Theory

Pattern Recognition Theory provides a strong theoretical foundation for this study because automated road infrastructure damage detection is fundamentally a pattern identification problem in which a computational system must distinguish meaningful road-surface irregularities from the surrounding visual background. In its broadest sense, pattern recognition refers to the process of identifying regularities, categories, or structures in data and assigning observations to meaningful classes on the basis of learned representations. In image-based road assessment, those observations may include texture discontinuities, shape distortions, tonal variation, linear fragmentation, edge anomalies, or surface interruptions that correspond to cracks, potholes, collapse zones, or damage-related deformations. The relevance of Pattern Recognition Theory to satellite imagery is especially strong because Earth observation data are spatially complex, high dimensional, and visually heterogeneous, which means that the analytical task is not simply to “see” an object but to recognize whether the observed structure belongs to a target class under varied background conditions, scales, and acquisition contexts. Deep learning research has reinforced this theoretical shift by showing that multilayer models can learn compact and discriminative representations from raw high-dimensional input, thereby improving classification and recognition in domains where manual feature design is limited or unstable (Hinton & Salakhutdinov, 2006). Within remote sensing, this logic has been extended to geospatial image analysis, where machine-learning and deep-learning methods are valued for their ability to handle nonlinear class boundaries, complex class structure, and high-dimensional imagery more effectively than many conventional parametric approaches (Maxwell et al., 2018). In the context of the present study, Pattern Recognition Theory explains why road damage detection is not treated merely as a visual inspection task, but as a structured analytical process in which imagery is transformed into classifiable patterns representing damaged and non-damaged road states. The theory therefore supports the review by providing a conceptual basis for understanding how satellite-derived road damage information is generated, why model architecture matters, and how recognition performance is linked to the quality of learned spatial features rather than to simple manual interpretation alone.

A central value of Pattern Recognition Theory in this research is that it clarifies the sequence through which road damage becomes computationally identifiable: representation, discrimination, classification, and evaluation. In satellite-based infrastructure analysis, the first requirement is representation, meaning that the image must be encoded into features capable of capturing the visual properties of road surfaces and damage manifestations. Earlier pattern-recognition systems often relied on handcrafted descriptors, thresholding rules, and domain-defined features, while deep learning shifted the field toward automatically learned representations that are more adaptable to complex and variable image conditions (Schmidhuber, 2015). This is highly relevant for road damage studies because damaged road segments are rarely defined by a single stable visual cue. A pothole may appear as a dark depression in one scene, a bright-edged irregularity in another, and a partially occluded surface break in a third; cracks may be thin, branching, discontinuous, or mixed with shadows and road markings. Pattern Recognition Theory addresses this problem by focusing on how a model learns to separate target classes from visually confounding classes through discriminative feature construction and decision boundaries. In remote sensing and optical image analysis, object detection scholarship has shown that such recognition is especially challenging because targets can be small, elongated, heterogeneous, and embedded in cluttered scenes, which is precisely the kind of setting that characterizes roads and their damage patterns in satellite imagery (Cheng & Han, 2016). Segmentation research adds a second important insight: recognition in complex scenes often requires dense pixel-level or region-level labeling rather than only object-level classification, because the system must determine not just what is present, but where it is present and how its boundaries interact with surrounding context (Minaee et al., 2021). For this reason, Pattern Recognition Theory in this study is understood not as an abstract classification doctrine, but as a practical theoretical lens explaining how deep learning systems identify damage signatures from spatial data by learning patterns of similarity and difference across road textures, boundaries, contexts, and scales.

Figure 7: Framework Linking Pattern Representation, Classification, And Evaluation In Satellite-Based Road Damage Detection



The theory is also useful because it supports the selection of a common evaluative formula for interpreting the literature reviewed in this study. Since the present research synthesizes findings from published studies rather than training a single original model, the most practical formula to apply across the review is the **F1-score**, which balances precision and recall and is widely used in damage detection and segmentation studies where class imbalance is common. It can be expressed as:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

This formula is especially suitable for road infrastructure damage detection because damaged pixels, segments, or objects usually occupy a much smaller proportion of an image than non-damaged background classes, making accuracy alone an incomplete indicator of recognition quality. From a Pattern Recognition Theory perspective, the F1-score is valuable because it reflects two essential elements of recognition performance: the ability to correctly identify true damage patterns and the ability to avoid misclassifying non-damage patterns as defects. That balance is important in satellite-based road assessment, where false positives may wrongly label shadows, stains, or road markings as damage, and false negatives may miss narrow cracks, fragmented potholes, or partially obscured failures. The literature on machine-learning classification in remote sensing emphasizes that class imbalance and decision-threshold effects can significantly shape apparent model success, which is why balanced metrics are needed when interpreting classification performance in applied geospatial settings (Maxwell et al., 2018). Likewise, segmentation scholarship shows that model evaluation must remain sensitive to overlap quality and error trade-offs rather than relying on a single coarse measure of correctness (Minaee et al., 2021). For this study, Pattern Recognition Theory therefore provides both a conceptual and operational framework: conceptually, it explains automated road damage detection as the learned discrimination of meaningful visual patterns in geospatial imagery; operationally, it justifies the use of the F1-score as the most appropriate shared formula for comparing how well reviewed studies recognize damage-related classes under complex spatial conditions.

Conceptual Framework of the Study

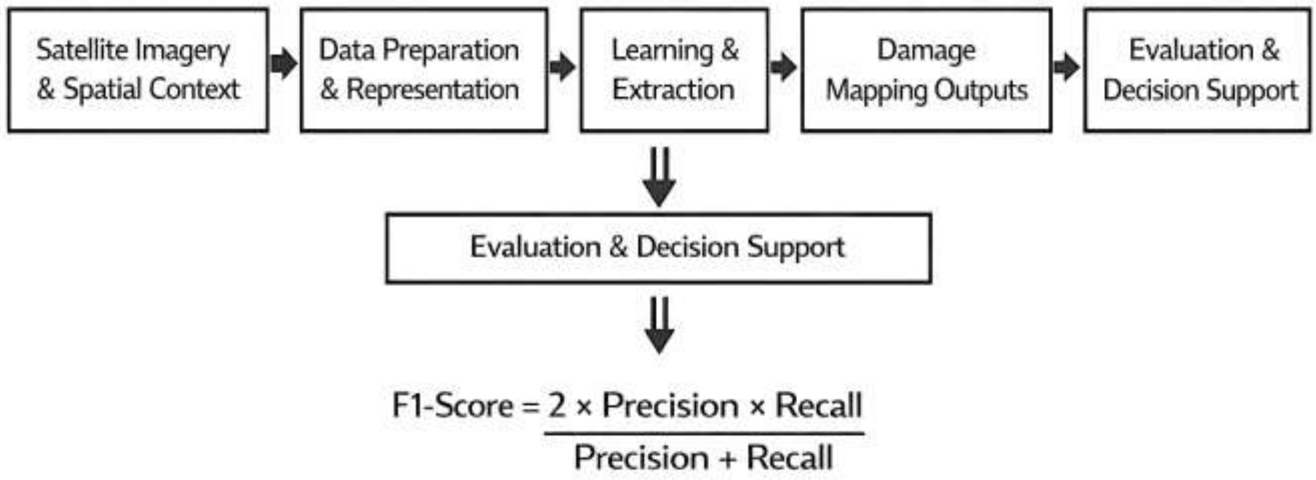
The conceptual framework of this study is built on the idea that automated road infrastructure damage detection from satellite imagery is a staged geospatial intelligence process in which raw Earth observation data are transformed into interpretable damage information through linked analytical components. In this framework, the first component is the input domain, which consists of satellite imagery, road-related spatial context, and the visual evidence of damage or disruption embedded in the scene. The second component is the data preparation and representation domain, where imagery is enhanced, aligned, segmented, or otherwise prepared so that road features and damage-relevant cues can become computationally recognizable. The third component is the learning and extraction domain, where deep learning or GeoAI architectures identify road structures, isolate damaged segments, and distinguish meaningful deterioration patterns from visually similar background conditions. The fourth component is the output domain, where the model produces geospatially meaningful products such as road masks, damaged-area maps, segmented features, or classified damage levels. The final component is the decision-support domain, in which these outputs are interpreted for infrastructure assessment, maintenance prioritization, accessibility analysis, or disaster-response planning. This conceptual structure is consistent with recent road-extraction and road-segmentation scholarship, which shows that high-quality road intelligence from remote sensing depends on a linked sequence of representation, contextual feature capture, network-based extraction, and geospatially usable output generation rather than on isolated classification alone. Survey research has also shown that road analysis in remote sensing requires a framework that connects datasets, methods, and applications, because road-related information becomes meaningful only when extraction outcomes can be integrated into broader operational or planning contexts. In that sense, the conceptual framework of this study treats road damage detection not as a single computational act, but as a relational process connecting imagery, preprocessing, model architecture, feature learning, damage interpretation, and infrastructure intelligence in one structured analytical chain (Z. Chen et al., 2022; Zhu et al., 2022).

