

EDGE NEURAL DETECTION AND WEB GEOGRAPHIC
INFORMATION SYSTEMS FOR AUTOMATED PAVEMENT DISTRESS
ASSESSMENT AND DYNAMIC LIFE-CYCLE COST ANALYSIS

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Abstract Continuous pavement assessment is required for sustainable highway management. Manual surveys are limited by subjectivity, delay, safety risks, and cost. Automated approaches can support objective and timely pavement assessment. This article presents an integrated method in which edge vision and global navigation satellite system (GNSS) telemetry are combined. A web geographic information system (WebGIS) is also included. Pavement condition index (PCI) prediction is linked with life-cycle cost analysis (LCCA). Pavement defects are detected through a hybrid deep learning approach. Physical defect areas are estimated through calibrated image transformation. Geospatial records are transmitted to the WebGIS platform. Pavement condition is predicted through a calibrated machine learning model. Independent test data are reserved for model evaluation. Regulatory thresholds are defined according to national pavement standards. Reactive and proactive maintenance strategies are compared over a long planning horizon. The results indicate reliable defect detection and PCI prediction. The proposed method provides rapid field assessment and geospatial reporting. Proactive maintenance provides lower lifecycle costs than reactive maintenance. Stable economic benefits are observed across the tested sensitivity cases.

Keywords: Pavement, deep learning, civil engineering, computer vision, edge artificial intelligence, You Only Look Once, life-cycle cost analysis, pavement management, simulation, applied mathematics, decision support, machine learning, intelligent transportation systems.

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1 Introduction

Trade, mobility, and regional access are supported by highway networks. Safe pavement conditions are therefore required. Automated pavement inspection is supported by recent artificial intelligence (AI) methods [1, 2]. Surface defects are detected by deep models [7, 14, 21]. On the other hand, manual pavement surveys are limited by delay, risk, and subjectivity. They are usually completed every two to four years and are associated with high costs. Pavement profiles and roughness are measured by laser-based inertial profilers [23, 24]. Results are displayed through geographic information systems (GIS) and cloud services [8, 22]. However, visual outputs are rarely converted into metric defect areas. Thus, distress density and pavement condition index (PCI) cannot be derived directly. PCI is commonly estimated from distress records [9, 11]. Life-cycle cost analysis (LCCA) is often separated from current pavement observations [10]. At the same time, national road standards are rarely linked directly to automated pavement detection results. Automobile Roads Design Requirements (ShNQ 2.05.02-23) provide requirements for road design [12], while Highway Condition Assessment Instructions (MShN 31-2007) support pavement condition and maintenance assessment [13].

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However, pavement observations, national standards, geospatial information, and life-cycle cost analysis are not usually combined within a single assessment process. This separation limits the direct use of field observations for condition assessment and maintenance planning. This study addresses this gap by connecting pavement detection with physical measurement, geospatial positioning, condition assessment, and cost analysis. Pavement defects are detected using a deep learning model, and inverse perspective mapping (IPM) is used to estimate their physical areas. GNSS telemetry provides the spatial position of detected defects, while a WebGIS supports their spatial reporting and visualization. The detected pavement distress information is further used for PCI prediction and LCCA. These components provide a continuous link from pavement observation to condition assessment and maintenance analysis.

The proposed method detects three pavement distress classes with 91.4% mean average precision at an intersection-over-union threshold of 0.5 (mAP@0.5). Each image frame is processed within 28.4 ms. The IPM-based area estimation has an error below 4.8%. The mean horizontal radial GNSS error is 0.38 m, and the measured telemetry latency is 320.0 ms. The PCI prediction model achieves an R^2 value of 0.968. Under the defined economic assumptions, the proactive maintenance strategy produces a 34.6% lower net present value (NPV).

The paper develops an integrated pavement assessment process that connects deep learning detection, IPM-based physical area estimation, GNSS telemetry, WebGIS, PCI prediction, and LCCA. The proposed IPM method converts image-based detections into physical defect areas, which are evaluated using independent measurements. The detected pavement distress is also connected with ShNQ 2.05.02-23 and MShN 31-2007 to support condition assessment and maintenance decisions [12, 13]. An automated PCI prediction model is developed using distress density, pavement age, and traffic information. Field observations are then linked to a 20-year LCCA to compare maintenance strategies under the defined economic assumptions. The integrated system is evaluated using detection accuracy, processing time, physical area error, GNSS positioning error, telemetry latency, PCI prediction accuracy, and life-cycle cost results.

