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Deep Learning on High-Resolution Satellite and Street-View Imagery for Automated Roadway Asset Classification and Pavement Condition Index (PCI) Prediction

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Abstract: *Deep learning is already showing good results in roadway asset classification, which plays a key role in safety management, regulatory compliance, and asset inventory in Transportation Asset Management (TAM). You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), and Faster R-CNN are models that are credible at detecting roadside structures, lane divisions, and traffic signs in varied conditions. In addition to approaches based on images, three-dimensional mapping (Light Detection and Ranging or LiDAR) makes classification processes more accurate, as there are geometric depth features that improve the ability to distinguish between visually similar objects, especially in high-density environments. Other, more recent, multimodal fusion approaches (LiDAR point clouds, RGB images, multispectral satellite images, and street-view images) enhance robustness in scenes where either there is occlusion or adverse lighting conditions. Taken together, these developments are compatible with scalable, automated roadway inventories, asset inventories that are compatible with TAM goals.*

Keywords: roadway asset classification, pavement condition index (pci) prediction, high-resolution satellite imagery, deep learning for infrastructure monitoring, automated roadway inspection

INTRODUCTION

Roadway systems are one of the most prized public resources, but they degrade quickly because of the aging infrastructure, the growing traffic demands, climate change, and the scarce maintenance funds. To maintain safe and functional transportation systems, pavement conditions and roadway assets should be assessed on a regular and precise basis; however, the conventional inspection methods still rely on manual inspection and are labor-intensive and subject to human mistakes. Traditional walking surveys and windshield surveys are time-intensive and personnel-intensive, and the subjective nature of their rating results in unreliable ratings among different inspectors and agencies, which ultimately influences the prioritization of maintenance and lifecycle planning (Radopoulou and Brilakis, 2016). Moreover, manual surveys present employees with safety hazards in busy settings and cannot keep pace with the escalating need to conduct subsequent, network-based surveillance as per current Transportation Asset Management Plans (TAMPs). Automated solutions that can generate objective, repeatable, and high-frequency evaluations have become an urgent requirement to support the data-driven maintenance and rehabilitation strategies as roadway agencies seek cost-effective and scalable solutions (El-Maissi et al., 2021).

Role of High-Resolution Satellite and Street-View Imagery

The development of remote sensing and photogrammetry has increased the accessibility and the application of high-resolution images to monitor infrastructure. Sub-meter spatial resolutions offered by satellite platforms (SPOT, WorldView, Sentinel, and NOAA) are currently used to screen roads at a large scale and monitor the environment (Crespi and De Vendictis, 2009; Zhang et al., 2020). These systems provide wide geographic coverage, frequent revisit cycles, and spectral information, which facilitates creating an effective classification of pavements and surface texture analysis on a network level. As a supplement to satellite imagery, ground-level street-view collections like Google Street View and Mapillary have become available and freely accessible crowdsourced collections of roadway imagery with small spatial resolution and dense contextual evidence. These photos present the angle that is required to locate cracks, potholes, lane markings, traffic signs, culverts, and other vertical assets that cannot be easily identified when viewed on overhead programs (Balali and Golparvar-Fard, 2015). The time depth of platforms like Google Street View that store historical imagery can also be used to make longitudinal estimates to model deterioration. These sources of imagery, together with the current methods of computation, constitute a potent and multi-scale road monitoring system.

Emergence of Deep Learning in Infrastructure Monitoring

Deep learning has not only revolutionized the computer vision field but has also quickly become an infrastructure inspection technology. The application of Convolutional Neural Networks (CNNs) has made it possible to identify and classify any pavement distress, such as alligator cracking, rutting, and potholes, with accuracy that is superior to conventional machine-learning approaches (Savino &Tondolo, 2023). U-Net and its variations are very useful in pixel-wise segmentation tasks, extracting detailed crack patterns, lane markings, and structural defects of aerial and street-view images (Islam et al., 2024). Architectures like YOLO have also shown great results in detecting roadway assets and have been utilized to perform automated inventories of signs, poles, barriers, and lane features at close-to-real-time frequencies (Flores-Calero et al., 2024). In more recent times, Transformer-based and hybrid fusion network models have added a new feature to deep learning to enable them to cope with complex conditions, multimodal information, and high-resolution imagery with a better sense of space and stronger resilience (Di Summa et al., 2023). These advancements depict a fast technological transformation of automated, scalable, and high-precision roadway evaluation systems led by deep learning innovations.

Research Gaps

The use of deep learning to assess pavement has been greatly improved, but there are still several significant gaps. The high-resolution satellite image data are not often combined with street-view data or mobile mapping data in the current literature, and, thus, the evidence of the advantage of the multimodal inputs to improve the predictions of PCI and the classification of assets is rather sparse. A comparative assessment across imagery platforms remains limited because most studies rely on a single data source and employ varying measurement approaches, assessment protocols, and validation methods. These inconsistencies restrict the ability to generalize the findings and complicate the comparison of studies. Besides, the deep-learning models are susceptible to poor performance when not in their training territory, which depicts domain adaptation and geographical transferability deficits. The literature addressing annotation quality, data limitations, and the operational implications of using these systems within transportation agencies is very limited. These gaps highlight the need for standard benchmarking practices, multimodal fusion models, and more robust and transferable deep learning frameworks.

Purpose of the Study

This paper provides an integrative literature review on the use of deep learning with high-resolution satellite and street-view imagery for automated roadway assets classification and the prediction of Pavement Condition Index (PCI). The review synthesizes evidence across different methodological paradigms andevaluatesthe comparative strengths and weaknesses of various imagery platforms. Emerging trends and unresolved issues impacting the performance of models, their scalability, and their generalizability are also explored. Relying on interdisciplinary studies in the field of remote sensing, transportation engineering, and computer vision, the paperaims to illuminate the existing level of knowledge, highlight the gaps in technology and practice, and reveal the potential opportunities of future research and practice.