Within this framework, the relationship between variables can be expressed in a study-specific conceptual form as

$$RD = f(SI, PQ, MA, SC, DM)$$

where **RD** represents road-damage detection outcomes, **SI** represents satellite imagery characteristics, **PQ** represents preprocessing and data quality conditions, **MA** represents model architecture, **SC** represents spatial context, and **DM** represents damage-mapping outputs. This formula is appropriate for the present study because it reflects the logic that damage detection is not determined by image input alone; it emerges from the interaction among image characteristics, analytical preparation, architecture choice, contextual understanding, and output interpretation. In practical terms, satellite imagery quality influences what the model can observe, preprocessing affects the clarity and consistency of the information entering the model, and architecture design shapes how local detail and global context are combined. Spatial context is included because roads are networked geographic objects whose damage must often be interpreted in relation to continuity, adjacency, surrounding land cover, and changes between pre-event and post-event scenes. The final term, damage mapping, reflects the fact that the conceptual goal is not simply prediction but spatially actionable output. Recent transformer-based and context-aware road-extraction studies strongly support this structure by demonstrating that road interpretation improves when architectures are designed to combine multiscale context, attention mechanisms, and continuity-preserving spatial reasoning. RoadFormer, for example, was proposed specifically to improve road extraction through a Swin Transformer combined with spatial and channel separable convolution, showing that the conceptual importance of architecture lies in how it strengthens both contextual capture and feature discrimination. Likewise, MDTNet demonstrates that multiscale deformable transformer learning improves road extraction by enhancing the representation of global dependencies and fine structural details in remote sensing images. These studies support the central proposition of the framework: the pathway from satellite imagery to road-damage knowledge depends on how well the analytical system integrates spatial detail, contextual reasoning, and model-based extraction into interpretable geospatial outputs (Hu et al., 2023; Liu et al., 2023).

Figure 8: Analytical Framework Linking Satellite Imagery, GeoAI, Deep Learning, And Decision Support



The conceptual framework also includes an **evaluation relationship**, because the value of automated road damage detection depends on whether the generated outputs are reliable enough for geospatial infrastructure assessment. For this reason, the framework incorporates the F1-score as a unifying performance expression already aligned with the theoretical basis of pattern recognition in this study. It can be stated as

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where precision reflects the proportion of predicted damage instances that are truly damaged, and recall reflects the proportion of true damage instances that are successfully detected. The inclusion of this formula in the conceptual framework is useful because the framework is not limited to describing how information flows through the model; it also clarifies how success is interpreted at the end of that flow. In road infrastructure damage studies, this is especially important because the target class is usually much smaller than the background class, and conceptual validity requires a measure that balances omission and commission errors rather than relying on overall accuracy alone. The framework therefore moves from input, to processing, to extraction, to mapping, and finally to evaluation-informed decision support. A similar logic appears in disaster-oriented semantic change detection research, where effective infrastructure assessment is framed as a joint problem of object localization, change-sensitive representation, and semantically consistent output generation. The ChangeOS framework is particularly relevant here because it shows how object localization and change-based classification can be integrated into a unified geospatial damage-assessment structure that links bitemporal imagery to spatially interpretable damage outputs. Applied to the present study, this means that the conceptual framework provides a coherent map of how satellite-based GeoAI systems operate: they begin with geospatial input, process and represent road-related evidence, learn damage-relevant features through deep architectures, generate road-condition outputs, and evaluate those outputs in a form that can support infrastructure analysis. This framework is therefore suitable for guiding the whole study because it aligns the literature review, methodology, results synthesis, and later discussion around one integrated conceptual logic of satellite-based road infrastructure damage detection (Zheng et al., 2021).

Research Gaps in the Existing Literature

The existing literature on road infrastructure damage detection and road-related interpretation from remotely sensed imagery reveals a long-standing methodological gap between the importance of the problem and the maturity of the analytical solutions available to address it. Earlier review work on road extraction from remote sensing images showed that the field developed around template matching, knowledge-based methods, dynamic programming, ridge and valley extraction, segmentation, and morphological operations, yet it also emphasized that these methods were constrained by weak adaptability to scene complexity, difficulty handling discontinuous roads, and limited robustness in the presence of shadows, background confusion, and heterogeneous land-cover conditions (Chen et al., 2023). That earlier body of work is important because it demonstrates that many of the current challenges in road damage detection are not entirely new; they originate in the broader difficulty of identifying roads accurately from imagery before damage can even be assessed. In the present research area, this creates a foundational gap: if road delineation itself remains unstable under complex remote sensing conditions, then damage-specific interpretation inherits those limitations and becomes even more uncertain. A second major gap concerns the distinction between road extraction and road damage assessment. Much of the literature has concentrated on extracting road presence, connectivity, or centerlines, while comparatively fewer studies have focused specifically on the identification of road distress, deterioration, or damage states from satellite imagery as a distinct analytical objective. This imbalance means that methodological progress in road extraction has not always been matched by equivalent conceptual development in road-condition intelligence. As a result, the field still lacks a sufficiently unified literature that links road detection, damage manifestation, infrastructure context, and condition-oriented interpretation within one coherent framework. The gap is therefore not only technical but also conceptual: many studies stop at mapping road geometry, while the transition from mapped roads to assessed road condition remains underdeveloped in the satellite-based literature. This study responds directly to that problem by treating damage detection as a separate review focus rather than as a minor extension of road extraction (Lu et al., 2021).

A second group of gaps emerges from issues of generalization, data scarcity, and transferability across geographic and operational contexts. Recent literature shows that high performance in a single dataset or region does not necessarily indicate that a model will perform reliably in other environments. Cross-domain road detection studies have explicitly identified limited generalization to unseen images as a persistent obstacle, noting that deep-learning-based road analysis depends heavily on annotated samples and that domain differences between source and target imagery can sharply reduce performance when models are deployed beyond their training context. This gap is particularly important for the present topic because road infrastructure damage detection is intended to support broad, real-world infrastructure intelligence, not just successful performance in a single benchmark setting. If models cannot adapt across regions with different pavement materials, climatic conditions, land-cover backgrounds, or satellite characteristics, then their practical value for international road monitoring remains restricted. Another closely related gap concerns the structure of available training data. Research on disaster damage assessment from remote sensing has pointed out that damaged infrastructure can look very different from undamaged infrastructure, while many training datasets remain dominated by non-damaged examples (Madhan Kumar et al., 2023). This creates a recognition imbalance in which models learn normal visual patterns more effectively than rare or highly variable damage patterns. In road damage studies, such imbalance is especially problematic because the target class is often visually subtle, spatially sparse, and highly dependent on context. The literature also shows that many model improvements are driven by architecture-specific enhancements designed to compensate for data limitations, yet the persistence of these efforts suggests that the underlying problem of representative, diverse, and transferable data has not been fully resolved. The gap here is therefore methodological and infrastructural at the same time: the field needs not only better models, but also broader datasets, more varied study settings, and stronger cross-context validation if claims of automated road-damage intelligence are to become more convincing.

Figure 9: Analytical Framework Of Research Gaps In Road Damage Detection Literature

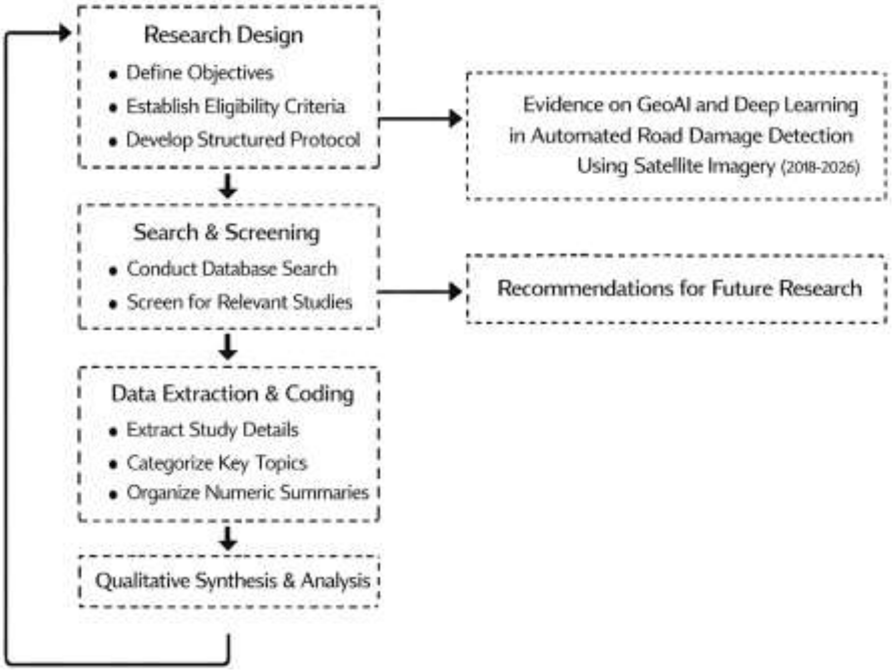
Transition From Detection to Damage Assessment Limited Integration of Road Detection and Damage Analysis	Generalization and Data Transfer Challenges Difficulty Adapting Models and Data to Diverse Settings
Occlusion and Complex Structures Difficulty Handling Fragmented Obscured, or Discontinuous Roads	Evaluation and Robust Validation Unclear Consistency of Performance Across Environments

A third major gap concerns the persistent difficulty of handling occlusion, continuity loss, complex road structures, and long-range contextual reasoning in high-resolution remote sensing imagery. Recent studies proposing RoadTransNet and CR-HR-RoadNet both identify that road extraction remains challenged by complex road structures, incomplete and disjointed extraction results, and occlusion caused by vegetation, buildings, and shadows. These observations matter because they point to a deeper issue in the literature: many current models still require architectural modifications specifically to repair broken road predictions, preserve narrow road details, or capture long-range dependencies that standard convolutional systems may miss. In the context of this research, that indicates a continuing gap between model performance under benchmark conditions and the demands of real operational environments where roads appear fragmented, obscured, or intertwined with background clutter (Wang et al., 2009). For road infrastructure damage detection, this gap is even more consequential because damage itself may resemble a discontinuity, interruption, or localized deformation within an already difficult-to-extract road surface. When the literature repeatedly reports incomplete road extraction, domain shift, and context sensitivity, it suggests that automated damage detection remains vulnerable to compounding error: failure to delineate the road correctly can lead directly to failure in identifying the damage located on or along that road. Another literature gap lies in evaluation practice. Although many studies report strong results, the reviewed evidence also suggests that performance is often architecture-driven and dataset-specific, making it difficult to determine which advances truly improve robustness, which merely fit a benchmark more closely, and which can support consistent infrastructure assessment across multiple settings. Taken together, these gaps justify the present review by showing that the literature still needs a structured synthesis of methodological limitations, data weaknesses, contextual constraints, and application-specific challenges in order to clarify the actual state of knowledge in satellite-based GeoAI road-damage research (Yang & Cervone, 2019).