2 Literature Review

Recent studies are grouped into three research areas. Vision methods form the first area. Geospatial systems form the second area. Lifecycle economics forms the third area.

2.1 Computer Vision and Object Detection Paradigms for Pavement Distress

Early systems are based on filters and morphological operations. Their reliability is reduced by shadows and texture changes. Localization is improved by Faster Region-Based Convolutional Neural Network (Faster R-CNN). However, substantial computation is required. Single-stage models are therefore preferred for rapid inspection. You Only Look Once (YOLO) methods are reported in [1]. Vehicle cameras are assessed in [2]. Long cracks remain difficult for local convolutions. Global relations are captured by transformer detectors [7, 14]. Difficult images are detected more accurately by these models. However, higher inference costs are imposed. Metric defect dimensions are omitted from most studies.

2.2 Multi-Sensor Fusion and Geospatial Infrastructure Mapping

Monocular depth limits are addressed through sensor fusion. Light detection and ranging (LiDAR) and red-green-blue (RGB) data are combined in [6]. Pothole volumes are then estimated from geometric depth. Tiny machine learning (TinyML) devices and acceleration sensors are assessed in [5, 17]. Detection outputs are connected with GIS [8, 22]. Connected mobile sensing is supported by vehicular intelligence [15]. However, costly hardware is required by LiDAR. High bandwidth and complex calibration are also required. Limited defect classification is provided by accelerometers. Long-term economic analysis remains absent.

2.3 Pavement Degradation Predictive Models and Life-Cycle Economics

Maintenance schedules are guided by PCI. PCI values range from zero to 100. Manual assessment requires detailed American Society for Testing and Materials (ASTM) D6433-24 classification. Condition is estimated from distress and contextual variables [9, 16]. Remaining service life and structural health are modeled through machine learning [25]. Deep learning supports pavement health monitoring and maintenance management [26]. Financial alternatives are compared through LCCA. Preventive treatments are evaluated in [10]. Reported defects are prioritized in [3]. However, static records are required by both approaches. Automated field data are not connected with lifecycle decisions.

2.4 Synthesis and Research Gap Identification

Five system capabilities are compared, as presented in Table 1. No reviewed study combines every capability. The proposed system is motivated by this gap. Detection transformer (DETR) methods are included in the comparison. Throughput is reported in frames per second (FPS). Artificial neural network (ANN) methods are also included. Multilayer perceptron (MLP) models represent predictive methods. The proposed detector uses a Real-Time Detection Transformer (RT-DETR) back end.

Table 1: Comparative analysis between existing literature approaches and the proposed integrated system.

Domain / system	Edge detection	Metric area	GIS telemetry	PCI prediction	LCCA
YOLO/DETR [1, 2, 7]	Yes, ≥ 30 FPS	No	No	No	No
LiDAR/TinyML [5, 6]	Partial	Yes	Partial	No	No
Vision + GIS [4, 8]	Yes	No	Yes	No	No
ANN + offline LCCA [9, 10]	No	Manual	No	Yes	Yes
Proposed system	RT-DETR, 35.2 FPS	IPM, m ²	Dual GNSS	Online MLP	20-year LCCA

3 Materials and Methods

Three connected levels are defined. Mobile vision is assigned to the first level. Cloud telemetry and WebGIS are assigned to the second. PCI prediction and regulatory LCCA are assigned to the third.