CONCEPTUAL AND EMPIRICAL FOUNDATIONS OF AUTOMATED ROADWAY ASSESSMENT

Transportation Asset Management (TAM)

TAM is a coordinated, data-driven framework that helps transportation agencies manage roadway networks through lifecycle strategies, prioritization, and performance-based investment decisions. Within this framework, Transportation Asset Management Plans (TAMPs) guide federal and state agencies in allocating resources and maintaining consistent levels of pavement performance (FHWA, 2020). Other roadway safety and continuity assets, including traffic signs, guardrails, lane markings, and drainage facilities, are also essential for ensuring the safe and reliable operation of transportation networks (AASHTO, 2019). Central to these decisions is the assessment of pavement conditions, for which the Pavement Condition Index (PCI) is widely used as the standard engineering measure of pavement quality, structural integrity, and serviceability.

Pavement Condition Index (PCI)

The most widely used indicator of pavement health worldwide is the PCI. The American Society for Testing and Materials Standard D6433 (ASTM D6433), formally titled *Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys*, defines the PCI scale as ranging from 0 to 100, reflecting the functional and structural condition of pavement based on the type, severity, and extent of observable surface distress. A low PCI indicates severe deterioration that requires substantial rehabilitation, whereas a high PCI reflects a pavement surface that is performing well. Distresses commonly included in PCI calculations include alligator cracking, potholes, rutting, block cracking, longitudinal and transverse cracking, depression, bleeding, and raveling. The deduct values assigned to each distress type are combined to produce the overall PCI score, making the index highly sensitive to both the intensity and distribution of defects. Despite its widespread use, PCI depends on manual field surveys, which introduce subjectivity and lead to inter- and intra-inspector variability. These limitationspresent the need for automated, image-based PCI estimation methods capable of producing reproducible, large-scale measurements across diverse roadway environments

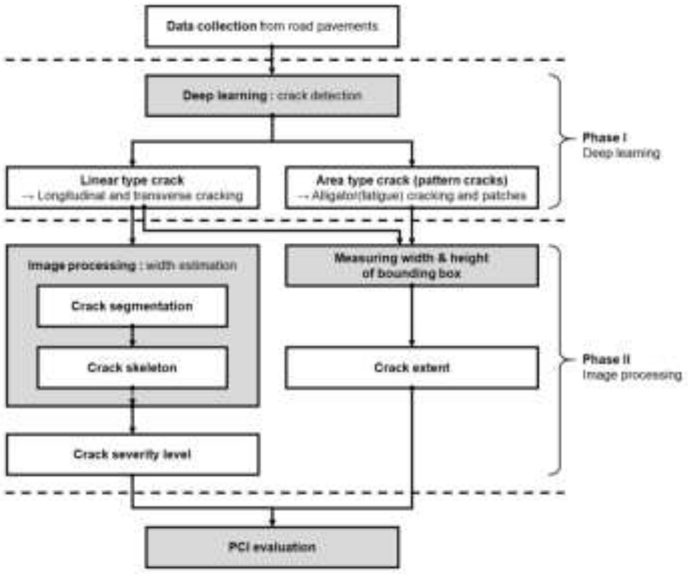

Figure 1. PCI Calculation Process Based on ASTM D6433 Distress Identification and Deduct Value Computation (Adapted from MDPI Sensors, 2024).

Deep Learning Foundations

Deep learning has been significant in augmenting the capabilities of computer vision by enabling it to learn high-level and contextualized representations of intricate visual data that is particularly suitable in automated roadway evaluation. CNNs are the architectural designs that are employed to classify pavement distress because of their ability to produce spatial patterns in pavement distress, including cracks, potholes, and rutting (Savino and Tondolo, 2023). U-Net and other encoder-decoder segmentation networks permit localizing defects and roadway structures by the pixel, which makes it possible to precisely trace the geometry of cracks, road signs, and abnormalities on the surface (Islam et al., 2024). Deep learning models such as YOLO can identify roadway objects, such as traffic signs, barriers, and poles, with high accuracy and within a relatively short period, and hence have great application in real-time-based applications in mobile mapping systems (Flores-Calero et al., 2024). More recent Transformer-based designs introduce attention to the architecture, which learns long-range spatial dependencies and improves the quality of segmentation and classification in difficult urban environments (Di Summa et al., 2023). Multimodal and new ensemble models combine CNNs, Transformers, LiDAR, multispectral images, and street-view data into more robust and context-focused instruments capable of serving the variability of visual situations of roadway scenes.

High-Resolution Satellite Imagery in Infrastructure Monitoring

High-resolution satellite images have become a valuable resource in the roadway monitoring process, thanks to their extensive geographic coverage and continuous availability. On-board systems such as WorldView, SPOT, Sentinel, and NOAA have spatial resolutions of between 0.3 and 10 meters, thereby enabling the identification of road layouts, pavement surfaces, and environmental contexts of the regions (Crespi and De Vendictis, 2009). Deep-learning models applied to satellite images have demonstrated high efficiency at network-level pavement classification, roadway detection, and initial PCI prediction, particularly in scenarios where the multispectral data is utilized, which highlights the patterns of material degradation (Zhang et al., 2020). The satellite data are, however, constrained by cloud cover and shadows, vegetation obscuration, and the capability of capturing fine-grained pavement defects. Even with sub-meter resolution, satellite platforms are not effective in detecting micro-level distress, e.g., hairline cracks or small potholes. Consequently, the application of satellite-based PCI is most appropriately implemented in macro-level screening and not in project-level, detailed assessments. Nevertheless, the ability to scale very high, cover large areas, and a relatively low price per square kilometer make the satellite images a necessity for automated systems of monitoring infrastructure.

