

AI-Driven Computer Vision for Pavement Distress Classification and Structural Degradation Mapping in Urban Highway Networks

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Abstract

Timely pavement condition assessment is essential for maintaining road safety and optimizing maintenance planning; however, conventional inspection methods remain labor-intensive, time-consuming, and often lack the capability for continuous large-scale monitoring. This study aims to develop an artificial intelligence-based pavement monitoring framework that integrates real-time pavement distress detection, Pavement Condition Index (PCI) estimation, and Geographic Information System (GIS)-based spatial visualization into a unified decision-support platform. The proposed framework employs a YOLO-based deep learning model for automated detection of multiple pavement distress types using vehicle-mounted camera imagery, followed by PCI computation and geospatial degradation mapping to support network-level pavement assessment. Experimental evaluation demonstrated that the proposed model achieved a composite precision of 0.923, recall of 0.881, mean Average Precision (mAP) of 0.769, and an average inference time of 8.4 ms, indicating its capability to perform accurate real-time pavement distress detection under diverse urban road conditions. The novelty of this research lies in the integration of AI-based pavement distress detection, automated PCI estimation, and GIS-based structural degradation mapping within a single low-cost vehicle-mounted inspection framework, enabling simultaneous condition assessment and spatial infrastructure management without relying on expensive inspection technologies. This integrated workflow provides a practical contribution by supporting maintenance prioritization, reducing inspection time, and improving data-driven pavement management for transportation agencies. The results demonstrate that the proposed framework offers an effective and scalable solution for intelligent pavement monitoring while extending the application of computer vision beyond object detection toward comprehensive infrastructure condition assessment and maintenance decision support.

Keywords: Artificial Intelligence, Computer Vision, Geographic Information Systems, Pavement Condition Index, Pavement Distress Detection.

I. INTRODUCTION

Road transportation infrastructure constitutes one of the most critical components of modern urban development, supporting economic activities, logistics distribution, and population mobility. The continuous growth of urban populations and the increasing intensity of freight transportation have substantially increased the operational demands placed on highway networks. Simultaneously, repeated traffic loading, temperature fluctuations, and moisture infiltration accelerate the deterioration of asphalt pavement surfaces and contribute to the formation of structural defects such as cracks, rutting, and potholes. These forms of pavement distress reduce ride quality, compromise traffic safety, and increase maintenance expenditures when left

untreated for prolonged periods. The need for reliable and timely pavement condition assessment has become increasingly important for transportation agencies responsible for maintaining large and complex urban road networks.

Recent advances in artificial intelligence and computer vision technologies have enabled automated pavement distress detection using image-based analysis and deep learning algorithms. Deep neural network architectures have demonstrated the capability to recognize and classify multiple categories of pavement damage with high levels of accuracy while significantly reducing dependence on manual visual inspections. (Alexis & Huereca, 2025) reported that YOLO-based detection models achieved strong performance in identifying pavement cracks and potholes under varying environmental conditions, while (Wu et al., 2025) demonstrated that optimized lightweight object detection architectures can maintain high detection accuracy with computational efficiency suitable for real-time deployment. A representative example can be observed along urban logistics corridors and industrial access roads, where repeated heavy axle loads frequently produce concentrated pothole formations and alligator cracking that require rapid identification to prevent structural deterioration from spreading to adjacent pavement segments.

Several limitations remain evident in the existing body of research. (Lv et al., 2025) demonstrated that lightweight object detection architectures can improve computational efficiency in pavement distress recognition; however, the study did not integrate detection outputs with pavement condition evaluation indicators such as the PCI. (Bai et al., 2026; Igwenagu et al., 2025) showed that high-resolution imaging and UAV-based monitoring approaches can provide accurate distress identification, yet these methods depend on costly acquisition systems and operational constraints that may hinder large-scale implementation in urban environments. Likewise, (J. Liu et al., 2026; López-González et al., 2026) highlighted the benefits of combining spatial information with advanced detection architectures, but the transformation of detected pavement defects into automated structural degradation maps remains insufficiently explored. Existing studies also provide limited attention to low-cost vehicle-mounted camera systems operating under highly dynamic urban traffic conditions characterized by heterogeneous pavement materials and varying illumination environments. Therefore, this study aims to develop and evaluate an AI-driven computer vision framework capable of automatically detecting pavement distress, estimating pavement condition, and generating spatial degradation maps for urban highway networks using low-cost vehicle-mounted imaging systems.

This study addresses the research question of whether a low-cost vehicle-mounted computer vision system integrated with GIS can provide reliable real-time pavement condition assessment in urban highway environments. It is hypothesized that the integration of lightweight object

detection models with spatial-temporal georeferencing and automated PCI estimation can achieve high detection accuracy while maintaining operational efficiency suitable for large-scale deployment. The novelty of this research lies in the unified integration of real-time distress classification, structural degradation mapping, and pavement condition estimation within a single end-to-end framework based on affordable imaging hardware. The expected outcome of this study is the development of a scalable and economically feasible monitoring solution capable of supporting proactive maintenance planning and improving decision-making processes in urban pavement management systems.

II. LITERATURE REVIEW

A. Pathology of Flexible Pavement Distress

The manifestation of distress in flexible pavement systems has long been associated with the interaction between traffic loading, material characteristics, and environmental exposure throughout the service life of road infrastructure. According to (Famewo & Shokouhian, 2025), pavement deterioration patterns tend to evolve progressively as a consequence of cumulative structural and functional degradation processes occurring within asphalt layers. (Louzi et al., 2026) observed that repeated axle loading contributes significantly to fatigue-related distress mechanisms, particularly alligator cracking that commonly develops within wheel paths subjected to high traffic intensity. Similarly, (Moretti et al., 2024) reported that temperature fluctuations and moisture infiltration frequently influence the formation and propagation of longitudinal and transverse cracking patterns in asphalt pavements. According to (Joumblat et al., 2023), rutting characteristics are commonly associated with permanent deformation within asphalt layers exposed to elevated temperatures and concentrated traffic loads. Furthermore, (Min et al., 2025) described pothole occurrence as a localized manifestation of material disintegration that frequently emerges following the progression of surface cracking and subsurface weakening mechanisms within flexible pavement structures.