3.1 Mobile Probe Inspection Platform and Field Experimental Setup

Sensors are mounted on a Chevrolet Lacetti inspection vehicle. Images are captured by a Sony IMX290 camera at 1920×1080 and 30 FPS. A 6.0 mm lens is mounted 1.65 m above

pavement. A downward pitch of 21.5° is applied. Road distances from 3.5 m to 25.0 m are observed. Positions are measured by a dual-frequency ZED-F9P receiver. Radio Technical Commission for Maritime Services (RTCM) correction data are used. Networked Transport of RTCM via Internet Protocol (NTRIP) delivers the corrections. Cellular long-term evolution (LTE) provides the connection. All coordinates are referenced to World Geodetic System 1984 (WGS 84) and projected into Universal Transverse Mercator (UTM) Zone 42N. Fifty surveyed control points are used for comparison. Horizontal radial error is

$$e_i = \sqrt{(E_i - E_i^{\text{ref}})^2 + (N_i - N_i^{\text{ref}})^2}.$$

The mean horizontal radial error is 0.38 m. The empirical 95th percentile is 0.72 m. This percentile is denoted by R_{95} ; it is not defined as circular error probable. Vertical error is excluded. Edge inference is executed on Jetson AGX Orin using TensorRT 8.5 and 16-bit floating-point (FP16) precision. Camera data are transferred through GStreamer and GNSS data through Universal Serial Bus (USB).

3.2 Edge Deep Learning Architecture (RT-DETR/YOLO Hybrid)

A serial connection is denoted by the term hybrid. A YOLOv8 extractor is connected to an RT-DETR detector; an ensemble of independent detectors is not used. Frames are resized to 640×640 pixels. A YOLOv8 stem and four two-convolution cross-stage partial fusion (C2f) stages are used, with 3, 6, 6, and 3 bottlenecks and channel widths of 128, 256, 512, and 1024. Spatial Pyramid Pooling Fast (SPPF) is attached to the deepest stage. Feature maps P_3 , P_4 , and P_5 have strides 8, 16, and 32. A modified YOLOv8 C2f-SPPF backbone is therefore implemented; CSPDarknet53 is not used.

Each feature map is projected to 256 channels by a 1×1 convolution. One attention-based intra-scale feature interaction (AIFI) encoder layer is applied only to P_5 , using eight attention heads and a 1024-unit feed-forward layer. The encoded maps are combined by a cross-scale feature-fusion module (CCFM) with top-down and bottom-up paths. Three fused maps are supplied to the RT-DETR decoder. Six decoder layers, 300 object queries, a 256-dimensional hidden state, and eight attention heads per layer are used. Each query returns class probabilities and one normalized box. Queries are assigned through Hungarian matching. Varifocal classification loss, L_1 loss, and generalized intersection-over-union loss have weights 1.0, 5.0, and 2.0. Distribution Focal Loss and non-maximum suppression are omitted. The complete module sequence and information flow are presented in Figure 1.

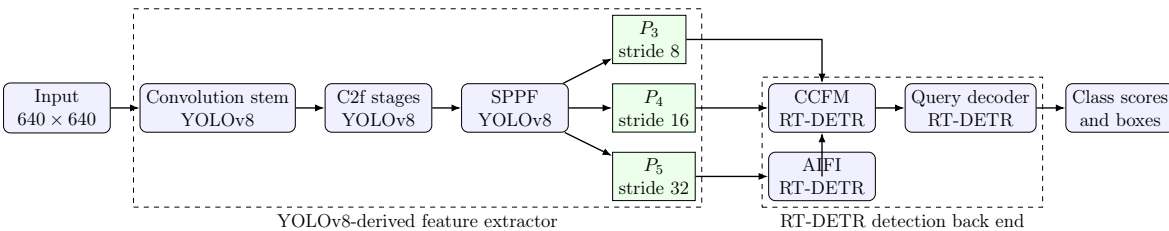


Figure 1: Module origin and exact information flow of the proposed YOLOv8-RT-DETR detector.

3.3 Dataset Characteristics, Augmentation, and Training Protocol

Video is collected across 42 km of Tashkent province highways, including M39, the Tashkent Ring Road, and collector roads. Several light, surface, and traffic conditions are repre-

sented. The dataset contains 4,850 verified images. Three distress classes are labeled in YOLO/Common Objects in Context (COCO) format. Road clips are separated to prevent data leakage. Model fitting uses 3,395 images, validation uses 728 images, and testing uses the remaining 727 images. Mosaic, MixUp, flips, hue-saturation-value shifts, and affine shifts are applied. PyTorch 2.1 and an RTX 4090 are used. AdamW is applied for at most 150 epochs with batch size 16 and early termination after 20 stagnant epochs.