Street View Imagery and Mobile Mapping Systems

Street-view imagery is ground-level visual data that helps to supplement satellite observations by getting the pavement and asset data that cannot be seen on overhead views. Google Street View (GSV) and similar platforms provide large collections of roadway images that can be used to conduct a temporal study of pavement degradation and changes in asset conditions (Balali and Golparvar-Fard, 2015). The Mobile Mapping Systems (MMS) take this to another level by incorporating high-resolution cameras, LiDAR sensors, GPS, and inertial measurement devices to produce engineering-grade three-dimensional representations of the pavement surfaces. MMS data can be used to measure the crack widths, rut depths, and surface irregularities with high accuracy, allowing project-level PCI measurements to be highly accurate (Jung et al., 2020). The combination of LiDAR and camera images increases the detection and grouping of the three-dimensional roadside assets, such as guardrails, signage, and utility poles, contributing to full asset lists as needed by TAM compliance. Street-view and MMS are better sources of imagery due to their high spatial fidelity to deep-learning models, which need the high-context visual input to perform distress detection and asset classification tasks.

Prior Research on PCI Prediction

There is a large literature on machine-learning and deep-learning-based PCI prediction methods on imagery, sensor, and environmental measurements. The conventional use of machine-learning techniques such as artificial neural networks, fuzzy neural models, and statistical regression demonstrated moderate success in predicting PCI, yet has been constrained in their capability to embrace the spatial aspect and heterogeneity of the patterns of pavement distress (George et al., 2022). Deep-learning models have overcome these limitations by allowing direct prediction of PCI by imagery or indirect prediction by using distress segmentation associated with the deduct-value computation. The use of climatic variables, including temperature extremes, precipitation, freeze-thaw cycles, and solar radiation, has also enhanced the precision of models based on data, proving the strong impact of environmental factors on pavement performance (Bouwmeester et al., 2023). Nonetheless, the studies are still disjointed, and there is a significant inconsistency in datasets and model structures, validation procedures, and performance indicators. All these discrepancies demonstrate the necessity of standard datasets and assessment systems that could enable a more serious comparison of studies.

Deep Learning for Asset Classification

Roadway asset classification tasks, a key area of safety management, regulatory compliance, and asset inventories driven by TAM, have always shown good results with deep learning. YOLO, SSD, and Faster R-CNN models are highly accurate in detecting traffic signs, lane marking segmentation, and recognizing roadside infrastructure in different conditions (Flores-Calero et al., 2024). Three-dimensional mapping of assets with the help of LiDAR further improves the classification credibility because it considers geometric depth data, which is much more effective in distinguishing between visually similar types of assets, especially those found in a highly populated city environment. The latest developments in multimodal fusion involve LiDAR point clouds, RGB images, multispectral satellite, and street-view images to produce more resilient classification systems that can overcome the issue of occlusions, bad lighting, and complex scenes (Di Summa et al., 2023). Such methodological advances show how deep learning can be more useful to support entirely automated and large-scale roadway asset inventories that can be seamlessly integrated with TAM systems.

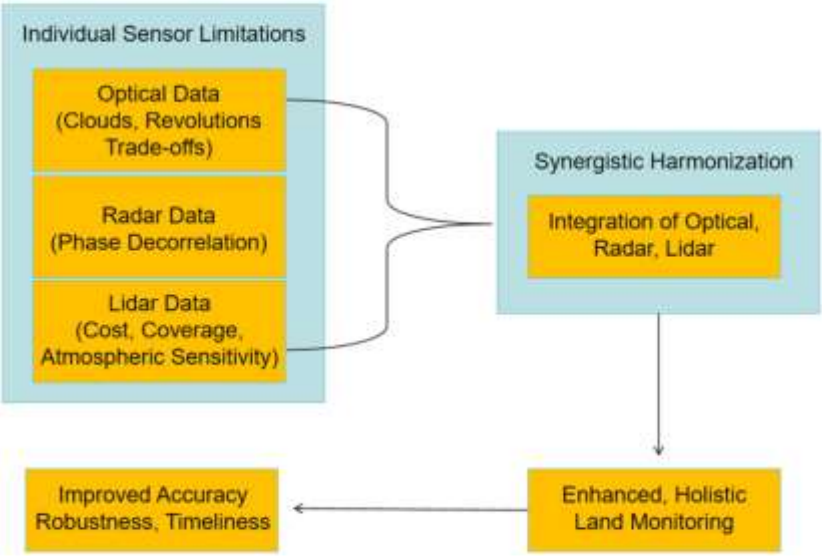

Figure 2. Theoretical Framework for Deep Learning–Based Automated Roadway Assessment Integrating Satellite Imagery, Street-View Data, and Multimodal Inputs (Adapted from MDPI Sensors, 2024).

RESEARCH METHODOLOGY AND ANALYTICAL FRAMEWORK

Research Design

The systematic, evidence-based analytical research design of this study is used to synthesize current research knowledge on how deep-learning techniques can be used on high-resolution satellite and street-view imagery to perform automated classification of roadway assets and predict Pavement Condition Index (PCI). The method is guided by systematic review principles that prioritize transparency, replicability, and methodological rigor during the picking, extracting, and interpreting research evidence (Snyder, 2019). The design incorporates both conceptual and empirical analysis through the identification of trends in the published studies, methodological approaches, and model performance in terms of imagery source, network conditions, and architectural options. In contrast to narrative reviews, such a systematic design allows comparing cross-studies of deep-learning methods across the board, which facilitates a better evaluation of their strengths, weaknesses, and portability. The method fits well into the best practices in transportation research, wherein systematic evidence synthesis is crucial in the identification of transferable technologies that can facilitate large-scale infrastructural monitoring and asset management efforts (FHWA, 2020).