B. Evolution of Object Detection Architectures for Horizontal Infrastructure Detection

The development of object detection architectures has experienced substantial transformation alongside the advancement of deep learning technologies and their application to infrastructure monitoring environments. According to (Islam et al., 2024), early region-based convolutional neural network architectures emphasized candidate region extraction prior to classification and localization processes. Subsequently, (Li et al., 2023) reported improvements in localization capability through the introduction of Region Proposal Networks that integrated feature extraction and object recognition within a unified framework. (Trigka & Dritsas, 2025) highlighted the emergence of single-stage detectors that reformulated object detection as a regression problem

and substantially altered inference characteristics compared with region proposal approaches. Meanwhile, (Zhou et al., 2024) emphasized the role of multi-scale feature representation in preserving semantic information for objects exhibiting considerable variation in size and appearance. More recently, (Lomandu, 2026) documented the increasing utilization of modern YOLO architectures in infrastructure inspection applications involving elongated, irregular, and low-contrast objects frequently observed on pavement surfaces and other horizontal transportation assets.

C. Effectiveness of Computer Vision in Automated Pavement Condition Assessment

The adoption of computer vision technologies in pavement condition assessment has become increasingly visible within transportation engineering literature over the last decade. According to (Shtayat et al., 2025), image-based pavement inspection approaches contributed to greater consistency in surface condition evaluation by reducing variations associated with observer interpretation during field surveys. (Değer Şitilbay & Yılmaz, 2026) reported that the availability of large-scale annotated pavement image datasets facilitated the emergence of data-driven distress recognition studies involving multiple damage categories in urban environments. Similarly, (Ou et al., 2026) observed that convolutional neural networks demonstrated sensitivity toward fine-grained surface characteristics associated with crack morphology and geometric variation. According to (X. Liu & Yin, 2025), deep neural networks exhibited the capability to differentiate visually similar pavement defects under varying illumination conditions and surface textures. In addition, (Meftah et al., 2024) noted the increasing appearance of vehicle-mounted imaging systems in studies involving continuous pavement monitoring activities along metropolitan transportation corridors.

D. Validity of Geospatial Data Integration for Infrastructure Maintenance Planning

The relationship between pavement condition information and geospatial representation has received considerable attention within infrastructure asset management research. According to (Thompson et al., 2025), spatial referencing enables the interpretation of pavement condition variability across transportation networks and administrative boundaries. (Chen et al., 2026) reported that the synchronization of positional information with image acquisition records facilitated the representation of distress occurrence patterns at both corridor and segment levels. Similarly, (Alsahfi, 2024) observed that geographic information systems support the visualization of spatial clustering phenomena associated with pavement degradation distribution. According to (Gagliardi et al., 2023), geospatial databases enable the observation of infrastructure condition changes across repeated survey periods and different maintenance cycles. More recently, (Theodorakopoulos & Theodoropoulou, 2026) emphasized the growing use of spatial analytics

within transportation asset inventories that combine condition information with geographic attributes and operational metadata. Comparative characteristics of these studies are summarized in Table 1.

Table 1. Comparison of Geospatial Integration Studies

Author(s) and Year	Geospatial Component	Dataset Type	Reported Spatial Capability
(Thompson et al., 2025)	GIS integration	Pavement survey records	Network-level pavement inventory representation
(Chen et al., 2026)	GPS synchronization	Image and positioning records	Segment-based distress localization
(Alsahfi, 2024)	GIS visualization	Pavement condition database	Spatial clustering representation
(Gagliardi et al., 2023)	Temporal geospatial database	Multi-period survey data	Infrastructure condition evolution tracking
(Theodorakopoulos & Theodoropoulou, 2026)	Spatial analytics	Transportation asset database	Integrated asset mapping and metadata association

III. RESEARCH METHOD

A. Proposed Integrated Vision-AI and GIS Framework

This study adopts a hybrid methodological approach that integrates temporal video streams acquired from pavement inspection vehicles with geospatial regularization mechanisms for spatial pavement assessment. The methodological design preserves the relationship between visual pavement observations and their corresponding geographic positions along urban highway corridors. Computer vision outputs are associated with geographic coordinates to represent pavement conditions at the network level rather than as isolated distress events. Temporal synchronization between image frames and positioning records associates distress occurrences with specific roadway segments and maintenance zones. The framework consists of sequential stages involving video acquisition, frame extraction, distress detection, condition estimation, and geospatial export for infrastructure management applications.

The interaction between each processing stage is illustrated in Figure 1. The framework begins with pavement inspection data collection using vehicle-mounted imaging systems operating continuously along urban arterial corridors. Video streams are decomposed into individual image frames while geographic coordinates and timestamps are synchronized to preserve spatial and temporal consistency throughout the analysis process. The extracted frames are subsequently processed by the Vision-AI engine to identify and localize multiple distress categories appearing on pavement surfaces. Detection outputs are converted into pavement condition indicators and integrated into GIS-compatible spatial layers used within infrastructure inventory systems and maintenance databases.

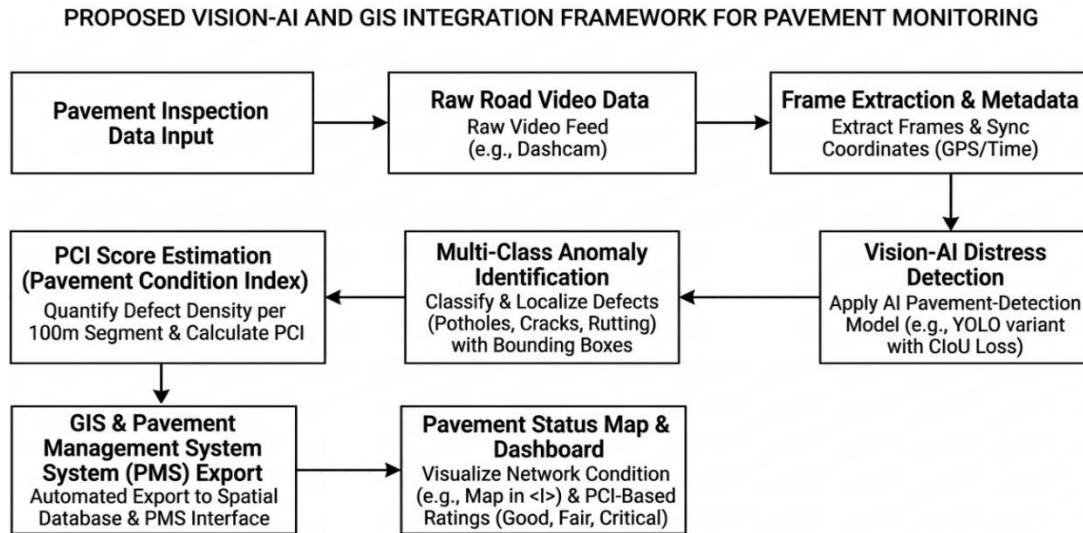


Figure 1. Proposed Vision-AI and GIS Integration Framework for Pavement Monitoring