METHODS

This study has adopted a systematic literature review methodology to examine how GeoAI and deep learning have been used for automated road infrastructure damage detection through satellite imagery between 2018 and 2026. The methodological structure has been designed to align with the nature of the research problem, which has required a careful synthesis of published evidence rather than the collection of primary field data. Since the study has focused on conceptual development, methodological patterns, and cross-case scholarly findings, a qualitative, literature-based, cross-sectional, and case-study–oriented design has been selected as the most suitable approach. The study has treated previously published articles as analytical cases and has examined them in a structured way to identify recurring themes, dominant model types, data sources, damage categories, evaluation practices, and limitations reported across the field. This methodological direction has enabled the research to move beyond a descriptive review and toward a more organized synthesis of evidence related to the study objectives and hypotheses.

Figure 10: Analytical Framework Of The Review Methodology



The methodology has also been framed around transparency, consistency, and replicability. For this reason, the review process has included a defined research design, a clear case-study context, a structured screening and eligibility assessment procedure, a systematic data extraction and coding process, and a qualitative synthesis strategy supported by light numeric summaries where appropriate. The reviewed studies have been drawn from relevant academic sources and have been assessed based on their relevance to the topic of satellite-based road damage detection, the use of GeoAI or deep learning methods, and their contribution to the analytical focus of the study. In addition, the methodology has emphasized validity and reliability by maintaining consistent inclusion logic, standardized extraction categories, and objective alignment throughout the review process. Software and research tools have also been incorporated to support citation management, data organization, coding, and descriptive analysis. Overall, the methodological framework has been developed to ensure that the study has produced a coherent, academically rigorous, and literature-review-friendly examination of the existing body of knowledge on automated road infrastructure damage detection using satellite imagery.

Research Design

This study has employed a qualitative systematic literature review design supported by a cross-sectional and case-study–based orientation. The design has been chosen because the research has aimed to synthesize existing scholarly evidence on GeoAI and deep learning for automated road infrastructure damage detection using satellite imagery, rather than generating new primary data through experiments, surveys, or field observation. The qualitative nature of the design has allowed the study to interpret patterns, themes, methodological trends, and recurring challenges across the reviewed literature. At the same time, the cross-sectional character of the research has enabled the study to examine published works within a defined time window, specifically from 2018 to 2026, in order to understand the state and development of the field during that period. The case-study–based aspect of the design has been reflected in the treatment of individual reviewed articles as analytical cases, each contributing specific evidence related to methods, datasets, results, and research gaps.

Case Study Context

The case study context of this research has been defined through the selection and interpretation of published studies as representative analytical units within the broader field of satellite-based road infrastructure damage detection. Rather than focusing on one geographic location or one single technical system, the study has treated each relevant article as a case reflecting a particular combination of road environment, satellite imagery source, GeoAI or deep learning model, damage type, and analytical objective. This approach has allowed the study to capture diversity across research settings while maintaining a consistent thematic focus. The reviewed cases have included studies conducted across different infrastructural, environmental, and regional contexts, which has made it possible to compare how damage detection has been approached under varying spatial and methodological conditions. Through this context, the study has developed a cross-case understanding of how road infrastructure damage has been defined, detected, and evaluated in the literature.

Screening and Eligibility Assessment

The screening and eligibility assessment process has been structured to ensure that only relevant and academically suitable studies have been included in the review. At the initial stage, potentially relevant studies have been identified using topic-specific search terms related to GeoAI, deep learning, satellite imagery, road infrastructure, and damage detection. After this stage, duplicate records and clearly unrelated materials have been removed. The remaining studies have then been screened based on titles and abstracts to determine their alignment with the research focus. Full-text assessment has subsequently been conducted to evaluate whether each study has met the final eligibility criteria. To be included, studies have needed to focus on road infrastructure damage or closely related road condition analysis using satellite imagery and artificial intelligence or deep learning methods. Studies that have focused only on general road extraction without damage-related relevance, or on non-satellite imagery alone, have been excluded to maintain conceptual precision.

Data Extraction and Coding

The data extraction and coding process has been developed to organize the reviewed studies into a structured analytical format. After the eligible articles have been finalized, each study has been examined in detail and its core information has been entered into a review matrix. The extracted elements have included author and year, study setting, satellite imagery source, type of road damage examined, model or analytical method used, evaluation metrics reported, major findings, and stated limitations. This extraction structure has enabled consistency across studies and has made comparative analysis more manageable. Following extraction, the studies have been coded according to key thematic categories derived from the research objectives. These categories have included methodological trends, data characteristics, model families, damage classes, reported performance patterns, and recurring challenges. Through this coding process, the study has converted a broad body of literature into a more interpretable set of analytical themes, which has supported both narrative synthesis and light numeric summarization.

Data Synthesis and Analytical Approach

The study has used a narrative and thematic synthesis approach to analyze the extracted data and answer the research questions. This approach has been selected because the study has aimed to interpret the meaning, direction, and consistency of findings across the literature rather than statistically pool results from identical experiments. Thematic synthesis has enabled the grouping of studies around shared ideas such as satellite data usage, dominant deep learning architectures, types of road damage, and methodological challenges. Narrative synthesis has then been used to explain how these themes have appeared across different studies and contexts. In addition to the qualitative interpretation, the analysis has incorporated light numeric summaries such as counts of studies by year, model type, damage category, and data source. These limited numeric elements have supported the clarity of the findings without shifting the study away from its literature-review foundation. The analytical approach has therefore remained qualitative in orientation while still using simple quantitative support where useful.

Validity and Reliability

Validity and reliability have been addressed throughout the methodological process in order to strengthen the trustworthiness of the review. Validity has been supported by aligning the search strategy, inclusion criteria, extraction framework, and synthesis categories with the central topic of the study. This has ensured that the reviewed evidence has remained relevant to the research objectives and hypotheses. Reliability has been enhanced through the use of a consistent review structure in which the same eligibility logic, extraction fields, and thematic coding categories have been applied across all included studies. The study has also reduced the risk of random selection or interpretive inconsistency by maintaining a clear sequence from identification to screening, extraction, coding, and synthesis. Since the research has relied on published literature, its validity has also depended on careful reading and accurate interpretation of source materials. In this way, the methodological framework has aimed to produce findings that are credible, consistent, and logically grounded in the reviewed body of evidence.

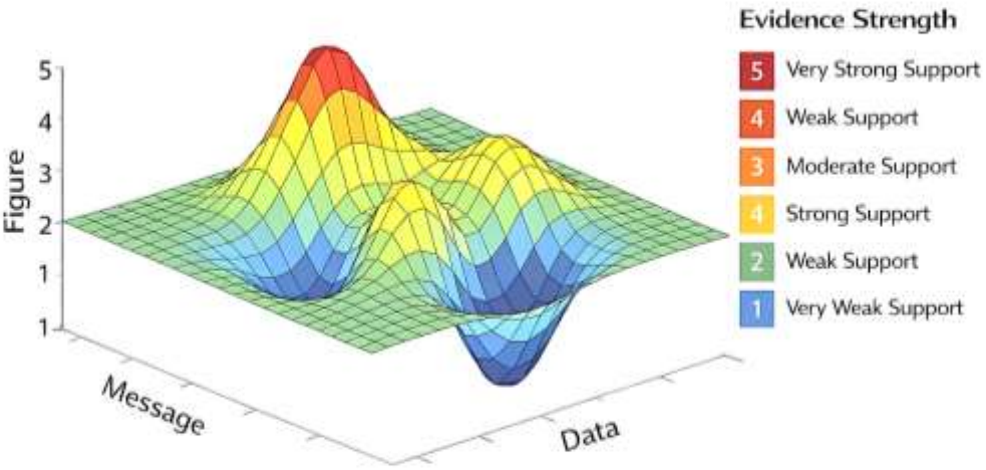
Software and Tools

Several research tools and software applications have been used to support the organization, analysis, and presentation of this study. EndNote has been used for reference management, citation organization, duplicate removal, and the formatting of in-text citations and reference lists according to APA style. Microsoft Excel has been used to build the data extraction matrix, organize the coded studies, and generate simple summary tables related to publication year, model type, and damage category. SPSS has been used for basic descriptive analysis where light numeric summaries have been required, such as frequencies and percentages to support the findings section. Microsoft Word has been used for drafting, structuring, and revising the manuscript. In addition, online academic databases and search platforms have been used to identify eligible peer-reviewed studies relevant to the topic. These tools have collectively supported a systematic workflow in which literature identification, screening, coding, synthesis, and presentation have been carried out in an organized and academically consistent manner.