3.4 Metric Area Conversion via Inverse Perspective Mapping (IPM)

Detection boxes are defined in image coordinates. Pixel area varies with distance, so a calibrated homography converts pixels into metric road coordinates:

$$\mathbf{P}_{\text{world}} = \mathbf{H}_{\text{IPM}} \mathbf{p}_{\text{img}} = (\mathbf{K} [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}])^{-1} \mathbf{p}_{\text{img}}. \quad (1)$$

The calibrated intrinsic matrix is $\mathbf{K}$. Rotation vectors are taken from $\mathbf{R}$. Pitch is fixed at 21.5° , yaw and roll at zero, and camera height at $H = 1.65$ m. Each box corner is projected onto the road plane. Polygon area $B_{c,j}$ is calculated by the Shoelace formula. Because sound pavement is included within rectangular boxes, box area is not used directly. Fill factors are estimated from field measurements; external fill factors are not adopted.

The calibration set contains 90 defects, with 30 defects per class and ten defects per class from each of three distance bands. Pothole boundaries are marked and measured as closed polygons. Crack area is calculated from centerline length and mean width, measured at five equally spaced sections. Reference area is $G_{c,j}$, and the coefficient is estimated by a median ratio:

$$f_c = \text{median}_{j \in \mathcal{C}_c} \left(\frac{G_{c,j}}{B_{c,j}} \right), \quad \hat{A}_{c,i} = f_c B_{c,i}.$$

The median limits effects from incomplete traces and irregular margins. The factors are 0.85 for potholes, 0.12 for longitudinal cracks, and 0.14 for transverse cracks. They are fixed after calibration and applied to 50 independent defects selected by stratified purposive sampling across all corridors, distance bands, and three severity levels. The set contains 18 potholes (six low, seven moderate, five high), 16 longitudinal cracks (six low, six moderate, four high), and 16 transverse cracks (six low, six moderate, four high). No validation defect is used for calibration, and their frames are excluded from model development. Mean absolute percentage area error is 4.8%.

3.5 Distress Density Formulation

The automated densities are predictor variables and do not replace the complete ASTM D6433-24 procedure. Certified engineers record all applicable distress types, severity, and density; distress deduct values and corrected deduct value are then obtained under ASTM D6433-24. The resulting PCI is the supervised target. National classes are assigned under MShN 31-2007. The detector observes only potholes and two crack types. Roads are divided into 100-meter segments, and segment area is calculated from length and paved width (typically 7.5 m or 15.0 m). Automated distress density for class k is

$$\text{DD}_k = \frac{\sum_{i=1}^{N_k} A_{k,i}}{A_{\text{segment}}} \times 100\%. \quad (2)$$

N_k is the detected defect count, $A_{k,i}$ the calibrated defect area, and A_{segment} the nominal paved area. Three density values, pavement age, and annual average daily traffic (AADT)

are supplied to the MLP. ASTM deduct values are represented indirectly through supervised calibration and are not reconstructed from the three densities. Other ASTM distress types are included in manual PCI but not detected by the present model. Predicted PCI is therefore an empirical surrogate, and manual reassessment is required for substantial unmodeled distress.

3.6 Cloud WebGIS Architecture and Telemetry Pipeline

A low-bandwidth process combines IPM results and GNSS coordinates by segment and produces a compact JavaScript Object Notation (JSON) record:

```
{“segment_id”: “UZ-M39-KM142”, “timestamp”: “2026-09-26T08:15:32.410Z”,
“gnss_start”: [41.2995, 69.2401], “gnss_end”: [41.3004, 69.2408], “dd_pothole”:
1.42, “dd_long_crack”: 3.85, “dd_trans_crack”: 2.10, “defect_count”: 14,
“survey_speed_kmh”: 68.4}
```

Records are sent through Message Queuing Telemetry Transport (MQTT), with Quality of Service level 1 over cellular LTE. An Eclipse Mosquitto broker receives each message. Records are stored in PostgreSQL 15 and PostGIS 3.3. Laravel, Blade, and Leaflet.js support the WebGIS service, which provides condition maps and defect heatmaps through browsers.