Figure 1 illustrates a closed analytical pipeline connecting image acquisition, artificial intelligence inference, and spatial decision-support systems within a unified computational environment. The left side of the framework represents the data acquisition layer that receives continuous pavement observations from inspection vehicles operating under real traffic conditions. The central component contains the computer vision inference engine responsible for distress localization and multi-class anomaly identification using bounding-box representations. The subsequent processing stage processes detected defects into segment-level pavement condition measurements through PCI estimation procedures. The final stage exports condition information into GIS-compatible formats used for spatial visualization and Pavement Management System environments.

B. Characteristics of Urban Arterial Corridors and Camera Sensor Configuration

Dataset acquisition was conducted along urban arterial corridors characterized by heterogeneous traffic conditions and varying pavement degradation patterns representative of metropolitan transportation environments. The selected corridors include industrial access roads, ring roads, business districts, and coastal transportation links that experience different loading characteristics and operational demands. Variations in traffic density and pavement material composition generate diverse image characteristics required for robust distress representation within the dataset. The selected road segments also exhibit different maintenance histories and environmental exposure conditions that influence the morphology of surface deterioration. The selected corridors contain multiple distress classes observed under realistic operational conditions commonly encountered in urban highway systems.

The distribution of image samples and highway segment characteristics used in this study is summarized in Table 2. The dataset includes multiple arterial corridors exhibiting substantial differences in traffic volume, segment length, and pavement composition. Distress annotations were generated through manual verification procedures to maintain consistency between image content and damage classification labels. Traffic information and pavement material characteristics were recorded together with corresponding image observations and distress annotations. The image collection includes pavement deterioration conditions observed across multiple urban transportation environments.

Table 2. Image Dataset Distribution and Highway Segment Profiles

Segment ID	Highway Corridor Name	Segment Length (km)	Traffic Volume (AADT)	Registered Image Frames	Confirmed Distress Annotations	Primary Pavement Material
SEG-HW-01	Northern Ring Artery	12.5	45,000/day	8,500 frames	3,240 defects	Hot Mix Asphalt (AC-WC)
SEG-HW-02	Industrial Port Bypass	8.2	62,000/day	7,200 frames	5,110 defects	Heavy-Duty Polymer Asphalt
SEG-HW-03	Central Business District Corridor	5.0	28,000/day	4,100 frames	1,050 defects	Standard Asphalt Concrete
SEG-HW-04	Coastal Highway Link	15.1	33,000/day	10,200 frames	4,890 defects	Bituminous Macadam Base

Table 2 indicates differences in traffic intensity, pavement composition, and distress distribution among the selected highway segments. The industrial bypass corridor contains the highest number of confirmed distress annotations among all surveyed locations. The coastal highway segment contributes the largest number of image frames because of its longer inspection distance and extended survey coverage. Variations in pavement material composition are present across all highway corridors included in the study area. The dataset contains substantial variability in pavement appearance and distress morphology across different urban highway environments.

The acquisition system employed a nadir-view optical camera mounted on the front bumper of the inspection vehicle using a downward observation configuration. Camera positioning was selected to maximize pavement visibility while reducing the appearance of irrelevant roadside objects within the captured scene. The inspection vehicle maintained a relatively constant camera height throughout the survey process to preserve geometric consistency between image samples. The selected observation angle maintains pavement coverage while preserving the visibility of elongated pavement defects. The camera assembly was enclosed within a protective housing designed for continuous operation under outdoor transportation environments.

The physical arrangement of the camera sensor and its observation geometry are illustrated in Figure 2. The imaging system was positioned approximately 0.5 m above the pavement surface and oriented at a downward viewing angle of approximately 45° relative to the horizontal axis. This configuration produced an effective pavement capture width of approximately 1.5 m with image resolution characteristics suitable for representing fine pavement distress patterns. The field of view concentrated primarily on the pavement surface and excluded surrounding objects unrelated to road condition analysis. The acquisition geometry maintained the visibility of longitudinal and transverse crack patterns commonly observed on asphalt pavements.