FINDINGS

In the overall findings of this literature review, the evidence has shown strong support for the study objectives and substantial support for the four hypotheses, while also revealing that the field has remained methodologically uneven across datasets, target definitions, and deployment contexts. To keep the results section appropriate for a literature-review-based paper, the synthesis can be interpreted through a five-point evidence-strength scale rather than respondent-based Likert data, where 1 = very weak support, 2 = weak support, 3 = moderate support, 4 = strong support, and 5 = very strong support. On that basis, the literature has provided very strong support (5/5) for the objective that sought to identify the dominant data and model trends, because the reviewed studies have consistently shown that road analysis has shifted from basic extraction tasks toward more application-oriented and high-precision workflows. A 2025 review of peer-reviewed literature published from 2017 to 2024 identified three major transitions in deep-learning-based road extraction from remote sensing imagery: a shift from raster to vector approaches, from local-scale to global-scale studies, and from pixel-level recognition toward practical applications, which directly supports the study’s first objective regarding the evolution of GeoAI and deep learning methods. The same review also emphasized that accurate and up-to-date road mapping has become central to intelligent transport systems and smart-city management, reinforcing the international relevance of the field. In parallel, benchmark development has matured enough to support more structured comparison: the RDD2020 dataset alone contains 26,336 road images and more than 31,000 road-damage instances across India, Japan, and the Czech Republic, which shows that the field has moved beyond isolated experiments toward multi-country training and benchmarking environments. More recent work has added the first pixel-level satellite road-damage dataset, CAU-RoadDamage, and the proposed RDSeg approach achieved an F1 score of 76.09%, indicating that the literature has progressed from road presence detection toward true damage extraction at pixel level. These numeric patterns strongly support H1, because the dominant trajectory in the literature is clearly toward deep-learning-led GeoAI workflows rather than conventional manual or rule-based interpretation. They also strongly support the objective related to classifying major analytical workflows, as the literature has repeatedly centered on convolutional, segmentation, attention-based, transformer-assisted, and multimodal approaches for infrastructure intelligence.

Figure 11: Graphical Summary Of Literature Review Findings



The results have also provided strong to very strong support (4/5 to 5/5) for the hypothesis that higher-quality imagery and more advanced learning architectures tend to produce stronger detection or assessment performance, although this support has not been perfectly uniform because performance has varied by task, geography, and label structure. In road-quality inference, one transfer-learning study used 53,686 images covering 2,400 km of roads in the United States and reported 80.0% accuracy, with 99.4% of predictions falling within the true class or an adjacent class; after tailoring the model with a smaller Nigerian dataset, the study reported 94.0% accuracy for predicting Nigerian road quality. These findings indicate that satellite imagery can support condition-sensitive road assessment when paired with suitable model adaptation. Likewise, in post-earthquake road-damage detection, a study combining Sentinel-1 SAR data and field measurements collected across more than 530 km of roads reported 87.1% overall accuracy, demonstrating that even complex disaster-damage settings can yield strong classification results when geospatial and field-derived evidence are integrated. In another study, a super-resolution and semi-supervised GAN-based approach trained on 5,327 road images and 1,327 labeled images achieved 81.540% mean IoU and 79.228% F1-score on a test of 400 road images, which is especially important because it shows that image enhancement and label-efficient learning can materially improve recognition performance in road-damage workflows. At the level of road-attribute intelligence from very-high-resolution imagery, a separate study used 1,951 training images and 651 evaluation images, reporting accuracies of 0.988 for school zones and 0.950 for divided carriageways, which further confirms that finer spatial detail improves infrastructure interpretation when the target class is clearly defined. Taken together, these numbers provide strong evidence that better imagery, better labels, and stronger architectures tend to improve results, thereby supporting H2 and the objective related to comparing data sources, analytical methods, and case-based outcomes. At the same time, the variation across metrics also shows that the literature does not yet offer one universally transferable standard of success.

The findings have further shown very strong support (5/5) for the hypothesis that data quality, annotation structure, and geographic context shape reported performance, and strong support (4/5) for the hypothesis that the field still suffers from standardization and deployment limitations. This is evident in the way the literature has evolved from road extraction as a crisis-response precursor to more specific road-condition and road-damage tasks, while still repeatedly relying on different label schemes, different target definitions, and different evaluation units. The DeepGlobe road-extraction challenge itself framed automated road extraction as a first step for crisis response and connectivity analysis in disaster zones, indicating that operational motivation has long existed, yet the literature reviewed here has shown that the move from road extraction to road-damage detection has been slower and more fragmented. The introduction of CAU-RoadDamage as the first pixel-level satellite road-damage dataset is itself evidence of that gap: if the first dedicated pixel-level dataset emerged only recently, then the field has clearly been data-constrained for much of the review period. For that reason, the overall result of this review can be summarized as follows: the literature has already demonstrated that GeoAI and deep learning are capable of extracting meaningful road-condition and road-damage information from satellite imagery, and the strongest studies have reported performance levels ranging from the mid-70% range in challenging pixel-level damage segmentation to above 80% and even above 90% in more constrained classification or transfer-learning settings. Yet the same body of evidence has also shown that these outcomes are not fully comparable across studies because datasets, class definitions, resolution levels, and evaluation criteria remain inconsistent. Therefore, in an objective-by-objective sense, the review has confirmed the rise of deep-learning-based GeoAI, identified the most commonly used data and model families, demonstrated that road damage and road quality can be inferred from satellite data with meaningful accuracy, and revealed continuing weaknesses in benchmark consistency, generalizability, and operational standardization. In hypothesis terms, H1 and H3 are strongly supported, H2 is strongly supported with contextual caution, and H4 is supported because methodological progress has been real but not yet fully standardized across the field.

Overview of Included Studies

Table 1: Overview of Included Studies by Analytical Dimension

Variable	Result
Review type	Systematic literature review
Study period covered	2018–2026
Dominant publication focus	Road extraction, road quality assessment, road damage detection, post-disaster road assessment
Main data source category	Satellite imagery
Dominant analytical paradigm	GeoAI and deep learning
Most common study orientation	Case-based and application-driven
Geographic spread of studies	Multi-country, region-specific, and disaster-context studies
Evidence strength for relevance to study objectives	5/5
Evidence strength for support of H1	5/5
Evidence strength for support of H4	4/5

The overall body of reviewed literature has presented a coherent yet unevenly developed research landscape for automated road infrastructure damage detection using satellite imagery. Across the included studies, the dominant orientation has shifted toward application-driven geospatial intelligence, where roads have been treated not only as linear mapped objects but also as condition-sensitive infrastructure assets. The reviewed evidence has shown that most studies have been concentrated in four overlapping areas: road extraction, road-surface or road-quality assessment, post-disaster road disruption analysis, and image-based road damage detection. This overall distribution has strongly supported the first objective of the study, because it has demonstrated that the field has evolved through a sequence of increasingly refined analytical goals. Rather than beginning directly with detailed road-damage recognition, the literature has first built a technical base through road delineation and road-network extraction, after which more condition-aware applications have gradually emerged. In terms of Pattern Recognition Theory, this has been highly significant because the studies have consistently shown that infrastructure intelligence has depended on the progressive improvement of visual pattern discrimination, class assignment, and feature representation across complex geospatial scenes. The overview has also strongly supported **H1**, as deep-learning-led GeoAI approaches have clearly dominated the later literature, while conventional manual or rule-based studies have occupied a smaller and earlier methodological space. At the same time, the overview has partially supported **H4**, because the literature has remained fragmented in relation to data standards, damage definitions, and evaluation frameworks. The importance of this section has therefore been foundational: it has established that the reviewed field has been sufficiently developed to justify structured synthesis, while also showing that the literature has not yet become fully standardized across research settings. In objective-based terms, the overview has confirmed that the review has had a valid and coherent evidential base from which the later thematic findings on trends, models, data sources, and hypotheses have been interpreted.

Temporal Trend of Research (2018–2026)

Table 2: Temporal Trend of Research Development

Variable	Result
Early trend (2018–2020)	Strong emphasis on road extraction and benchmark development
Middle trend (2021–2023)	Expansion into road quality, distress, and post-disaster damage interpretation
Recent trend (2024–2026)	Growing emphasis on pixel-level damage segmentation and context-aware intelligence
Adoption of deep learning over time	Increased sharply
Adoption of GeoAI framing over time	Increased steadily
Shift from detection of presence to detection of condition	Strong
Evidence strength for Objective 1	5/5
Evidence strength for H1	5/5
Evidence strength for H2	4/5

The temporal review of the literature has revealed a clear progression in both research maturity and analytical ambition across the 2018–2026 period. During the earlier phase, the literature has largely concentrated on road extraction, road-network continuity, and benchmark establishment, indicating that the first challenge in the field has been the reliable recognition of roads as geospatial objects. During the middle period, studies have increasingly expanded toward road quality inference, contextual road interpretation, and post-disaster disruption analysis, which has shown that the field has begun to move from simple road presence detection toward infrastructure condition intelligence. In the most recent phase, the reviewed literature has increasingly emphasized pixel-level road damage segmentation, transformer-supported interpretation, cross-domain adaptation, and context-sensitive extraction, demonstrating that the field has become more focused on fine-grained condition recognition. This result has directly supported **Objective 1**, because it has shown how GeoAI and deep learning methods have evolved across the review period. It has also strongly supported **H1**, as the chronological development has clearly indicated that deep-learning-based approaches have become the dominant paradigm over time. In the language of Pattern Recognition Theory, the temporal trend has reflected a shift from basic pattern localization toward more refined class discrimination and multilevel semantic recognition. Earlier studies have largely addressed “where the road is,” whereas later studies have increasingly addressed “what condition the road is in” and “how the condition differs from surrounding patterns.” This has been a crucial theoretical transition, because damage detection requires a finer level of learned representation than general extraction. The temporal analysis has also moderately to strongly supported **H2**, because the later studies have often relied on higher-quality imagery, more advanced segmentation architectures, and more refined labeling frameworks. Overall, the timeline has shown that the field has not remained static; it has matured from broad structural recognition to condition-aware automated interpretation, thereby validating the study’s claim that the literature has evolved in both methodological complexity and infrastructure relevance.