3.7 Continuous Pavement Condition Index Prediction via Multi-Layer Perceptron

PCI is estimated from 150 reference pavement sections, each 100 m long. Certified engineers assign manual values under ASTM D6433-24 and MShN 31-2007. Sections are grouped by survey corridor before division: 120 form the development set and 30 the held-out test set. Test sections are excluded from all model choices. Five normalized inputs are supplied:

$$\mathbf{X} = [\text{DD}_{\text{pothole}}, \text{DD}_{\text{long}}, \text{DD}_{\text{trans}}, \text{Age}_t, \text{AADT}]^T. \quad (3)$$

The network uses five input neurons; hidden layers of 64, 32, and 16 neurons; rectified linear units; batch normalization; 0.10 dropout; and one PCI output. Adam and mean squared error loss are used for at most 300 epochs with batch size 16. Feature statistics are estimated from development data only. Grouped five-fold cross-validation keeps complete corridors within individual folds. Hyperparameters and stopping epochs are selected from these folds. The selected model is refitted on 120 sections and evaluated once on 30 untouched sections. All baselines use the same protocol.

3.8 Regulatory Integration: ShNQ 2.05.02-23 and MShN 31-2007

ShNQ 2.05.02-23 provides current highway design requirements. It replaced ShNQ 2.05.02-07 on 14 October 2024 and is used for geometric and design context. Operational condition and maintenance classes are defined by MShN 31-2007. PCI values are not presented as proof of complete ShNQ compliance. Excellent condition is assigned above PCI 70, satisfactory condition between PCI 50 and 70, and lower values to poorer classes. Conventional treatment is often delayed below PCI 45, when costly structural repair is required. Microsurfacing alerts are issued between PCI 65 and 70. Crack sealing is scheduled after localized crack detection to limit moisture entry and extend pavement life.

3.9 Dynamic Life-Cycle Cost Analysis Formulation

A 20-year model estimates cumulative maintenance and rehabilitation NPV:

$$\text{NPV} = C_{\text{init}} + \sum_{t=1}^T \frac{M_t + R_t + U_t}{(1+r)^t} - \frac{S_T}{(1+r)^T}. \quad (4)$$

C_{init} is zero for existing assets; M_t , R_t , and U_t are maintenance, rehabilitation, and user-delay costs; r is the discount rate; and S_T is salvage value. A 3.0% real discount rate is adopted [19, 20]. Treatment effects follow two calibrated curves based on mechanistic-empirical practice [18], where τ is years since restoration:

$$\text{PCI}(\tau) = \begin{cases} 100 - 2.62\tau^{1.57}, & \text{new, overlaid, or reconstructed pavement,} \\ 90 - 1.35\tau^{1.57}, & \text{pavement restored by microsurfacing.} \end{cases} \quad (5)$$

New pavement reaches PCI 67.2 after five years and 44.4 after seven years. Microsurfaced pavement is restored to PCI 90 and reaches 67.5 after six years. Decisions are evaluated after each year:

$$\mathcal{A}(t) = \begin{cases} \text{major rehabilitation,} & \text{PCI}(t) \leq 45, \\ \text{microsurfacing,} & 65 \leq \text{PCI}(t) \leq 70, \\ \text{localized crack sealing,} & \text{PCI}(t) > 70 \wedge \text{DD}_{\text{crack}}(t) \geq \text{DD}_{\text{seal}}, \\ \text{routine maintenance,} & \text{otherwise.} \end{cases} \quad (6)$$

Crack sealing does not reset the deterioration clock. Microsurfacing resets PCI to 90 and major rehabilitation to 100. AADT is 18,000 vehicles/day, with 28% heavy vehicles. Uzbekistan 2024–2025 rates are: crack sealing 3.50 EUR/m, microsurfacing 12.00 EUR/m², overlay 38 EUR/m², reconstruction 110 EUR/m², and local repair 45 EUR/m².