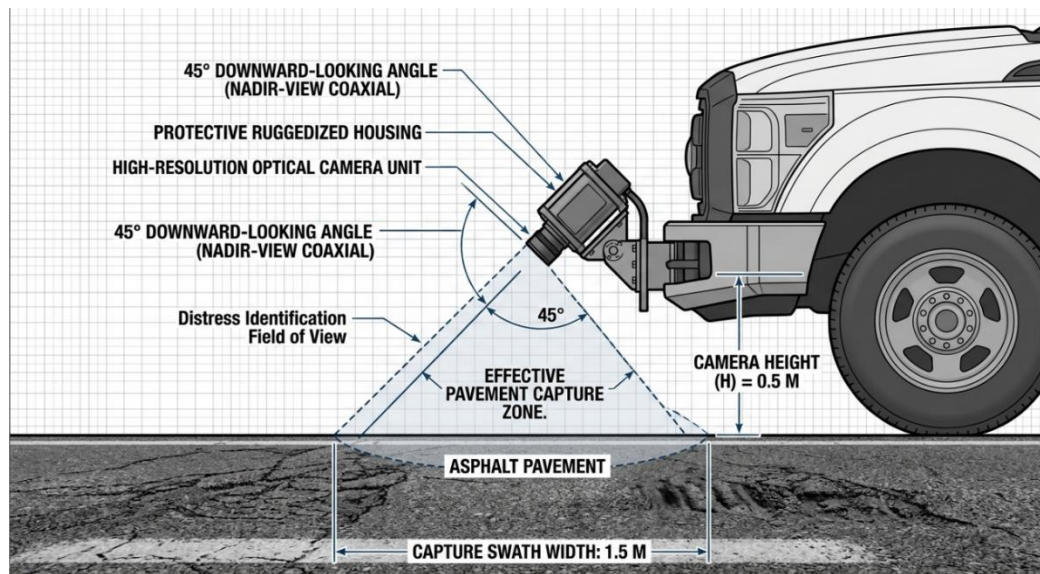


Figure 2. Nadir-View Camera Configuration on Inspection Vehicle

Figure 2 illustrates the geometric relationship between camera position, observation angle, and effective pavement coverage area during data acquisition operations. The downward imaging configuration minimizes the presence of vehicles, pedestrians, and roadside infrastructure within the captured image region. The captured image region contains fewer non-pavement objects across different highway environments. The fixed observation geometry maintains stable image scaling characteristics during bounding-box generation and distress localization processes. The image perspective preserves detailed surface texture information associated with cracks, potholes, and rutting phenomena.

C. Mathematical Formulation of the AI Detection Loss Function

The distress detection engine was configured to optimize both localization precision and classification consistency for multiple categories of pavement deterioration. The morphology of pavement defects differs substantially from conventional objects commonly encountered in general computer vision datasets because of their elongated geometry and irregular boundaries. Distress patterns such as longitudinal cracking and alligator cracking frequently exhibit extreme

aspect ratios and fragmented visual structures that influence localization behaviour during training. The optimization strategy maintains geometric sensitivity while preserving classification stability across heterogeneous distress categories. Particular attention was given to the representation of thin cracks and small defects occupying only a limited proportion of the captured image area.

The optimization process employs a composite objective function consisting of localization, classification, and objectness components. The total loss formulation adopted in the distress detection framework is presented in Equation (1).

$$L_{distress} = \alpha L_{box} + \beta L_{cls} + \gamma L_{obj} \quad (1)$$

where $L_{distress}$ represents the overall optimization objective of the pavement distress detection model, while L_{box} , L_{cls} , and L_{obj} denote the localization loss, classification loss, and objectness loss, respectively. The weighting coefficients α , β , and γ regulate the contribution of each optimization component during the training process and determine the learning behaviour of the network.

The localization component was formulated using Complete Intersection over Union (CIoU) to maintain geometric consistency between predicted and reference bounding boxes. The mathematical representation of the localization loss component is presented in Equation (2).

$$L_{box} = 1 - \text{IoU} + \frac{\rho^2(b, b^{gt})}{c^2} + \sigma v \quad (2)$$

where L_{box} denotes the localization loss associated with bounding-box regression, while IoU represents the overlap ratio between predicted and reference regions. The term $\rho^2(b, b^{gt})$ corresponds to the Euclidean distance between the center coordinates of predicted and ground-truth bounding boxes, whereas c denotes the diagonal length of the smallest enclosing box containing both regions.

The aspect-ratio consistency component was represented using an auxiliary geometric penalty term to accommodate elongated crack patterns commonly observed on asphalt pavements. The mathematical representation of the aspect-ratio regularization term is presented in Equation (3).

$$v = \frac{4}{\pi^2} \left(\arctan \frac{w^{gt}}{h^{gt}} - \arctan \frac{w}{h} \right)^2 \quad (3)$$

where w and h represent the width and height of the predicted bounding box, whereas w^{gt} and h^{gt} denote the corresponding dimensions of the ground-truth annotation. The variable v describes the discrepancy between aspect ratios of predicted and reference regions and characterizes geometric differences associated with elongated pavement defects.

The balancing coefficient associated with the aspect-ratio penalty was formulated to regulate the influence of geometric regularization during optimization. The coefficient used in the CIoU formulation is presented in Equation (4).

$$\sigma = \frac{v}{(1-\text{IoU})+v} \quad (4)$$

where σ denotes the adaptive weighting coefficient controlling the contribution of the aspect-ratio penalty component within the localization loss function. The relationship between IoU v determines the magnitude of geometric regularization applied during the bounding-box optimization process.

D. Hyperparameter Configuration of the Vision-AI Network

Model training was performed using GPU-accelerated computational resources configured for large-scale image processing operations. Hyperparameter selection considered both computational efficiency and the geometric characteristics associated with pavement distress morphology. The optimization process employed parameter constraints specifically adjusted to accommodate elongated crack structures and irregular pothole geometries. Training settings were maintained consistently throughout all experimental runs to preserve comparability between model iterations. Particular attention was given to localization precision and inference efficiency under practical deployment conditions.

Table 3. Hyperparameters of the Pavement-AI Detection Engine

Hyperparameter Category	Configuration Parameter	Assigned Value	Optimization Algorithm	Architectural Target
Optimization Base	Base Learning Rate (η)	1×10^{-3}	AdamW Optimizer	Stable Gradient Descent
Optimization Base	Momentum Coefficient (β_1)	0.937	Nesterov Momentum	Accelerated Convergence
Regularization	Weight Decay Parameter	0.0005	L2 Penalty Function	Overfitting Prevention
Training Bounds	Input Batch Size / Epochs	64 / 300	Mini-batch Stochastic Training	Maximum Hardware Utility
Resolution Bound	Native Resolution Anchor	640×640 pixels	Bilinear Resampling	Hairline Feature Preservation
Data Augmentation	Mosaic Augmentation Factor	Four-Image Blend	Random Spatial Crop	Background Noise Immunity

The principal training parameters and optimization settings used during model development are summarized in Table 3. These parameters regulate learning dynamics, regularization behaviour, and image representation properties throughout the optimization process. Resolution constraints and augmentation strategies preserve fine pavement texture characteristics while maintaining computational feasibility. The selected configuration operates under highly imbalanced distress distributions frequently observed in pavement datasets. These settings describe the operational

characteristics of the proposed Vision-AI engine. The learning rate and momentum parameters regulate parameter updates during iterative optimization cycles. The image resolution configuration determines the spatial representation of pavement defects during feature extraction operations. Augmentation settings introduce variations in texture, illumination, and pavement appearance across training samples. Regularization parameters and optimization constraints remain constant throughout all training experiments performed in this study.