Data Sources for Literature

The sources of literature used in the analysis of this research were selected among a variety of sources in the scientific domain to provide the full richness and diversity of the images of deep-learning use in the roadway assessment. The peer-reviewed articles were accessed in major academic databases, as these databases include most of the modern research on computer vision, remote sensing, and transportation infrastructure. The technical reports of transportation agencies and remote sensing organizations were also checked to put operational usage of imagery-based asset monitoring into perspective.The studies that employed high-resolution satellite imagery on platforms like WorldView, SPOT, Sentinel-2, and NOAA were also incorporated due to their applicability to network-level roadway modeling (Zhang et al., 2020). The sources on ground-level imagery, such as Google Street View (GSV), Mapillary, and Mobile Mapping Systems (MMS), were included because of their role in detecting signs of pavement distress and tracking the assets on the roadway (Balali and Golparvar-Fard, 2015). Benchmark evaluations of asset classification and segmentation tasks were conducted on the review of public datasets like TT100K, Mapillary Vistas, and Cityscapes.

Besides datasets, the review has also incorporated case studies that show real-world applications of deep-learning-based PCI prediction, distress segmentation, and asset detection in diverse geographic contexts. The range of sources allowsthe study to reflect both emerging theoretical developmentsand practical implementation trends in automated roadway monitoring.

Table 1. Classification of Deep Learning Architectures Used in Reviewed Studies

Model Architecture	Primary Function	Representative Studies	Strengths	Limitations
CNN (e.g., ResNet, VGG, EfficientNet)	Pavement distressclassification, PCI regression	Savino &Tondolo(2023), George et al. (2022)	Strong spatial feature extraction; good for classification tasks	Limited ability to detect fine cracks without segmentation
U-Net and derivatives	Pixel-level pavement distress segmentation	Islam et al. (2024)	Accurate segmentation of cracks and markings; high spatial precision	Computationally expensive; sensitive to training data quality
YOLO / SSD	Roadway asset detection (signs, guardrails, poles)	Flores-Calero et al. (2024)	Real-time performance; high detection speed	Detects objects butlimited in segmentation detail
Transformer-based models	Semantic segmentation; multimodal integration	Di Summa et al. (2023)	Superior contextual learning; handles large images well	High training cost; requires large datasets
Ensemble/Multi-modal models	Fusion of LiDAR, RGB, and satellite	Bouwmeester et al. (2023)	Improved robustness and generalization	Increased complexity; requires multimodal data

Analytical Framework

The analytical system focuses on comparative analysis of deep-learning models' performance in imagery platforms, architecture families, and application domains. It compares imagery features-spatial resolution, spectral information, temporal frequency, and viewpoint geometry and model performance, which includes classification accuracy, mean Average Precision (mAP), F1-scores, Intersection-over-Union (IoU), and regression-based PCI predictions. Such an organized comparison allows determining what sources of imagery and what types of models would be most appropriate to a particular task, such as the segmentation of distress, the detection of assets, and the estimation of network quality at the PCI level.

Operational limitations, such as imagery cost, acquisition capability, resolution sensitivity, climatic variability, and interregional generalizability, are also included in the analysis because they have a significant impact on the performance of deep-learning models and the real-world application (Bouwmeester et al., 2023). To distinguish between CNNs, U-Nets, YOLO detectors, and Transformer-based models, the framework is used to determine the consistency of performance regardless of different imagery conditions. This methodical design facilitates holistic assessment, which connects the conventional computer vision measures with transportation engineering needs.

Inclusion and Exclusion Logic

This category included studies that applied deep-learning algorithms to categorize roadway assets, forecast pavement distress, or detect PCI or other imagery-based infrastructure assessment. The studies needed to be eligible, and therefore, they needed to employ high-resolution satellite imagery, street-view, unmanned aerial vehicle (UAV) imagery, or mobile mapping data to enable compatibility with the multiscale imaging central to this study.
Papers whose results were based purely on traditional computer vision algorithms (such as thresholding, edge detectors, etc.) or hand-crafted feature detectors were also eliminated unless they offered comparative information with respect to deep-learning algorithms. Other editions that did not contain quantitative performance-based measures, are not in English, or are not accessible in full text, were also deleted. This choice criterion provides analytical consistency and preserves the quality of the methodology of the literature reviewed.

Data Extraction and Synthesis

Data were extracted using a structured template that captured model architecture, image source, spatial resolution, performance measures, geographic setting, and application category. Model types were grouped into major deep-learning architectures, including CNNs, U-Nets, YOLO models, and Transformers. Imagery sources were classified as satellite, street-view, UAV, or mobile mapping systems (MMS) to enable platform-level comparisons. Performance metrics were standardized where necessary to facilitate cross-study comparison despite variations in evaluation protocols. The synthesis process involved organizing the extracted information into thematic categories that characterize the capabilities and limitations of each imagery platform and deep-learning approach.