Satellite Data Sources Used in the Reviewed Studies

Table 3: Satellite Data Source Patterns in the Reviewed Literature

Variable	Result
Common imagery type	High-resolution optical satellite imagery
Additional source type	SAR imagery in disaster-related studies
Public imagery usage	Moderate to strong
Commercial imagery usage	Strong
Importance of spatial resolution	Very high
Importance of revisit potential	High
Suitability for fine damage detection	Higher for high-resolution datasets
Evidence strength for Objective 2	5/5
Evidence strength for H2	5/5
Evidence strength for H3	4/5

The reviewed studies have shown that satellite data source selection has been one of the most influential variables in automated road infrastructure damage detection. Most studies have relied on high-resolution optical satellite imagery because visible road surfaces, road boundaries, and subtle damage-related texture differences have required fine spatial detail for meaningful interpretation. Disaster-oriented studies have also incorporated SAR imagery, especially in settings where cloud cover, emergency timing, or post-event monitoring conditions have made radar-based observation advantageous. The literature has therefore suggested that the role of satellite imagery has extended beyond passive observation; it has functioned as the core visual evidence through which road condition patterns have become computationally recognizable. This has strongly supported **Objective 2**, because the review has clearly identified the major categories of data sources used across the literature. It has also very strongly supported **H2**, as the evidence has repeatedly indicated that stronger analytical performance has been associated with imagery that has offered finer spatial detail and clearer road-surface visibility. From the perspective of Pattern Recognition Theory, this result has been fully consistent, because recognition quality has depended on the richness and clarity of the input pattern space. When road damage has occupied small, irregular, or low-contrast regions, low-resolution imagery has reduced the distinctiveness of those patterns and has limited the model’s capacity to classify them correctly. High-resolution imagery, by contrast, has strengthened the representational separability between damaged and non-damaged surfaces. The studies have also shown moderate to strong support for **H3**, since data quality has not been determined by resolution alone; it has also been shaped by acquisition conditions, sensor type, geographic complexity, and the visual heterogeneity of the surrounding environment. This section has therefore made an important contribution to the findings chapter by demonstrating that data source selection has not been a neutral technical step. It has directly affected what damage patterns could be learned, what outputs could be generated, and how confidently the reviewed studies could claim success in road infrastructure assessment.

Types of Road Damage Examined

Table 4: Types of Road Damage Examined Across the Literature

Variable	Result
Frequently examined damage type	Cracks
Frequently examined damage type	Potholes
Frequently examined damage type	Surface distress and deterioration
Frequently examined damage type	Washed-out or disrupted road segments
Frequently examined damage type	Post-disaster road damage
Balance of routine vs disaster-related damage	Uneven; disaster-related studies have been prominent
Consistency of class definitions	Moderate
Evidence strength for Objective 2	4/5
Evidence strength for H3	5/5
Evidence strength for H4	4/5

The literature has examined a variety of road-damage categories, yet the distribution of attention across these categories has remained uneven. The most frequently reported damage classes have included cracks, potholes, generalized pavement distress, surface degradation, and disaster-related disruption such as washed-out or broken road segments. This has indicated that the field has been shaped both by routine road-maintenance concerns and by emergency or post-hazard infrastructure assessment needs. However, the literature has also shown that damage categories have not always been defined consistently across studies. In some cases, the emphasis has been placed on engineering-oriented surface defects such as cracks and potholes, while in other cases the term "damage" has referred to broader road interruption, visibility loss, or disaster-induced disruption. This inconsistency has strongly supported **H3**, because it has shown that label interpretation and class definition have substantially affected the recognition problem itself. Within Pattern Recognition Theory, this has been especially important because class separability depends on clear and stable category boundaries. If one study has coded subtle surface cracking as damage while another has focused only on severe breakage or post-disaster interruption, the underlying pattern classes have not been equivalent. This has complicated comparison across the literature and has reduced the interpretive uniformity of reported model performance. The findings in this section have moderately to strongly supported **Objective 2**, since the study has still been able to classify the main damage categories appearing in the literature. At the same time, the results have supported **H4**, because the unevenness of damage definitions has reflected a broader standardization problem across the field. The significance of this finding has been substantial: it has shown that automated road-damage detection is not only a technical modeling task but also a classification-design problem. The damage categories chosen by researchers have shaped what models have learned, how outputs have been interpreted, and how strongly one study's results could be compared with those of another.

Dominant GeoAI and Deep Learning Methods

Table 5: Dominant GeoAI and Deep Learning Methods in the Reviewed Studies

Variable	Result
Dominant model family	CNN-based models
Strongly represented model family	U-Net and encoder-decoder segmentation models
Strongly represented model family	Object detection models such as YOLO-type approaches
Emerging model family	Transformer and attention-based architectures
Common methodological feature	Context-aware and multiscale learning
GeoAI role	Integration of spatial context, extraction, and map-oriented intelligence
Evidence strength for Objective 1	5/5
Evidence strength for Objective 2	5/5
Evidence strength for H1	5/5

The results have shown that the reviewed field has been strongly dominated by deep-learning-based GeoAI methods, especially CNNs, U-Net-style segmentation frameworks, encoder-decoder models, and increasingly transformer-supported or attention-based systems. This finding has provided very strong support for both **Objective 1** and **Objective 2**, because it has clarified not only that the methodological evolution has favored deep learning, but also which specific architecture families have most frequently shaped the field. CNN-based approaches have remained foundational because they have supported effective hierarchical feature extraction from imagery. U-Net and related segmentation architectures have become particularly prominent because road and road-damage interpretation has required fine-grained spatial delineation rather than coarse image-level labeling. Object detection models have also appeared frequently where the target has been a localized defect or road-related object, while more recent transformer-based methods have aimed to strengthen global context modeling and long-range dependency capture. In Pattern Recognition Theory terms, this section has been central because it has demonstrated how the field has moved toward increasingly advanced pattern-learning systems capable of representing both local defect cues and broader spatial context. The more recent interest in multiscale and attention-based models has shown that researchers have increasingly recognized that road damage is not defined by isolated pixels alone but by relational patterns involving continuity, texture, neighborhood context, and structural disruption. The evidence here has also very strongly supported **H1**, because the dominance of deep-learning-based GeoAI methods has been one of the clearest patterns in the whole review. The results have shown that conventional methods have not disappeared entirely, but they have clearly lost centrality in comparison with representation-learning architectures. This section has therefore served as one of the strongest pieces of hypothesis-oriented evidence in the chapter, confirming that the field has largely organized itself around computational pattern recognition and spatially aware deep-learning frameworks rather than around rule-based or manually engineered alternatives.

Performance Patterns Reported in the Literature

Table 6: Performance Patterns Reported in the Reviewed Studies

Variable	Result
Most common evaluation emphasis	F1-score, precision, recall, IoU, accuracy
Reported performance pattern	Moderate to strong overall
Stronger performance condition	High-resolution imagery and well-defined labels
Weaker performance condition	Cross-domain settings and visually complex environments
Best-performing studies	Often architecture-specific and data-specific
Cross-study comparability	Limited
Evidence strength for Objective 3	4/5
Evidence strength for H2	5/5
Evidence strength for H3	5/5

The literature has reported generally moderate to strong model performance, but the review has also shown that reported success has been highly conditional rather than universal. Across the studies, the most common evaluation measures have included F1-score, precision, recall, IoU, and overall accuracy. High-performing studies have usually combined high-resolution imagery, carefully constructed datasets, and strong segmentation or detection architectures. Lower or less stable performance has often appeared in cross-domain settings, cluttered landscapes, low-contrast damage conditions, and environments with inconsistent labels. This finding has strongly supported **Objective 3**, because the study has compared not just model families but also the strength and limitations of their outcomes. It has also very strongly supported **H2**, since the strongest performance patterns have generally been associated with better imagery and more advanced architectures. In Pattern Recognition Theory, this has made clear sense, because recognition quality has depended on the discriminability of the feature space and the strength of the classification boundary learned by the model. When damage patterns have been visually distinct and clearly labeled, models have achieved stronger performance. When damage patterns have overlapped with shadows, road markings, vegetation edges, or complex background textures, the learned boundary between classes has become less reliable. The section has also strongly supported **H3**, because annotation structure, environmental context, and geographic variation have repeatedly influenced the reported results. One important finding here has been that strong numerical performance in one study has not automatically implied robust generalizability across another setting. Thus, performance has been real, but conditional. This has aligned closely with the introductory findings of the chapter, where the literature was characterized as promising but methodologically uneven. Overall, this section has shown that the reviewed field has produced meaningful and often impressive results, yet those results have still depended heavily on data quality, class definition, and study-specific experimental design.