The Year-14 composite rehabilitation applies full-depth repair to 556 m² and overlay to 14,444 m²:

$$C_{14} = 110(556) + 38(14,444) = 610,032 \text{ EUR} \approx 610,000 \text{ EUR}.$$

Full-depth reconstruction covers 3.7% of the segment and the combined treatment renews the complete surface. The Year-20 Strategy B overlay is a partial renewal covering 13,684 m² (91.23%):

$$C_{20,B} = 38(13,684) = 519,992 \text{ EUR} \approx 520,000 \text{ EUR}.$$

The remaining 1,316 m² comprises excluded junction tapers, bridge approaches, drainage zones, and renewed local areas. The unit price is unchanged. Treatment effects are

$$\text{PCI}_t^+ = \begin{cases} \text{PCI}_t^-, & \mathcal{A}(t) \in \{\text{routine maintenance, crack sealing}\}, \\ 90, & \mathcal{A}(t) = \text{microsurfacing}, \\ 100, & \mathcal{A}(t) \in \{\text{overlay, reconstruction}\}. \end{cases} \quad (7)$$

Localized crack density is reset by crack sealing, but no section-level PCI increase is assigned. The clock τ is reset by microsurfacing and major rehabilitation. The next annual PCI is generated by Equation (5). Mean condition uses annual pre-treatment values:

$$\overline{\text{PCI}}_s = \frac{1}{20} \sum_{t=1}^{20} \text{PCI}_{s,t}^-, \quad s \in \{A, B\}. \quad (8)$$

4 Results and Discussion

Field measurements and economic simulations are reported separately. Field tests cover 42 highway kilometers. Detection, telemetry, and PCI are assessed first; economic results are obtained from 20-year simulations.

4.1 Distress Detection Model Performance and Per-Class Evaluation

The independent test set contains 727 images and 2,180 reference defects. Precision, recall, F1 score, and average precision (AP) are calculated, with confidence intervals (CIs) from 1,000 bootstrap samples. An $\text{mAP}@0.5$ of 91.4% (95% CI: 89.8–92.7%) and $\text{mAP}@0.5:0.95$ of 68.7% are obtained. Pothole AP reaches 94.2%, longitudinal crack AP 90.1%, and transverse crack AP 89.9%. Lower crack scores are associated with dust and motion blur. The class-level detection results are presented in Table 2.

Table 2: Quantitative distress detection performance on the independent test dataset ($\text{IoU} = 0.50$).

Class	Instances	Precision	Recall	F1	AP@0.5	AP@0.5:0.95
Pothole	642	93.8	91.2	92.5	94.2	72.1
Longitudinal crack	824	89.6	88.4	89.0	90.1	67.4
Transverse crack	714	88.7	90.1	89.4	89.9	66.5
Global mean	2,180	90.7	89.9	90.3	91.4	68.7

4.2 Latency Decomposition and Real-Time Telemetry Performance

Complete telemetry latency is reported separately from inference latency. Five hundred M39 transmissions are assessed. Edge inference requires 28.4 ms, giving 35.2 FPS and exceeding the 30-FPS acquisition rate at 80 km/h. This comparison establishes only inference capacity: complete frame retention is not measured, and camera buffers, preprocessing, and transfer stages are not instrumented. Zero pipeline frame loss is therefore not claimed. MQTT transmission requires 282.5 ms, database storage 9.1 ms, and total latency is 320.0 ms.

PCI evaluation uses 150 manually assessed sections: 120 development sections and 30 independent test sections. Grouped cross-validation is restricted to development data, and each model is refitted on all development sections and evaluated once on untouched test data. The MLP achieves $R^2 = 0.968$, root mean square error (RMSE) 3.14, mean absolute error (MAE) 2.38, and mean absolute percentage error (MAPE) 3.82%. Multiple linear regression (MLR), support vector regression with radial basis function (SVR-RBF), and random forest regression (RFR) use the same split. Intervals are estimated from 1,000 test-set bootstrap samples. The held-out comparison of the four predictive models is presented in Table 3.

Table 3: Held-out PCI test performance (30 test sections; 120 development sections).