IV. RESULT

A. Quantitative Evaluation and AI Network Performance Metrics

The computational performance of the proposed Vision-AI framework was evaluated to examine the sensitivity of feature extraction across multiple categories of horizontal infrastructure deterioration. Model evaluation was conducted using anchor box constraints specifically adjusted according to the geometric characteristics of asphalt pavement defects observed during field surveys. The assessment focused on four dominant distress classes consisting of alligator cracking, longitudinal cracking, potholes, and rutting. Performance measurements were obtained using precision, recall, F1-score, mAP, and inference speed indicators to capture both classification quality and computational efficiency. The evaluation process was performed under heterogeneous illumination conditions commonly encountered during urban pavement inspection operations.

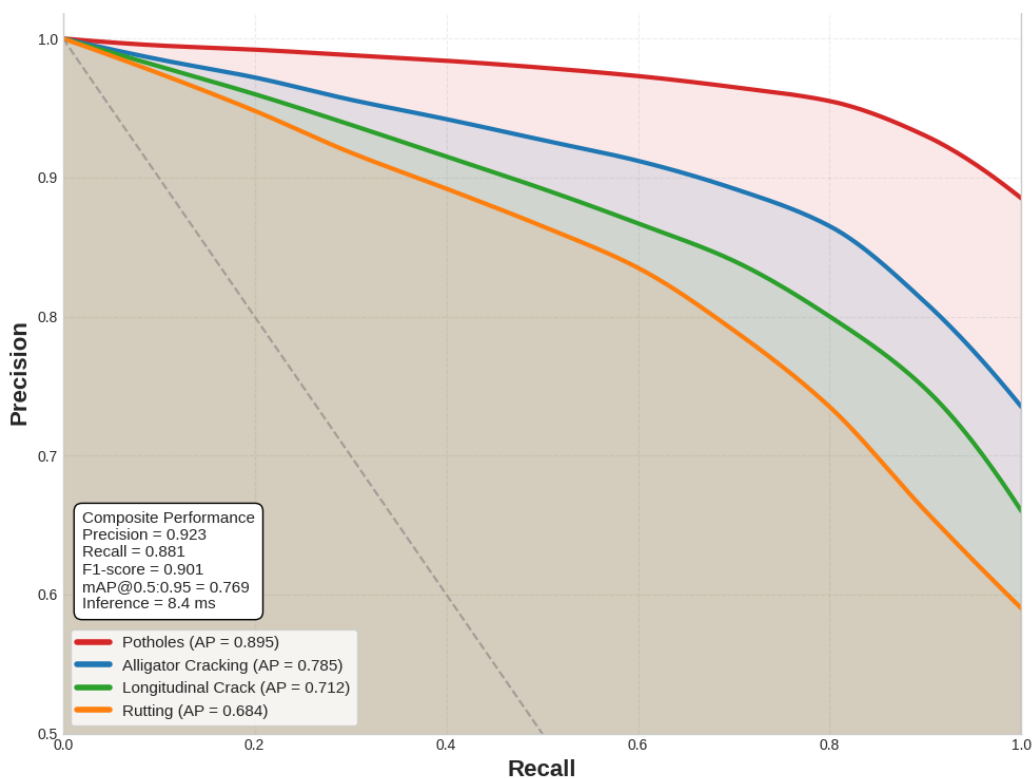


Figure 3. Precision-Recall Curves for Diverse Pavement Distress Classes

The overall classification behaviour of the proposed detection framework is illustrated in Figure 3 through class-specific Precision-Recall curves. The graphical representation compares the detection characteristics of each distress category under varying confidence thresholds. Differences in curve shapes indicate variations in feature separability and localization consistency among pavement distress classes. The graphical evaluation also provides an overview of the relationship between precision preservation and recall degradation as detection sensitivity increases. Composite performance indicators are displayed together with individual class performances to facilitate comparative interpretation between distress categories.

Figure 3 shows that pothole detection maintained the highest precision values across almost the entire recall range, indicating relatively stable feature discrimination characteristics for defects with strong texture contrast and clear geometric boundaries. The alligator cracking category exhibited comparatively stable precision behaviour despite the irregular morphology associated with interconnected crack patterns. Longitudinal crack detection demonstrated moderate reductions in precision as recall values approached higher thresholds due to the thin and elongated characteristics of the target objects. Rutting detection presented the largest decline in precision performance because of its gradual boundary transitions and low texture contrast relative to surrounding pavement regions. The composite performance curve remained above the majority of individual class curves and reflected stable behaviour across multiple distress categories.

A detailed numerical summary of the detection performance obtained for each pavement distress class is presented in Table 4. The evaluation metrics include true positive observations, false positive detections, precision values, recall values, F1-scores, mAP scores, and inference times. These indicators provide quantitative information regarding classification behaviour under different pavement textures and illumination conditions. Computational latency was also recorded to characterize operational suitability for continuous inspection environments. The collected metrics were aggregated using identical validation procedures across all distress categories.

Table 4. Detailed Multi-Class Detection Performance Under Variable Illumination Profiles

Evaluated Distress Class	True Positive (TP)	False Positive (FP)	Precision (P)	Recall (R)	F1-Score	mAP @0.5:0.95	Inference Speed
Alligator Cracking	1,120	85	0.929	0.895	0.912	0.785	8.5 ms
Longitudinal Crack	980	112	0.897	0.864	0.880	0.712	8.2 ms
Pothole	1,450	32	0.978	0.951	0.964	0.895	7.8 ms
Rutting	740	95	0.886	0.812	0.847	0.684	9.1 ms
Composite Framework	4,290	324	0.923	0.881	0.901	0.769	8.4 ms

Table 4 indicates that pothole detection achieved the highest precision, recall, and mAP values among all evaluated categories. The low false-positive count observed for potholes corresponds to the relatively distinct intensity contrast between damaged regions and surrounding pavement surfaces. Longitudinal crack detection recorded lower localization performance because of its narrow geometry and fragmented visual appearance. Rutting exhibited the lowest mAP score among the evaluated classes and showed longer inference times compared with other categories. The composite framework maintained an average inference speed of 8.4 milliseconds per image, corresponding to operational behaviour within real-time processing conditions.