Table 2. Imagery Platforms Compared by Resolution, Cost, Scalability, and Use Case

Imagery Platform	Typical Resolution	Cost and Accessibility	Scalability	Best Use Case
High-Resolution Satellite (WorldView, SPOT)	0.3–2 m	Moderate to high cost; commercial licensing required	Excellent for statewide or national coverage	Network-level PCI screening; roadway extraction
Street-View Imagery (GSV, Mapillary)	10–20 cm	Free or low-cost; crowdsourced	High but dependent on road access	Distress detection; traffic sign identification
Mobile Mapping Systems (MMS + LiDAR)	1–5 cm	High equipment and operational cost	Limited to local corridors	High-fidelity PCI assessment; 3D asset inventory
UAV Imagery	2–5 cm	Moderate cost; flexible acquisition	Good but limited by regulations	Project-level inspections; detailed crack mapping

EMPIRICAL RESULTS AND PERFORMANCE EVALUATION

Deep Learning for PCI Prediction

Deep learning has shown substantial potential for predicting PCI values from satellite and street-level imagery through two primary approaches: direct PCI prediction and indirect distress-based estimation. In the direct approach, regression or classification models are trained to predict PCI scores from entire pavement images without explicitly identifying individual distresses. CNN-based and hybrid regression architectures have demonstrated promising results, with studies reporting prediction accuracies exceeding 85 percent when high-resolution imagery is available at a network scale (George et al., 2022). In contrast, indirect estimation strategies rely on semantic segmentation or object detection to identify distresses such as cracking, rutting, and potholes, which are then translated into ASTM deduct values to compute PCI. U-Net and Transformer-based models have performed well in capturing distress geometry and severity, achieving high IoU and F1-scores across various datasets (Islam et al., 2024).

However, model performance is strongly influenced by imagery resolution, lighting variation, pavement material differences, and inconsistencies in labeling. A common limitation is poor geographic generalization, where models trained in a single region do not transfer well to areas with different climatic or construction conditions (Bouwmeester et al., 2023). Overall, the evidence indicates that deep learning holds considerable promise for automated PCI prediction, yet reliability remains closely tied to dataset diversity, image quality, and model architecture.

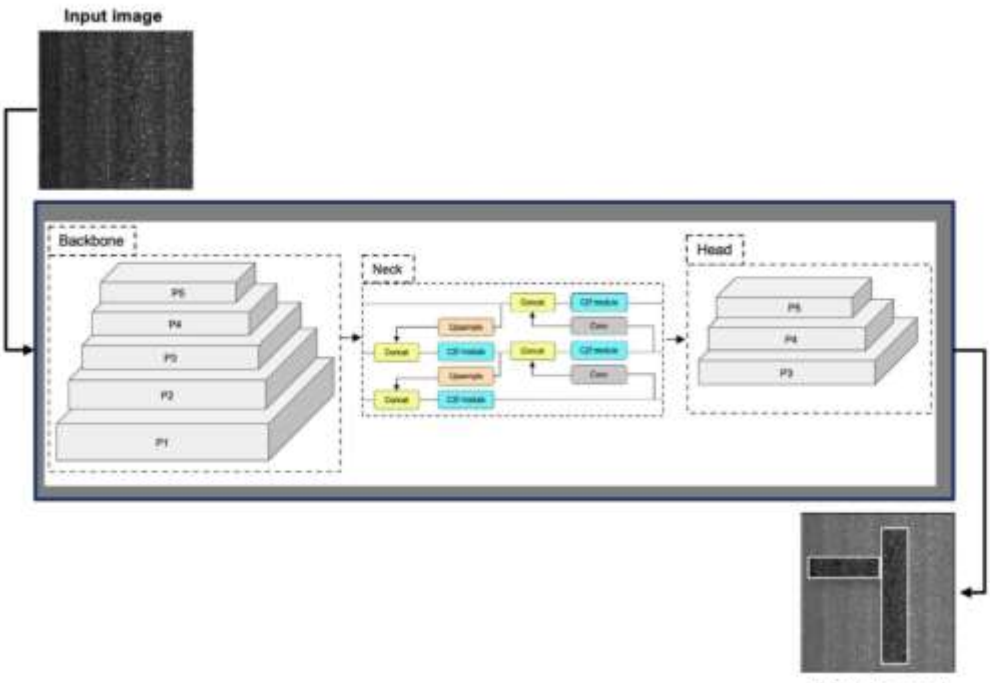

Figure 3. Workflow of Automated PCI Prediction Using Deep Learning, featuring direct regression and distress-segmentation pathways (Adapted from MDPI Sensors, 2024).

Satellite Imagery Results

Experiments with the WorldView-3, SPOT-6, and Sentinel-2 platforms show that deep learning models can categorize the state of roadway conditions and predict the PCI on a network scale (Zhang et al., 2020). Even though satellite images lack the resolution that identify micro-level distress, the use of multispectral information improves the recognition of surface deterioration patterns, including material oxidation and deterioration of texture. Several studies indicate classification accuracies greater than 90 percent when determining wide categories of pavements based on CNN-based architectures (Crespi and De Vendictis, 2009). Continued challenges have been low spatial resolution, shadowing, and vegetation occlusion, and the expense of high-resolution commercial satellite data. Such limitations render satellite imagery superior to macro-level screening in contrast to project-level PCI analysis that needs a millimeter-scale visibility.

Figure 4. Comparative Performance of Satellite, UAV, Street-View, and MMS Imagery for Pavement Assessment (Adapted from MDPI Sensors, 2025)

Street-View Imagery Results

Street-view images, including Google Street View (GSV), Mapillary, and MMS camera feeds, are always better at fine-grained examination of the pavement compared to satellite images because of their ground-level viewpoint and spatial resolution. U-Net and YOLO architectures with training on street-view data reach a high pothole detection accuracy, crack segmentation accuracy, and texture-based condition prediction; most of them show F1-scores exceeding 0.90 (Balali and Golparvar-Fard, 2015). GSV archives with time stampings have made longitudinal studies possible to monitor trends in deterioration and structural change with time. MMS systems offer other benefits by integrating LiDAR-cameras, enabling centimeter-level 3D pavement modeling and accurately measuring the dimensions of distress (Jung et al., 2020). The weaknesses of the street-view imagery are that it does not cover all rural areas, has spatial gaps between acquisition cycles, and is affected by natural blockers such as traffic, parked vehicles, or other environmental conditions.