Model	Inputs	R^2 (95% CI)	RMSE (95% CI)	MAE	MAPE
MLR	5	0.814 (0.782–0.842)	7.62 (6.95–8.28)	5.88	9.40%
SVR-RBF	5	0.884 (0.858–0.908)	5.92 (5.34–6.48)	4.41	7.15%
RFR	5	0.921 (0.901–0.939)	4.85 (4.32–5.37)	3.65	5.91%
MLP	5	0.968 (0.954–0.979)	3.14 (2.76–3.52)	2.38	3.82%

4.3 System Configuration Scenario Analysis

The system-configuration scenario comparison is presented in Table 4; it is not a causal component ablation. All configurations use a 20-year horizon, a 3.0% real discount rate, and fixed traffic, area, and unit costs. Strategy A provides the baseline NPV of 1,240,450 EUR/km. Configuration 1 retains the reactive schedule. Configuration 2 adds GNSS and WebGIS targeting while retaining major treatment years; an assumed 15% reduction in duplicated local work produces an NPV of 1,188,351 EUR/km and savings of 4.2%. Configuration 3 adds metric IPM and PCI alerts, uses Equation (6) for surface treatments, and retains the reactive major rehabilitation schedule. Its NPV is 1,085,394 EUR/km, a saving of 12.5%. Configuration 4 applies Strategy B, including the Year-20 partial overlay, and produces an NPV of 811,280 EUR/km and savings of 34.6%. These savings follow the stated scenario assumptions and are not measured effects of individual software modules. Without IPM, area error exceeds 38%. Automated PCI calculation requires 1.8 ms per segment.

Table 4: Twenty-year system-configuration scenarios under common assumptions.

Config.	Vision	GNSS	IPM	MLP	PCI	LCCA	NPV/savings
1	Yes	No	No	No	No	No	1,240,450 EUR / 0.0%
2	Yes	Yes	No	No	No	No	1,188,351 EUR / 4.2%
3	Yes	Yes	Yes	Yes	No	No	1,085,394 EUR / 12.5%
4 (full)	Yes	Yes	Yes	Yes	Yes	Yes	811,280 EUR / 34.6%

4.4 Econometric 20-Year LCCA Simulation for State Budget Analysis

A 20-year simulation is applied to one highway kilometer with 15,000 m² paved area, 18,000 AADT, and initial PCI 100. Treatments are governed by Equations (5)–(7). Untreated PCI reaches 67.2 in Year 5 and 44.4 in Year 7. Strategy A applies a full-width overlay in Year 7 at a cost of 570,000 EUR and composite rehabilitation in Year 14: full-depth reconstruction of 556 m² and overlay of 14,444 m², costing about 610,000 EUR. Each major treatment resets PCI to 100.

Strategy B applies microsurfacing in Years 5, 11, and 17, resetting PCI to 90. Crack sealing is applied in Years 3, 9, and 14 based on localized crack-density triggers, not section-level PCI; the associated PCI values are 85.3, 78.1, and 82.4. The Year-20 overlay is terminal renewal and is not generated by Equation (6). It covers 13,684 m² and costs 519,992 EUR, rounded to 520,000 EUR. Strategy A reaches 1,240,450 EUR/km and Strategy B 811,280 EUR/km, saving 429,170 EUR/km or 34.60%. With $P_u(\tau)$ and $P_m(\tau)$ denoting the two deterioration functions, annual pre-treatment means are

$$\begin{aligned}\overline{\text{PCI}}_A &= \frac{2 \sum_{\tau=1}^7 P_u(\tau) + \sum_{\tau=1}^6 P_u(\tau)}{20} = 75.7, \\ \overline{\text{PCI}}_B &= \frac{\sum_{\tau=1}^5 P_u(\tau) + 2 \sum_{\tau=1}^6 P_m(\tau) + \sum_{\tau=1}^3 P_m(\tau)}{20} = 81.4.\end{aligned}\tag{9}$$

Crack sealing is omitted from Equation (9), because Equation (7) assigns no immediate PCI increase. The terminal overlay follows the final condition observation. The annual and discounted cash flows for both maintenance strategies are presented in Table 5.

Table 5: Twenty-year LCCA cash-flow comparison for a 1-km Class-I highway ($r = 3.0\%$).