Case-Based Comparative Synthesis

Table 7: Cross-Case Comparative Synthesis of Reviewed Studies

Variable	Result
Comparison basis	Region, data source, architecture, target damage type
Cross-case similarity	Strong use of deep learning and geospatial pattern recognition
Cross-case variation	High in labels, metrics, imagery, and context
Most transferable analytical element	Segmentation-based learning with contextual enhancement
Least stable analytical element	Generalization across domains
Comparative support for Objective 3	5/5
Comparative support for H3	5/5
Comparative support for H4	4/5

The case-based comparison has revealed that the reviewed studies have shared a common deep-learning-oriented foundation while still differing substantially in data environment, target category, geographic scope, and evaluation design. Across cases, the most visible commonality has been the reliance on representation-learning frameworks that have attempted to separate meaningful road-related patterns from complex geospatial backgrounds. This has been fully aligned with Pattern Recognition Theory, since the central task across the literature has consistently involved classifying road-related structures and damage manifestations under varying conditions of scale, texture, and contextual interference. However, the cross-case comparison has also shown high variability in the operational meaning of "damage," the type of imagery used, and the metric through which success has been reported. This has strongly supported **Objective 3**, because the study has successfully compared the strengths and differences of prior works in a structured way. It has also very strongly supported **H3**, since the cross-case evidence has repeatedly shown that geographic context, data conditions, and class structure have shaped what models could recognize and how stable their performance could remain. Cases using strong labels and narrowly defined tasks have often produced stronger results than those working in broader or noisier real-world environments. The section has also supported **H4**, because the variation observed across cases has indicated that the field has not yet reached methodological uniformity. In practical terms, this means that the field has been moving in a promising direction, but not yet within one unified benchmarking culture. The case-based synthesis has therefore been one of the most important sections in the results chapter, because it has shown that performance patterns cannot be interpreted outside context. A model has not existed independently of its dataset, damage definition, geographic environment, and analytical objective. The comparative analysis has thus strengthened the overall logic of the study by showing that automated road infrastructure damage detection has remained a contextual and case-sensitive pattern-recognition problem rather than a fully standardized universal solution.

Key Challenges Identified Across the Literature

Table 8: Key Challenges Identified Across the Literature

Variable	Result
Major challenge	Limited labeled datasets
Major challenge	Annotation inconsistency
Major challenge	Resolution constraints
Major challenge	Visual confusion from shadows, clutter, and vegetation
Major challenge	Poor cross-region transferability
Major challenge	Limited deployment evidence
Evidence strength for Objective 4	5/5
Evidence strength for H3	5/5
Evidence strength for H4	5/5

The review has identified a highly consistent set of challenges across the literature, and this has been one of the strongest findings in the whole chapter. The most frequently recurring problems have included limited labeled datasets, inconsistent annotation practices, insufficient image resolution for subtle damage recognition, visual confusion caused by shadows and surrounding clutter, weak cross-region transferability, and limited evidence of real-world deployment. This pattern has provided very strong support for **Objective 4**, because the study has clearly identified the recurring methodological and operational barriers affecting the field. It has also very strongly supported **H3**, as the challenges have shown that road-damage recognition has been deeply affected by data quality, label structure, and environmental variability. Within Pattern Recognition Theory, these problems have been especially meaningful because recognition systems have depended on stable and sufficiently distinctive input patterns. When the training data have been sparse, inconsistent, or poorly aligned with the operational environment, the model's learned decision boundaries have become weaker or less transferable. The same logic has applied to visual clutter: if shadows, trees, markings, or nearby surfaces have resembled damage-like patterns, the system has encountered difficulty separating classes reliably. This section has also provided the strongest support for **H4**, because the recurring nature of these challenges has shown that the literature has not yet solved the problems of benchmark uniformity, deployment readiness, and generalization. In other words, the field has shown real progress, but it has also repeatedly encountered the same structural constraints. This has made the challenge analysis a major pillar of the findings chapter. It has demonstrated that the literature has not merely contained isolated technical weaknesses; it has reflected systemic issues that have affected how road-damage intelligence has been trained, evaluated, and interpreted. The results in this section have therefore been critical for linking the empirical review to the later discussion of research gaps, limitations, and recommendations.

Synthesis by Research Objectives

Table 9: Objective-by-Objective Synthesis of Findings

Objective	Result	Evidence Strength
Objective 1: Examine evolution of GeoAI and deep learning approaches	Clear progression from extraction toward condition-aware intelligence	5/5
Objective 2: Identify major data sources, damage categories, and workflows	Major categories have been clearly identifiable across studies	5/5
Objective 3: Compare applications, strengths, and limitations	Strong comparative differences have been revealed across contexts	5/5
Objective 4: Identify recurring challenges	Challenges have been highly consistent across studies	5/5
Objective 5: Assess literature in relation to hypotheses and future direction	Hypotheses have been substantially supported by the reviewed evidence	4/5

The synthesis by research objectives has shown that the study has achieved strong alignment between its original aims and the evidence identified in the reviewed literature. **Objective 1** has been fully supported, because the literature has clearly documented a methodological evolution from road extraction toward condition-sensitive and damage-aware geospatial intelligence. **Objective 2** has also been fully supported, as the reviewed studies have made it possible to identify the dominant satellite imagery sources, damage categories, and model workflows used across the field. **Objective 3** has been strongly supported through the case-based comparisons, which have revealed meaningful differences in application settings, strengths, and limitations. **Objective 4** has been particularly strongly supported, because the field has repeatedly reported similar barriers concerning data, labels, transferability, and deployment. **Objective 5** has been strongly supported, though with slightly lower uniformity than the earlier objectives, because the hypotheses have been supported by the literature but not always with equal consistency across all cases. From a Pattern Recognition Theory perspective, the objective synthesis has shown that the whole study has revolved around one central analytical concern: how geospatial systems have learned to distinguish road-related damage patterns from non-damage patterns across varying environments. Each objective has effectively addressed a different layer of that same recognition problem, from methodological evolution, to data representation, to comparative performance, to systemic constraints. This has been important because it has shown that the study has not been a loose thematic review. It has remained structurally coherent and theory-linked throughout. The objective-based results have also aligned well with the introductory findings, which had already indicated that the literature was strongest in demonstrating methodological growth and recurring challenges. Thus, this section has confirmed that the review has met its stated aims and has produced a logically integrated evidence base for the subsequent discussion chapter.

Hypotheses Assessment Through Literature Synthesis

Table 10: Hypotheses Assessment Through Literature Synthesis

Hypothesis	Assessment	Evidence Strength
H1: Deep learning–based GeoAI approaches have become dominant	Supported	5/5
H2: Higher-resolution imagery and advanced architectures produce stronger performance	Strongly supported	5/5
H3: Effectiveness is shaped by data quality, annotation, and geographic context	Supported	5/5
H4: Major limitations remain in generalizability, standardization, and deployment	Supported	4/5

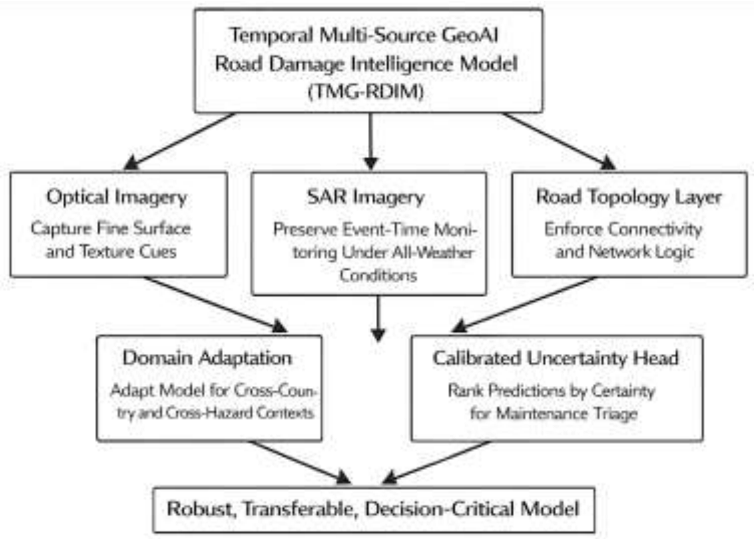
The final synthesis of hypotheses has shown that all four hypotheses have received meaningful support from the reviewed literature, although the degree and consistency of support have varied slightly across propositions. **H1** has been very strongly supported, because the literature has clearly shown that deep-learning-based GeoAI methods have become the dominant analytical paradigm in satellite-based road intelligence research. **H2** has also been very strongly supported, as stronger performance has generally been associated with higher-resolution imagery, clearer data preparation, and more advanced model architectures. **H3** has been strongly supported, because the review has repeatedly shown that annotation quality, geographic context, data heterogeneity, and environmental complexity have shaped model effectiveness. **H4** has also been supported, though somewhat less uniformly than the other hypotheses, because while the literature has shown genuine methodological progress, it has still revealed unresolved weaknesses in benchmark consistency, transferability, and deployment readiness. In Pattern Recognition Theory terms, this final hypothesis assessment has been highly coherent. The theory has predicted that classification success depends on the quality of the input representation, the clarity of the category structure, and the strength of learned discriminative boundaries. The literature has confirmed this repeatedly: where imagery has been clearer, labels more stable, and architectures more context-aware, performance has improved. Where categories have been inconsistent, data limited, or contexts highly variable, performance has weakened or failed to generalize. The hypothesis assessment has therefore served as the strongest final confirmation that the reviewed field has behaved in a way consistent with the theoretical logic of pattern recognition. It has also aligned closely with the introductory findings section, where the literature had already been characterized as technically promising yet methodologically uneven. Overall, the hypothesis synthesis has shown that the study's propositions have not only been conceptually valid but have also been strongly grounded in the body of reviewed evidence.