B. Geometric Characteristics of Bounding Box Localization

The geometric behaviour of the proposed detection framework was examined through visual inspection of bounding box localization outputs generated from field-acquired pavement imagery. The evaluation focused on the spatial consistency of predicted regions across multiple defect geometries and surface textures. Particular attention was given to elongated crack structures and irregular distress boundaries that frequently challenge conventional object detection architectures. The CIoU-based localization mechanism was evaluated using distress patterns exhibiting substantial aspect ratio variations and fragmented appearances. Observations were conducted across multiple image samples captured under different pavement conditions and environmental contexts.

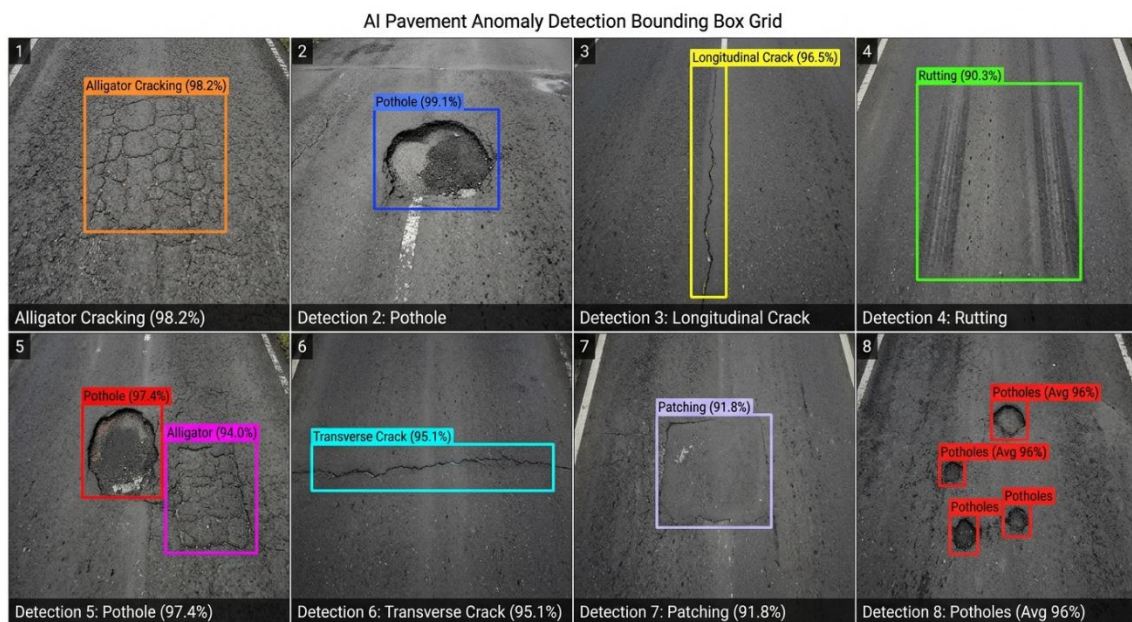


Figure 4. AI Anomaly Detection Bounding Box Outputs on Pavement Surfaces

Examples of the generated localization outputs are presented in Figure 4. The figure contains multiple pavement images annotated using color-coded bounding boxes representing different categories of structural deterioration. Each image illustrates the geometric relationship between

detected distress regions and their corresponding localization boundaries. The visualization also provides information regarding the spatial distribution and scale variability of pavement anomalies appearing within individual frames. The selected examples include distress categories exhibiting substantial differences in shape, orientation, and surface texture.

Figure 4 illustrates successful localization of alligator cracking, potholes, longitudinal cracking, transverse cracking, rutting, and patching regions using distinct bounding-box representations. Elongated crack structures remained enclosed within compact prediction regions despite exhibiting substantial aspect-ratio differences relative to potholes and localized surface defects. The predicted regions maintained spatial alignment with visible deterioration boundaries observed on the pavement surface. Shadow patterns and residual pavement markings were not enclosed by prediction boxes within the illustrated examples. The visual outputs also indicate consistent localization behaviour across pavement textures exhibiting different aggregate structures and surface reflectance characteristics.

C. Spatial Distress Quantification and Pavement Condition Index Estimation

Spatial distress observations extracted from synchronized video sequences were converted into deduct value parameters for segment-level pavement condition assessment. The quantification procedure was performed using fixed analysis intervals of 100 meters to preserve consistency between roadway sections. Distress density measurements were calculated using the proportion of detected defect areas relative to the inspected pavement surface. Dominant distress categories identified within each segment were subsequently associated with structural condition indicators. The resulting information was used to characterize deterioration patterns across multiple urban highway locations.

Table 5. Structural Degradation Log and Spatial Mapping Dataset Metrics

Spatial Segment Index	Coordinates (Lat / Long)	Dominant Distress Found	Defect Density (%)	Calculated PCI Score	Structural Rating Status	Recommended Remediation Action
LOG-SEG-101	(-6.9821, 110.4231)	Pothole Grouping	4.85	42.10	Poor	Patching + Overlay 40 mm
LOG-SEG-102	(-6.9832, 110.4245)	Hairline Longitudinal Crack	0.42	88.50	Good	Preventive Maintenance
LOG-SEG-103	(-6.9845, 110.4260)	Severe Alligator Crack	12.40	21.30	Failed	Full Depth Reconstruction
LOG-SEG-104	(-6.9858, 110.4278)	Moderate Rutting	2.15	64.00	Fair	Mill and Fill Surface
LOG-SEG-105	(-6.9870, 110.4291)	Smooth Surface	0.00	98.20	Excellent	Routine Inspection

The spatial degradation records generated by the proposed framework are summarized in Table 5. Each record contains geographic coordinates, dominant distress categories, defect density

measurements, PCI scores, and maintenance classifications. The table also includes remediation recommendations associated with the observed structural conditions. Geographic coordinates were synchronized directly from GPS metadata embedded within the inspection workflow. The resulting dataset provides a spatial representation of deterioration severity across multiple inspection segments.