Year	Factor	A annual	A discounted	A cumulative	B annual	B cumulative
1	0.9709	12,000	11,651	11,651	8,000	7,767
2	0.9426	15,000	14,139	25,790	8,000	15,308
3	0.9151	18,000	16,472	42,262	26,500	39,558
4	0.8885	25,000	22,213	64,475	10,000	48,443
5	0.8626	35,000	30,191	94,666	180,000	203,711
6	0.8375	48,000	40,200	134,866	8,000	210,411
7	0.8131	570,000	463,467	598,333	8,000	216,916
8	0.7894	12,000	9,473	607,806	8,000	223,231
9	0.7664	15,000	11,496	619,302	28,500	245,073
10	0.7441	20,000	14,882	634,184	10,000	252,514
11	0.7224	32,000	23,117	657,301	180,000	382,546
12	0.7014	45,000	31,563	688,864	8,000	388,157
13	0.6810	58,000	39,498	728,362	8,000	393,605
14	0.6611	610,000	403,271	1,131,633	30,000	413,438
15	0.6419	15,000	9,629	1,141,262	12,000	421,141
16	0.6232	20,000	12,464	1,153,726	12,000	428,619
17	0.6050	28,000	16,940	1,170,666	180,000	537,519
18	0.5874	38,000	22,321	1,192,987	10,000	543,393
19	0.5703	45,000	25,664	1,218,651	10,000	549,096
20	0.5537	55,000	30,454	1,249,105	520,000	837,020
Salvage	0.5537	-15,624	-8,655	1,240,450	-46,480	811,280

4.5 Multi-Parameter LCCA Sensitivity Analysis

Parameter uncertainty is assessed through eight cases: one baseline, three discount-rate cases, two treatment-cost cases, and two deterioration cases. Discount rates range from 2.0% to 5.0%, treatment costs change by 20%, and deterioration coefficients change by 25%. Proactive savings range from 28.4% to 39.1% and remain substantial at a 5.0% discount rate. Accelerated deterioration produces the largest savings. The results of all sensitivity cases are presented in Table 6. Probabilistic uncertainty analysis is not performed.

Table 6: Multi-parameter sensitivity analysis of cumulative 20-year LCCA expenditures.

Scenario	A NPV	B NPV	Savings	Savings (%)
Baseline, $r = 3.0\%$	1,240,450	811,280	429,170	34.60
$r = 2.0\%$	1,392,110	882,400	509,710	36.61
$r = 4.0\%$	1,112,680	750,220	362,460	32.58
$r = 5.0\%$	1,004,850	696,150	308,700	30.72
Unit costs +20%	1,488,540	973,536	515,004	34.60
Unit costs -20%	992,360	649,024	343,336	34.60
Deterioration +25%	1,520,300	925,600	594,700	39.12
Deterioration -25%	1,048,200	750,100	298,100	28.44

5 Conclusions

This article connects edge vision, GNSS, WebGIS, PCI, and LCCA for automated pavement distress assessment and dynamic life-cycle cost analysis. Field observations are linked with Uzbekistan maintenance standards. The detector achieves an mAP@0.5 of 91.4% and 35.2 FPS. IPM area error remains below 4.8%. Mean horizontal radial GNSS error is 0.38 m and telemetry delay 320.0 ms. The PCI model achieves $R^2 = 0.968$, RMSE 3.14, and MAE 2.38. MShN classes and maintenance alerts are assigned automatically. Proactive treatment reduces NPV by 34.6%, with stable savings across eight tested cases. The study's limitations include the followings. The image quality is reduced by rain, water, fog, and darkness. IPM estimates

are affected by steep grades and vehicle pitch. Only 50 defects are used for area validation and only 13 are high-severity cases. Although all classes and distance bands are represented, uncommon shapes remain insufficiently represented; the 4.8% error is therefore preliminary. Inference throughput is measured without complete frame tracking, so frame identifiers should be recorded across all pipeline stages. Only one vehicle is evaluated across 42 km. Larger fleet tests and class-balanced validation samples are required. Thermal and multispectral sensors should be assessed. Municipal vehicles and federated models could support wider data collection. Future LCCA studies should include multiple objectives, including costs, emissions, service quality, and delay.

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