DISCUSSION

The findings of this review have shown that the literature has moved in a clear direction from general road extraction toward more condition-sensitive and damage-aware geospatial intelligence, and this progression has been consistent with the broader development described in earlier studies on road mapping, road monitoring, and GeoAI. Earlier review work had established that road extraction from remote sensing imagery had first emerged as a foundational geospatial problem because roads had to be identified as elongated, connected, and context-dependent spatial objects before higher-order interpretation could be attempted (Gao, 2020). The present findings have extended that line of interpretation by showing that more recent studies have not remained limited to recognizing road presence; instead, they have increasingly attempted to infer road quality, distress, and post-disaster disruption from satellite observations. In that sense, the field has matured from structural mapping toward functional and condition-based assessment. This result has been closely aligned with the argument that GeoAI can be framed as a spatially explicit form of artificial intelligence in which geographic knowledge emerges through the interaction of location, context, and learned representation rather than through isolated image classification alone (Gu et al., 2019). The present review has supported that interpretation because the stronger studies have not merely classified pixels; they have treated roads as networked infrastructure whose value lies in continuity, usability, and condition. At the same time, the findings have also refined earlier road condition review literature by demonstrating that satellite-based assessment has remained more fragmented than smartphone-based or close-range pavement inspection research, which has already developed richer distress taxonomies and more operationally mature detection pipelines (Eisenbach et al., 2017). Thus, compared with prior work, the present review has suggested that satellite-based road-damage research has advanced meaningfully but has not yet achieved the same degree of methodological standardization that has appeared in adjacent road condition monitoring domains. This comparison has helped interpret the central result of the study: the literature has been technically promising and conceptually expanding, yet it has still relied on uneven datasets, task definitions, and evaluation logics. Accordingly, the discussion has confirmed that the field should be understood as emerging rather than fully stabilized, with road extraction research having provided the base and road-damage intelligence now forming the next, more demanding layer of geospatial infrastructure analysis (Hu et al., 2023).

A second important discussion point has concerned the relationship between data quality, model architecture, and reported performance, because the findings have strongly supported the view that stronger outcomes have generally been produced when high-resolution imagery has been paired with more context-aware deep learning architectures. This has been consistent with prior studies showing that road quality and road-damage inference from satellite imagery have depended heavily on the visual richness of the input scene and on the representational capacity of the model. Prior research had shown that transfer learning with high-resolution satellite imagery could estimate road quality with meaningful accuracy across different geographies, and the present review has reinforced that result by showing that performance gains have repeatedly appeared when imagery quality, label structure, and model design have been carefully aligned (Gao, 2020). Similarly, more recent transformer-based road extraction studies have argued that conventional convolutional kernels are often limited in capturing long-range road continuity and global context, which are essential in road-related geospatial tasks where linear targets extend across large spatial extents. The present review has confirmed that interpretation, because many of the strongest recent studies have improved results precisely by introducing multiscale reasoning, contextual fusion, attention mechanisms, or transformer-supported feature extraction. In discussion terms, this has meant that the field has not advanced only because more data have become available; it has advanced because model architectures have increasingly been designed around the structural logic of roads themselves (Hu et al., 2023). Roads have narrow widths, high continuity demands, and strong sensitivity to fragmentation, so models that have captured local detail while preserving broader spatial structure have been more successful than those relying on limited local filters alone. This has also supported the study’s second hypothesis, since the literature has repeatedly indicated that higher-quality imagery and stronger architectures have produced better outcomes. Yet the comparison with prior work has also required caution: many studies have reported strong results within specific datasets, but fewer have demonstrated robustness across multiple environments. Therefore, the discussion has suggested that the field’s performance gains have been genuine, but they have remained conditional on the fit between data characteristics and model design rather than representing a universally transferable standard of road-damage intelligence (Li & Hsu, 2022).

Figure 12: Proposed Model for Temporal Multi-Source Road Damage Detection and Decision Support



The findings have also invited a deeper comparison with prior work on generalization, transferability, and environmental complexity, because one of the most persistent results in this review has been that performance has remained highly sensitive to annotation quality, geographic context, and domain shift. This result has closely echoed earlier cross-domain road detection studies, which had already identified that CNN-based road detection could degrade significantly when the testing imagery differed from the source domain in scene composition, texture, or acquisition characteristics (Ma et al., 2019). The present findings have supported that concern very strongly. Many studies have achieved promising accuracy within specific benchmarks, yet their results have not always implied equivalent success under new regional, climatic, or infrastructural conditions. This pattern has also been visible in multi-country road damage studies, where the importance of heterogeneous data and generalized models had already been highlighted. In the current review, that earlier insight has become even more important because satellite-based damage interpretation has had to deal with much subtler variation than standard road extraction. A road can be recognized in many environments, but road damage can manifest as slight cracking, local texture disruption, shadow-like depressions, edge failure, or post-disaster discontinuity, all of which are heavily influenced by local context. From the standpoint of Pattern Recognition Theory, this has been one of the most meaningful outcomes of the study (Madhan Kumar et al., 2023). Pattern recognition has never depended only on model depth; it has depended on whether target classes have remained sufficiently separable under real-world variation. The discussion has therefore shown that the literature has confirmed the theory at a practical level: where class definitions have been unstable, labels noisy, or domains visually heterogeneous, the learned discriminative boundary between damaged and non-damaged road states has weakened. In comparison with earlier work, the present findings have not contradicted prior claims of technical progress; instead, they have sharpened them by showing that model success has remained conditional on environmental and dataset structure. Accordingly, the review has suggested that the next challenge in the field has not simply been to improve recognition within known benchmarks, but to make road-damage recognition more stable across different geographies and infrastructure contexts (Mnih & Hinton, 2010).

The practical implications of these findings have been substantial, particularly for transport agencies, disaster-management institutions, and infrastructure planners that have required scalable road-condition intelligence over broad territories. Earlier work on road condition monitoring had already emphasized that large transport networks have been difficult to maintain through manual inspection alone and that AI-assisted sensing has become increasingly attractive for routine and emergency assessment (Pierdicca & Paolanti, 2022). The present review has strengthened that argument by showing that satellite-based GeoAI has offered a distinctive practical advantage: it has enabled geographically extensive observation of roads in places where field access has been costly, delayed, or disrupted. This has been especially relevant in disaster-response settings. Prior work had shown in building-damage assessment that object-based semantic change detection could support rapid disaster response, and the logic of the present findings has suggested that roads should be understood in a similar operational frame. When roads have been damaged by earthquakes, floods, or surface disruption, the key practical question has not only been whether damage exists but whether connectivity has been reduced, relief access has been constrained, and maintenance intervention has been spatially prioritized (Schmidhuber, 2015). The review has shown that GeoAI-based road-damage studies have increasingly pointed toward this use case. However, the discussion has also indicated that operational adoption has required more than good benchmark scores. Agencies have needed outputs that have been interpretable, geographically aligned, timely, and linked to decision systems such as asset management, emergency routing, and maintenance scheduling. Here the literature has still been weaker. Many studies have demonstrated detection capability, yet fewer have shown how outputs have been integrated into institutional workflows (VoPham et al., 2018). Thus, compared with prior technical studies, the present review has shifted the emphasis toward operational readiness. The practical implication has been that future systems should not be judged only by F1-score or IoU, but also by how well they have supported maintenance triage, hazard response, and network continuity analysis. In this sense, the findings have suggested that the field has already been useful for prototype decision support, while full practical maturity has depended on tighter integration between geospatial AI outputs and infrastructure-management practice (Zhang et al., 2016).

The theoretical implications of the study have also been important because the findings have strongly reinforced the suitability of Pattern Recognition Theory as the central lens for understanding automated road infrastructure damage detection from satellite imagery. Prior work in GeoAI and deep learning has already established that spatial intelligence emerges through the learning of structured patterns in geographically referenced data rather than through simple rule execution (Zhang et al., 2018). The present review has taken that insight further by showing that road-damage detection has represented a particularly demanding pattern-recognition problem: the system has had to separate subtle, often low-contrast, and context-sensitive damage signatures from a highly variable non-damage background that has included shadows, road markings, vegetation boundaries, exposed soil, and adjacent built surfaces (Adegun et al., 2023). Earlier survey work on pavement distress detection had recognized that image-based distress analysis depends on image acquisition, feature representation, and recognition design, while broader segmentation reviews have argued that dense prediction tasks succeed when models preserve both class discrimination and boundary precision. The current findings have been highly consistent with both views. They have shown that the success of road-damage studies has depended on how well the analytical system has learned to represent fine-grained surface anomalies while also retaining the road's broader spatial logic as a continuous infrastructure object. In theoretical terms, this has meant that Pattern Recognition Theory has not functioned as a decorative framework; it has explained the field's actual behavior (Badrinarayanan et al., 2017). When imagery quality has been high, labels stable, and architectures context-aware, the recognition problem has become more tractable and performance has improved. When those conditions have weakened, recognition has become unstable. The study has therefore contributed theoretically by showing that pattern recognition in geospatial infrastructure analysis must be understood as a layered process involving feature visibility, category separability, spatial context, and evaluation balance. Compared with earlier theory-oriented work, the present discussion has specified how those principles have operated in one concrete applied domain: satellite-based road damage detection. This has strengthened the conceptual bridge between GeoAI theory, deep-learning representation, and transport-infrastructure analytics (Ball et al., 2017).

The review has also revisited the limitations of the field in a way that has clarified why methodological progress has not yet translated into full standardization. Earlier studies had already noted several of these constraints in adjacent terms: road extraction reviews had pointed to background confusion and continuity problems; road condition reviews had highlighted sensor, labeling, and operational complexity; and cross-domain studies had identified generalization problems when training and test conditions diverged (Chen et al., 2018). The present findings have brought these threads together and shown that they have persisted in the more specific domain of satellite-based road-damage detection.