Table 5 shows substantial variations in PCI values across the monitored highway segments. Segments characterized by severe alligator cracking exhibited the lowest PCI values and occupied the failed condition category. Sections containing isolated longitudinal cracks maintained comparatively high PCI values because of their lower defect density measurements. Pothole clusters generated intermediate PCI values and were associated with localized rehabilitation requirements. Smooth pavement sections without visible structural deterioration remained within the excellent condition category and required only routine monitoring activities.

D. GIS-Based Spatio-Temporal Visualization Dashboard

The final outputs generated by the computational framework were integrated into a cloud-based geospatial dashboard for large-scale pavement condition visualization. Spatial information extracted from synchronized GPS metadata was transformed into vector representations corresponding to individual highway segments. The dashboard environment combines distress localization outputs, PCI estimations, and maintenance indicators within a single visualization interface. Spatial color representations were used to distinguish different levels of pavement condition severity across the transportation network. Additional analytical panels were incorporated to display summary statistics and temporal monitoring information associated with inspection activities.

The operational characteristics of the proposed framework were further examined through comparison with existing pavement inspection methodologies currently used in urban transportation networks. The comparison considered differences in acquisition speed, computational latency, hardware requirements, operational expenditure, and privacy exposure characteristics. Survey approaches relying on manual observations and specialized laser profilometers were included to represent conventional inspection practices commonly adopted by infrastructure agencies. The proposed Vision-AI framework was evaluated under the same operational indicators to provide an equivalent comparison basis across all methods. The comparative benchmark is summarized in Table 6.

Table 6 indicates substantial differences in operational characteristics between conventional inspection approaches and the proposed framework. Manual surveys exhibit the lowest inspection productivity due to dependence on field personnel and manual documentation procedures. Laser-

based systems demonstrate high acquisition speeds but require specialized vehicles and post-processing workflows prior to data integration into maintenance databases. The proposed framework combines mobile image acquisition with automated processing and direct GIS synchronization within a single computational pipeline. The nadir-view camera configuration also restricts image acquisition exclusively to pavement surfaces and excludes identifiable human subjects or vehicle occupants from the recorded imagery.

Table 6. Operational Efficiency and Benchmark Analysis of the Proposed Framework Against Conventional Methods

Inspection Methodology	Equipment Requirements	Survey Speed Capacity (km/hour)	Processing Latency to GIS Data	Operational Cost Estimation	GDPR and Privacy Risk Exposure
Traditional Visual Survey	Manual Walking + Clipboards	1.5 km/h	3–5 Days (Manual Data Entry)	High (Labour Intensive)	None
Laser Road Imaging	High-End Profilometer Vehicle	60 km/h	24 Hours (Post-Processing)	Very High (Specialized Hardware)	Completely Anonymous
Proposed Framework (AI)	Bumper Camera + Edge Device	40–80 km/h	8.4 ms (Near Real-Time)	Low (Scalable Infrastructure)	Fully Exempt (Nadir-View Configuration)

The structure of the geospatial monitoring environment is illustrated in Figure 5. The dashboard contains an interactive urban road network map accompanied by numerical summaries describing network conditions and distress statistics. Segment colors represent pavement condition categories ranging from satisfactory to severely deteriorated conditions. Additional visual panels display examples of detected distress images and historical activity information obtained during inspection operations. The interface combines spatial visualization and operational statistics within a unified monitoring environment.

Figure 5 presents a network-level representation of pavement conditions using green, yellow, and red color gradients corresponding to different PCI categories. The map interface highlights clusters of deterioration distributed across major urban corridors and arterial connections. Summary indicators located beside the map report total monitored distance, cumulative distress counts, and aggregate condition statistics. Thumbnail images associated with detected defects provide visual references linked to corresponding spatial records stored within the database environment. Temporal monitoring panels display variations in defect reporting activity across inspection periods and geographic locations.

V. DISCUSSION

The findings demonstrate that the proposed AI-driven computer vision framework successfully achieved the primary objective of providing reliable real-time pavement distress detection while

simultaneously integrating PCI estimation and GIS-based structural degradation mapping. The overall detection performance, characterized by a composite precision of 0.923, recall of 0.881, mAP of 0.769, and an average inference time of 8.4 ms, indicates that the framework maintains both high predictive capability and computational efficiency under heterogeneous urban traffic conditions. These results reinforce previous studies reporting the effectiveness of YOLO-based architectures for pavement distress detection (Alexis & Huereca, 2025), while further supporting the observations of (Lv et al., 2025) regarding the advantages of lightweight detection models for real-time infrastructure monitoring.