Asset Classification Using Deep Learning

Deep learning has performed well on roadway asset classification based on both street-view and MMS data. Common models of object detection, like YOLO, SSD, and Faster R-CNN, obtain a mean Average Precision (mAP) score of over 95 percent on benchmark datasets like TT100K and Mapillary Vistas (Flores-Calero et al., 2024). In addition to traffic signs, deep-learning structures are useful in identifying guardrails, utility poles, lane markings, and traffic lights. Segmentation models based on transformers have enhanced the detection of lane markings because they capture long-range spatial-level dependencies, particularly in scenarios with low contrast or in pavements of poor quality (Di Summa et al., 2023). The 3D mapping with LiDAR can give a structural context that can enhance the strength of asset classification in urban settings that are densely populated. These findings indicate that deep learning can assist in providing automated and quality roadway asset inventories as per the Transportation Asset Management Plan (TAMPs).

Comparative Findings

Comparative analyses of imaging platforms show clear differences in their suitability for pavement assessment and roadway asset monitoring. Satellite imagery provides extensive geographic coverage and can be acquired cost-effectively at statewide or network scales, but its usefulness is constrained by lower spatial resolution and occlusions from shadows, vehicles, or vegetation. Street-view imagery offers greater spatial detail, yet its coverage depends on crowdsourced or agency-led data collection, resulting in inconsistent geographic availability. Mobile Mapping Systems (MMS) deliver the most precise and comprehensive three-dimensional surface information, making them ideal for project-level analysis; however, their operational complexity and high costs restrict large-scale deployment. Unmanned Aerial Vehicle (UAV) imagery occupies an intermediate position, offering high resolution and flexible deployment while being limited by flight regulations, battery life, and operational constraints. These trade-offs suggest that imagery selection should be guided by required spatial detail, desired coverage scale, and the institutional resources available for data acquisition and processing.

Synthesis of Trends

Recent developments show increasing interest in multimodal and multi-sensor fusion models that integrate satellite imagery, street-view imagery, UAV data, and LiDAR to leverage the strengths of each platform. Transformer-based architecture has also become more prominent, often outperforming traditional CNN models in tasks such as high-resolution segmentation and capturing long-range spatial dependencies (Di Summa et al., 2023). Self-supervised learning approaches are gaining attention because they reduce dependency on extensive manual labeling, which remains one of the most significant challenges in distress segmentation research. Despite these advances, data annotation continues to be a major bottleneck, particularly for pixel-level crack mapping where detailed ground truth is difficult and expensive to obtain. The literature highlights the need for standardized datasets, improved cross-regional generalization techniques, and greater use of temporal data to strengthen predictive performance and enhance operational reliability.

Table 3. Summary of Deep Learning Models with Performance Metrics

Model Type	Imagery Source	Application	Performance Metrics	Representative Studies
CNN Regression Models	Satellite Imagery (WorldView, SPOT)	Direct PCI Prediction	Accuracy up to 88%	Zhang et al. (2020); George et al. (2022)
U-Net Segmentation	Street-View / MMS	Crack Detection & Severity Mapping	IoU 0.85–0.93;F1> 0.90	Islam et al. (2024); Jung et al. (2020)
YOLOv5/YOLO v7	Street-View / UAV	Traffic Sign & Asset Detection	mAP> 95%	Flores-Calero et al. (2024)
Transformer Models	Satellite & Street-View	Semantic Segmentation; Lane Markings	Improved context modeling; F1 0.92–0.96	Di Summa et al. (2023)
Multimodal Fusion Networks	LiDAR+ RGB+ Satellite	3D Asset Classification; Distress Detection	Enhanced robustness; reduced false positives	Bouwmeester et al. (2023)

ANALYTICAL DISCUSSION AND INTERPRETATION OF RESULTS

Interpretation of Key Findings

The results indicate that deep learning has emerged as a highly effective method for roadway asset detection and pavement condition assessment across various spatial scales. Unlike conventional computer-vision approaches, deep-learning models learn hierarchical and context-sensitive representations directly from satellite and street-view imagery, enabling markedly improved performance (Savino and Tondolo, 2023). Satellite-based models are particularly advantageous for large-scale pavement condition screening due to their broad geographic coverage, frequent revisit cycles, and relatively low acquisition cost. When supplemented with multispectral information, these models can capture surface oxidation and coarse deterioration patterns, supporting reliable network-level PCI predictions (Zhang et al., 2020). However, their spatial resolution is insufficient for detecting the centimeter-scale distress features required for engineering-grade measurements.

In contrast, street-view imagery provides high-resolution visual detail capable of revealing fine-scale pavement defects such as cracking, rutting, potholes, and raveling. This level of detail enables U-Net, Transformer-based, and other segmentation-driven models to operate effectively within PCI estimation frameworks that rely on ASTM D6433 deduct values. Mobile Mapping Systems (MMS) equipped with LiDAR further advance distress measurement by generating highly accurate three-dimensional surface models, making them particularly suitable for project-level inspection and asset extraction

(Jung et al., 2020). Overall, the evidence suggests that deep-learning performance is optimized when the spatial resolution and contextual characteristics of the imagery align with the requirements of the evaluation task, with satellite imagery best suited for large-scale screening and street-view or MMS data most effective for high-fidelity pavement inspection.