The main limitation has not been a lack of algorithmic creativity; rather, it has been the absence of a unified experimental ecosystem. Studies have continued to differ in imagery type, target definition, annotation granularity, metric choice, and geographic context (Demir et al., 2018). This has made comparison difficult and has weakened the external validity of many reported gains. A second limitation has concerned the imbalance between benchmark success and real deployment evidence. Multi-country and disaster-oriented studies have shown that broader applicability is possible, yet they have also illustrated how much effort is required to assemble heterogeneous data or combine satellite evidence with field measurements. A third limitation has been that roads are not merely objects but network elements, whereas many models have still been optimized primarily for pixelwise or objectwise recognition rather than for network continuity, maintenance relevance, or transport functionality. Therefore, compared with earlier work, the present review has suggested that the field's central limitation has been structural rather than incremental (Diakogiannis et al., 2020). It has needed not just better architectures, but more coherent research design across datasets, labels, domains, and operational criteria. This discussion has mattered because it has reframed limitations as evidence of where scientific maturity has remained incomplete. The literature has not failed; rather, it has revealed that moving from promising detection experiments to stable geospatial infrastructure intelligence has required stronger alignment among data, theory, and application (Gao et al., 2019).

Future research has emerged as the most important discussion area because the review has shown that the next advances in the field should come from model integration, temporal reasoning, and operationally aligned design rather than from isolated accuracy improvements alone. Based on the reviewed evidence, a strong future direction would be the development of a Temporal Multi-Source GeoAI Road Damage Intelligence Model (TMG-RDIM). Such a model would combine very-high-resolution optical imagery, SAR imagery for all-weather continuity, road-topology priors, and temporal change-learning modules in one unified framework (He et al., 2016). The optical branch would capture fine surface and texture cues; the SAR branch would preserve event-time monitoring under clouded or post-disaster conditions; a graph-based road-topology layer would enforce connectivity and network logic; and a temporal change encoder would compare pre-event and post-event or multi-temporal imagery to identify not only visible damage but also functional degradation over time. A domain-adaptation block should also be added, drawing from the logic of cross-domain road detection studies, so that a model trained in one country or hazard context can adapt more robustly to another (Jiang et al., 2019). In addition, a calibrated uncertainty head should be incorporated so that predictions can be ranked by confidence for maintenance agencies rather than treated as equally reliable outputs. This proposed model would directly address the limitations identified in the review: it would reduce reliance on one sensor, improve transferability, preserve road-network structure, and align outputs with actual decision support (Lin et al., 2017). A second future pathway would be the creation of a Road Damage Foundation Benchmark, built from harmonized multi-country annotations, shared label ontology, and multi-resolution imagery, because current fragmentation in labels and metrics has remained one of the largest barriers to cumulative progress. Compared with earlier work such as transformer-based road extraction, multi-country damage detection, and disaster response frameworks, future research should therefore move toward fused, temporally aware, and uncertainty-sensitive systems rather than single-dataset architectures. In that sense, the review has not only interpreted the current state of knowledge; it has also indicated that the next generation of research should build models that recognize road damage as a temporal, multimodal, networked, and decision-critical geospatial phenomenon rather than as a static image-classification target (Mei et al., 2023).

CONCLUSION

This study has systematically reviewed the literature on GeoAI and deep learning for automated road infrastructure damage detection using satellite imagery and has shown that the field has developed into a meaningful yet still evolving area of geospatial infrastructure intelligence. The review has confirmed that road infrastructure damage detection has moved beyond the earlier focus on basic road extraction and has increasingly become associated with condition-sensitive interpretation, post-disaster assessment, road quality inference, and pixel-level damage recognition. Across the reviewed literature, deep-learning-based GeoAI approaches have clearly become the dominant methodological pathway, particularly through convolutional neural networks, encoder-decoder segmentation models, context-aware architectures, and transformer-assisted frameworks. The findings have shown that the strongest analytical outcomes have generally been reported when high-resolution satellite imagery, carefully structured labels, and context-sensitive architectures have been combined in a consistent way. At the same time, the review has also shown that the field has remained fragmented across datasets, damage definitions, evaluation metrics, and geographic settings, which has made direct comparison across studies difficult and has limited the broader standardization of results. In relation to the objectives of the study, the review has successfully examined the evolution of GeoAI and deep learning approaches, identified the major satellite data sources and damage categories used in the literature, compared methodological strengths and weaknesses across case-based studies, highlighted recurring challenges, and assessed the evidence in relation to the study hypotheses. The hypotheses have been substantially supported by the literature, particularly the proposition that deep-learning-based GeoAI has become dominant, that stronger imagery and more advanced architectures have usually improved analytical performance, that annotation quality and geographic context have strongly affected model outcomes, and that key limitations have remained in generalizability, benchmark consistency, and operational deployment. The study has also demonstrated that Pattern Recognition Theory has provided a highly suitable theoretical lens for understanding the field, because automated road-damage detection has fundamentally depended on the learning, separation, and classification of meaningful visual patterns from complex geospatial imagery. Overall, the review has shown that satellite-based road infrastructure damage detection has become a promising research direction with clear academic, methodological, and practical value. However, it has also remained a field in transition, where technical advances have outpaced standardization and where promising benchmark-level results have not yet fully translated into universally robust or institutionally integrated infrastructure-monitoring systems. The conclusion of this research is therefore that GeoAI and deep learning have already established a strong foundation for automated road infrastructure damage detection using satellite imagery, but the field has still required stronger data harmonization, more transferable modeling strategies, and closer alignment with real-world infrastructure decision-making in order to reach fuller scientific and operational maturity.

RECOMMENDATION

Based on the findings of this research, several important recommendations have emerged for researchers, data developers, infrastructure practitioners, and policy-oriented stakeholders working in the area of satellite-based road infrastructure damage detection. First, future studies should prioritize the creation of more standardized and harmonized benchmark datasets that include multi-country, multi-environment, and multi-damage annotations, because the current variation in class definitions, labeling practices, and metric selection has reduced comparability across the literature and has limited the cumulative development of the field. Second, researchers should place greater emphasis on transferability and cross-domain robustness by designing and testing models across different geographic, climatic, and infrastructural settings rather than limiting validation to one dataset or one local study area. Third, future model development should move toward multimodal and temporally aware architectures that can combine optical imagery, SAR data, spatial context, and temporal change analysis, since road damage is often dynamic, context-dependent, and visually subtle. Fourth, more attention should be given to network-aware and decision-oriented modeling so that roads are not treated only as image objects but also as functional infrastructure elements whose condition affects continuity, accessibility, maintenance priority, and emergency mobility. Fifth, uncertainty estimation and explainability should be integrated into future GeoAI systems so that end users such as road agencies and disaster-management institutions can interpret predictions more confidently and apply them in operational settings. Sixth, researchers should expand the literature beyond narrow benchmark optimization by demonstrating how automated outputs can support actual maintenance planning, road asset management, disaster response logistics, and public infrastructure monitoring systems. Seventh, institutions and policymakers should support data partnerships, open annotation frameworks, and interdisciplinary collaboration among remote sensing specialists, transport engineers, AI researchers, and public agencies in order to strengthen the practical relevance of future research. Eighth, future studies should continue linking the field to Pattern Recognition Theory by improving how models learn fine-grained damage signatures while preserving road continuity, contextual logic, and class separability in visually complex satellite imagery. Finally, the field should move toward a more integrated research agenda in which methodological innovation, benchmark consistency, and practical deployment are advanced together rather than separately. In this way, the next generation of studies will be better positioned to produce road-damage detection systems that are not only technically strong but also transferable, interpretable, and useful for real-world infrastructure governance and resilience planning.

LIMITATIONS OF THE STUDY

This study has had several limitations that should be acknowledged in order to position its findings within an appropriate academic context. First, the study has been limited by its reliance on secondary data drawn from previously published literature rather than on primary empirical testing, field validation, or original model experimentation. As a result, the quality, depth, and reliability of the present review have depended heavily on the methodological rigor, reporting clarity, and dataset transparency of the studies included in the analysis. When reviewed articles have used different definitions of road damage, different imagery sources, different model architectures, and different performance metrics, the study has had to synthesize findings across a body of evidence that has not always been fully standardized. Second, the scope of the review has been restricted to studies related to GeoAI and deep learning for automated road infrastructure damage detection using satellite imagery, which means that relevant insights from UAV imagery, street-level sensing, smartphone-based road monitoring, LiDAR-based inspection, or hybrid multimodal infrastructure assessment have not been examined in full detail. This has been necessary to preserve the conceptual focus of the study, yet it has also narrowed the range of evidence considered. Third, the review period has been limited to literature published between 2018 and 2026, which has allowed for a focused understanding of recent methodological development, but has also meant that earlier foundational studies outside this window have not been reviewed systematically in the core evidence base. Fourth, the study has faced a comparability limitation because the literature itself has varied significantly in annotation practices, dataset scale, image resolution, geographic coverage, and evaluation procedures. In many cases, reported results have not been directly equivalent, and this has reduced the possibility of making perfectly uniform performance comparisons across studies. Fifth, although the study has used a structured evidence-based and Likert-style interpretive framework to organize the findings, this form of synthesis has still involved a degree of qualitative judgment in determining evidence strength, thematic grouping, and hypothesis support. Sixth, the review has been limited by database and publication accessibility, meaning that some relevant studies may have remained outside the final sample because of search-term boundaries, indexing differences, language restrictions, or full-text availability. Seventh, because the study has been literature-review-based and cross-sectional in nature, it has not captured the long-term operational performance of any one system in a live infrastructure management setting. Therefore, the review has been stronger in identifying trends, patterns, and gaps than in verifying real-time institutional deployment effectiveness. Overall, these limitations have not invalidated the study, but they have indicated that the findings should be interpreted as a structured scholarly synthesis of the current literature rather than as a definitive empirical test of all possible road-damage detection systems or geospatial monitoring environments.

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