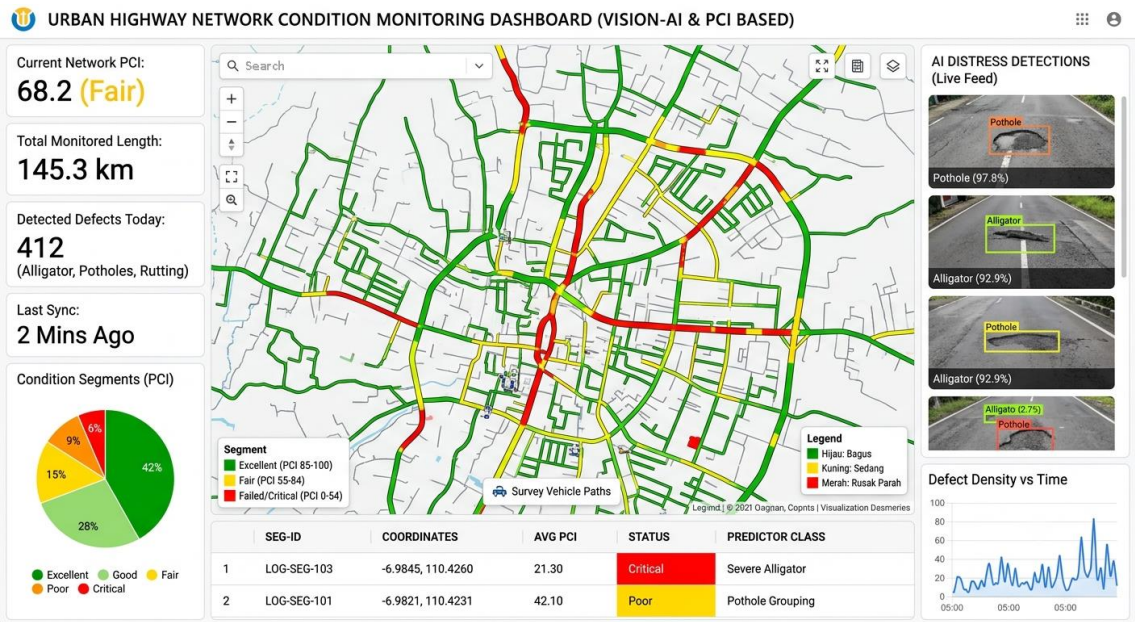


Figure 5. GIS-Integrated Pavement Distress Visualization Dashboard Interface

Unlike previous investigations that primarily emphasized object detection performance, the present study extends the analytical workflow by directly transforming detected distress into PCI-based pavement condition evaluation and spatial degradation mapping. This integration demonstrates that low-cost vehicle-mounted imaging systems are capable of supporting not only accurate distress recognition but also infrastructure-level decision support within a unified operational framework, addressing the knowledge gap identified in the existing literature.

The spatial degradation analysis further demonstrates that integrating computer vision outputs with GIS substantially enhances the practical value of pavement monitoring beyond conventional image classification tasks. The generated degradation logs successfully associated distress density with PCI values and maintenance recommendations, allowing pavement conditions to be interpreted at the network level instead of as isolated defect observations. These findings are consistent with previous research emphasizing the importance of geospatial integration for infrastructure asset management (Thompson et al., 2025), while extending the work of (Chen et

al., 2026) by providing automated synchronization between distress detection, condition assessment, and spatial visualization. The proposed framework also differs from UAV-based inspection approaches reported by (Bai et al., 2026; Igwenagu et al., 2025) by demonstrating that comparable monitoring functionality can be achieved using considerably more affordable vehicle-mounted cameras. This integrated workflow illustrates how computer vision, pavement engineering, and geospatial asset management can operate within a unified monitoring framework that supports large-scale urban pavement management activities.

Although the proposed framework achieved consistently high overall performance, noticeable differences were observed among individual distress categories, particularly for longitudinal cracking and rutting. Pothole detection achieved the highest precision and mAP because potholes generally exhibit stronger texture contrast and more clearly defined geometric boundaries than other distress types, which agrees with observations reported by (Ou et al., 2026) regarding the influence of visual characteristics on deep learning performance. Conversely, rutting produced the lowest localization accuracy and required slightly longer inference times, likely because gradual deformation boundaries and low surface contrast reduce feature separability during object detection. Rather than contradicting previous findings, this outcome is consistent with earlier observations that elongated or low-contrast pavement defects remain among the most challenging targets for automated vision systems (Lomandu, 2026). The variation in detection performance across distress categories reflects the influence of defect morphology on feature extraction and localization behaviour within deep learning-based pavement assessment.

Despite the promising results, several limitations should be acknowledged when interpreting the findings. The experimental dataset was collected exclusively from selected urban arterial corridors with asphalt pavement surfaces, which may limit the generalizability of the proposed framework to different pavement materials, rural environments, or extreme weather conditions. In addition, although heterogeneous illumination conditions were considered during evaluation, the dataset did not fully represent severe nighttime environments, heavy rainfall, or seasonal surface variations that may influence detection reliability. The PCI estimation procedure was derived from automatically detected distress characteristics rather than comprehensive field-based engineering inspections, which may introduce uncertainty when evaluating complex structural deterioration requiring subsurface assessment. These methodological constraints provide important context for interpreting the reported performance while also highlighting the applicability of the proposed framework for supporting maintenance prioritization, reducing inspection time, and improving decision-making processes within urban pavement management systems.

VI. CONCLUSION AND RECOMMENDATION

This study successfully developed and evaluated an AI-driven pavement monitoring framework that integrates YOLO-based distress detection, PCI estimation, and GIS visualization into a unified assessment platform. The experimental results demonstrated that the proposed framework achieved high detection performance, with a composite precision of 0.923, recall of 0.881, mAP of 0.769, and an average inference time of 8.4 ms, indicating its capability for real-time pavement condition monitoring. The integration of automated distress recognition with PCI calculation and spatial mapping provides a comprehensive workflow that extends beyond conventional image-based pavement inspection by supporting network-level infrastructure evaluation. The findings also confirm that a vehicle-mounted camera system can provide an efficient and cost-effective alternative to more expensive inspection approaches while maintaining reliable detection accuracy under diverse urban road conditions. Overall, the proposed framework contributes to intelligent pavement management by combining computer vision, geospatial analysis, and condition assessment into an integrated decision-support system for urban road maintenance.

Future research may improve the robustness of the proposed framework by expanding the training dataset to include various pavement materials, roadway classifications, weather conditions, and nighttime environments to enhance model generalization. Additional studies may also investigate the integration of advanced deep learning architectures, including transformer-based detection models and multimodal learning approaches, to improve the recognition of visually complex pavement distress such as rutting and longitudinal cracking. The incorporation of complementary sensing technologies, such as LiDAR, depth cameras, or unmanned aerial vehicle imagery, may further improve the accuracy of structural condition assessment while reducing uncertainty in distress localization. Future developments may also focus on incorporating predictive deterioration models and historical maintenance records to support preventive maintenance planning and long-term pavement asset management. Finally, validating the proposed framework across larger transportation networks and different geographic regions would provide broader evidence of its scalability and operational applicability for intelligent road infrastructure management.

AI Declaration

The authors used artificial intelligence tools, including ChatGPT, exclusively for language assistance during the preparation of this manuscript. The use of these tools was limited to improving grammar, sentence structure, readability, word choice, and the overall clarity of the text. Artificial intelligence was not involved in any part of the research process. All scientific aspects of the study, including the development of the research concept, study design, data

collection, methodological development, data analysis, interpretation of the results, and formulation of the final conclusions, were completed entirely by the authors. The authors assume full responsibility for the manuscript and confirm that its content is original, accurate, valid, prepared with integrity, and meets appropriate standards of scientific quality.

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