Technical Challenges

Even though the findings are impressive, multiple technical problems limit the applicability of deep-learning-based roadway evaluation and its scaling. The issue of occlusion also stands out particularly in street-view images where cars, trees, shadows, and road infrastructure objects tend to cover pavements most of the time. Such interruptions reduce the degree of segmentation accuracy, although the model uses advanced attention processes (Islam et al., 2024). The other difficulty is the case of class imbalance in distress datasets, where cracks and potholes frequently absorb a small portion of the imagery compared to healthy pavement, and this causes the models to mis-classify the severe cases.

A major unresolved challenge is the geographic generalization of models. Deep-learning models developed in one region often perform poorly when applied elsewhere due to differences in pavement materials, construction practices, climatic conditions, and lighting environments (Bouwmeester et al., 2023). Platform incompatibility also complicates cross-source analysis: satellite imagery lacks the spatial resolution needed for accurate distress segmentation, while street-view imagery provides the required detail but does not offer global or uniform coverage. Another persistent limitation is the high cost of expert-labeled datasets. PCI-based annotation requires trained inspectors and substantial manual effort, and the limited availability of standardized benchmark datasets restricts reproducibility and slows model development within transportation agencies.

Platform-Level Trade-Offs

The comparative results show that there are obvious trade-offs transportation agencies need to consider when choosing imagery platforms to use for automated pavement evaluation. Satellite images are well-suitedfor statewide or regional screening since they have a high coverage at a relatively low cost and provide a regular acquisition frequency. Although it is good at determining large-scale trends of degradation, it cannot compute PCI in a detailed manner.

Street-view images have spatial fidelity and are more competent at identifying small-scale disasters and assisting asset cataloguing; this is especially true in the high-density urban road systems. Mobile Mapping Systems present optimal data quality at the project level analysis. Their combination of LiDAR and high-resolution cameras allows a centimeter level of both geometric and photometric accuracy, which renders them the best for engineering-grade PCI estimation and pre-construction documentation.

UAVs provide the benefits of a high-resolution, flexible method of localized inspections. Nevertheless, their scalability in extending their network reach is limited by regulatory limitations, short flight range, and battery size. In general, these platform-related trade-offs highlight the necessity of aligning the process of acquiring data with the coverage issues, accuracy needs, and organizational capacity.

Emerging Opportunities

The current disadvantages of automated roadway evaluation can be surmounted by using several new technologies. Self or weakly supervised forms of learning are potentially effective in reducing the necessity to use manually annotated data to enable models to learn structural representations by training on unlabeled images (Di Summa et al., 2023). These methods might significantly promote the process of generalization and minimize the cost of constructing a dataset.

Even the integration of LiDAR-cameras cannot limit the possibilities of accurate 3D definition of distress and asset identification by integrating geometrical depth information with visual features. Edge computing also provides additional development capabilities, allowing real-time deep-learning inference to be done on MMS vehicles and UAVs, as well as on mobile devices, reducing the time required to process and increasing the responsiveness of identifying hazards and emergency assessments.
Among the most transformative of them, predictive Digital Twin systems that use deep-learning outputs should be mentioned. Simulation of pavement deterioration process can be performed with the help of Digital Twins and can optimize maintenance timelines and support proactive asset management strategies with live image streams, historical business trends, environmental conditions, and predictive modelling (FHWA, 2020). Such trends in technology are designed to go towards more automated, connected, and intelligent roadway assessment ecosystems that can support next-generation transportation infrastructure management.

IMPLICATIONS FOR TRANSPORTATION RESEARCH AND INFRASTRUCTURE PRACTICE

Research on deep-learning applications for roadway monitoring offers several important considerations for agencies seeking to modernize their asset management practices. The demonstrated performance of deep-learning models across different imagery platforms highlights the value of multimodal data fusion. Integrating satellite, street-view, MMS, UAV, and LiDAR data within unified analytical frameworks can substantially improve predictive accuracy and support model transferability across regions with different pavement materials, climatic conditions, and construction standards. Another significant research gap lies in the lack of standardized benchmark datasets and consistent evaluation protocols. Uniform benchmarks for distress segmentation, asset classification, and PCI prediction are essential for advancing reproducibility, enabling meaningful cross-study comparisons, and supporting the development of machine-learning methods that agencies can confidently deploy at engineering-grade standards.

From a practical perspective, the findings suggest that transportation agencies can greatly enhance the efficiency of roadway monitoring by incorporating deep-learning-based image analysis into their asset management systems. Satellite imagery provides a scalable means of network-level pavement screening and can help identify priority corridors before investing in costly and time-consuming field inspections. Street-view and MMS imagery offer the high spatial detail required for reliable distress characterization and project-level PCI estimation. In particular, LiDAR-enhanced MMS data supports the generation of precise three-dimensional pavement models, improving deterioration forecasting and enabling more informed maintenance planning in alignment with Transportation Asset Management Plans (FHWA, 2020). These tools also help reduce reliance on manual windshield surveys, improving both operational safety and staff efficiency.

UAV-based imaging adds further flexibility, enabling targeted corridor assessments, rapid post-disaster inspection, and access to locations that traditional survey methods cannot easily reach. Although UAV operations face regulatory and logistical constraints, they provide a cost-effective means of collecting high-resolution imagery at local scales and can serve as a valuable complement to satellite, street-view, and MMS data in integrated, multi-scale roadway evaluation workflows.

Moreover, the implementation of deep-learning-based assessment systems requires adequate institutional capacity. Agencies must invest in staff training for imagery processing, model interpretation, and quality assurance, as well as in computing infrastructure capable of handling large-scale image workloads. Incorporating deep-learning outputs into real-time pavement performance models will support proactive maintenance planning, lifecycle optimization, and long-term budget forecasting as agencies transition toward predictive Digital Twin environments. These considerations underscore that successful adoption depends not only on technological advancement but also on organizational readiness to enable sustainable, accurate, and responsible automated roadway assessment practices.

CONCLUSION

Thisreview paper has evaluated the upsurge in the application of deep learning to both high-resolution satellite and street-view imagery to assess roadway assets and forecast PCI. The findings show that deep-learning algorithmsto be applied in managing the transportation infrastructure, provided that the source of images is adaptable to the spatial and contextual requirements of the task. Satellite images can also be utilized to screen pavement conditions over a large geographic space and yield valuable spectral information and are most appropriate where screening pavement conditions and prioritizing corridors on a macro level. It is not powerful enough to identify small-sized defects, yet the satellite-based methods maintain a high level of performance in terms of large-area classification and provide an efficient base to watch over a state (Zhang et al., 2020). Conversely, mobile mapping systems (MMS) and street-view images offer spatial data that is necessary in engineering-level distress detection. These high-fidelity platforms enable deep-learning models to localize cracks, potholes, and lane markings and roadway assets with accurate localization that is appropriate at project-level tests (Jung et al., 2020). The combined results confirm that the combination of various imagery platforms can generate an augmentative and operationally robust workflow of automated roadway assessment.

Other factors that continue to limit widespread adoption were also identified in this review. Model transferability remains a major challenge, since geographic differences in pavement materials, climate, and construction practices reduce cross-regional generalization (Bouwmeester et al., 2023). Additional technical issues, such as data occlusions, class imbalance, and inconsistent imagery resolutions, also affect performance across deep-learning architectures. The considerable effort required to generate high-quality ground-truth labels, particularly pixel-level distress annotations, makes it difficult to develop large and diverse training datasets. Even so, advances in self-supervised and semi-supervised learning provide promising pathways for reducing annotation requirements and improving long-term model performance across varied environments.

The reviewed studies generally conclude that deep learning represents a significant shift in automated roadway inspection and Transportation Asset Management. With integration into TAMPs, deep-learning-based imagery analysis can improve safety, reduce inspection costs, and support data-driven maintenance planning. Satellite imagery offers an efficient approach for network-level pavement screening, while MMS data, along with street-view, UAV, and LiDAR imagery, provide the detail required for engineering decisions at the project level. These technologies form the foundation of next-generation predictive maintenance frameworks, including Digital Twin environments that incorporate real-time imagery, historical PCI trends, and environmental predictors. Although further work is needed to standardize datasets, strengthen model generalization, and refine multimodal integration, current evidence suggests that imagery analytics powered by deep-learning methods will play an increasingly important role in roadway condition assessment and transportation infrastructure management.

FUTURE RESEARCH

The future of automated roadway evaluation will need to prioritize the development of scalable, generalizable, and multimodal deep-learning frameworks that can adapt to the wide range of conditions present in transportation networks across different regions of the world. A key research direction is the advancement of self-supervised and semi-supervised learning approaches that reduce reliance on labor-intensive, expert-labeled datasets required for distress quantification and for meeting standards such as ASTM D6433. Self-supervised learning offers the ability to train models that extract structural and textural pavement features from large collections of unlabeled satellite and street-view imagery, improving model performance and helping to mitigate challenges such as class imbalance (Di Summa et al., 2023).

Improving geographic generalization is another research priority. Deep-learning models often underperform when applied outside the regions where they were trained due to variations in pavement materials, construction practices, climate conditions, and traffic patterns (Bouwmeester et al., 2023). Addressing this limitation will require the creation of broad, standardized benchmark datasets that include satellite, street-view, UAV, and MMS imagery across multiple countries and roadway typologies. These datasets would also support more accurate PCI prediction and deterioration modeling when combined with environmental factors such as freeze-thaw cycles, precipitation, and traffic loading.

The multimodal data fusion is a significant future direction. Though earlier studies have addressed the integration of LiDAR, RGB, and multispectral imagery, there are limited studies that provide fully integrated architectures that could support real-time reasoning at the spatial, spectral, and geometric scales. Future research directions include Transformer-based fusion models and graph neural networks (GNN) to make it possible to analyze all of them in a single study, on a scale of corridors and networks. This concept of multimodal systems will be critical in driving predictive Digital Twin architecture, which will dynamically simulate the performance of pavements and make the best maintenance decisions.

There is also a need to improve real-time deployment capabilities. Advancements in edge computing, on-board graphics processing units (GPUs), and lightweight neural network architectures can enable near-instant crack detection, hazard recognition, and asset identification using MMS vehicles, UAVs, and roadside devices. Research on model compression, quantization, and efficient inference pipelines is necessary to maintain high accuracy under limited computational resources (Islam et al., 2024). These advancements would enhance rapid post-disaster assessment, continuous monitoring, and integration with smart transportation systems

Finally, future research should address the organizational and operational factors involved in adopting deep-learning-based assessment tools. This includes examining data governance models, interoperability requirements, and long-term cost–benefit considerations to support informed agency adoption. As transportation agencies shift toward automated and predictive infrastructure management ecosystems, studies that explore workforce training needs, lifecycle cost optimization, and environmental implications of improved maintenance planning will be crucial. Prioritizing these research directions will support the development of interdisciplinary and operationally viable systems for monitoring roadway conditions and managing transportation assets.

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