



ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR INTELLIGENT ROAD CONSTRUCTION: A SYSTEMATIC REVIEW OF PAVEMENT MATERIALS, CONSTRUCTION QUALITY, MONITORING AND MAINTENANCE

Shreyash Sanjay Sangave¹, Varad Ravindra Thorat², Harshad Prakash Dakare³

^{1,2,3} Department of Artificial Intelligence and Machine Learning, Dr. D.Y. Patil Technical Campus Talsande, Kolhapur, India

Article Info

Article History:

Published: 07 Oct 2026

Publication Issue:

Volume 03, Issue 10
October 2026

Page Number:

118-127

Corresponding Author:

Shreyash Sanjay Sangave

Abstract:

Road construction is increasingly becoming a data-intensive engineering activity because modern projects generate information from laboratory tests, construction equipment, global positioning systems, cameras, ground penetrating radar, thermal sensors, unmanned aerial vehicles, traffic systems and pavement-management databases. Artificial Intelligence (AI) and Machine Learning (ML) provide methods for converting these heterogeneous data into predictions, classifications and decision-support outputs. This paper presents a structured review of AI/ML applications across the road-construction and pavement-management lifecycle, including asphalt mix design, soil and subgrade assessment, intelligent paving and compaction, construction monitoring, pavement inspection, distress detection, condition prediction, deterioration forecasting and maintenance prioritization. The review synthesizes recent peer-reviewed studies, with emphasis on the engineering problem addressed, data source, model family, reported benefit and deployment limitation. The evidence shows that computer vision and deep learning are prominent in automated distress assessment, while tree-based ensembles, support vector methods and neural networks are widely used for tabular prediction. Intelligent compaction combines sensing, positioning and machine learning to improve spatial monitoring of construction quality. Recent research is also moving toward explainable AI, physics-informed neural networks and road digital twins. However, the literature remains constrained by project-specific datasets, inconsistent reporting, domain shift, limited field validation, uncertainty and weak integration with established engineering workflows. The paper argues that AI should be deployed as an engineering decision-support layer, with independent validation, uncertainty assessment and professional judgment retained for safety-critical decisions.

Keywords: Artificial intelligence, machine learning, road construction, pavement engineering, intelligent compaction, computer vision, pavement management, explainable AI, digital twin.

1. INTRODUCTION

Road infrastructure is a long-life public asset whose performance depends on the interaction of materials, pavement structure, traffic, climate, drainage, construction quality and maintenance. The construction stage is particularly important because deficiencies in material selection, placement, temperature control or compaction can influence later pavement performance. Federal Highway Administration (FHWA) guidance identifies compaction as a critical pavement-construction process and notes that conventional methods can suffer from non-uniform material properties, moisture variation, temperature variation and limited feedback to roller operators [1].

Digital technologies are changing the way road assets are measured and managed. Intelligent compaction systems, for example, combine positioning, accelerometers, temperature sensing and onboard computation to provide spatial

information about roller passes and material response [1], [2]. At the same time, pavement inspection is moving from manual visual surveys toward automated data acquisition using vehicle-mounted cameras, laser systems, ground penetrating radar (GPR), LiDAR and other sensors [3], [4]. These developments create large datasets for machine-learning models.

AI/ML is attractive because road-engineering relationships are often nonlinear and involve many interacting variables. In asphalt construction, ML has been used to predict physical properties and support decisions related to construction scheduling and compaction. A 2024 systematic review identified 30 eligible peer-reviewed studies published between 2011 and 2023 and found wide variation in input variables, sensors and model choices. The review also found strong emphasis on artificial neural networks but insufficient evidence to conclude that ANN is consistently superior to alternatives, together with inadequate reporting of training and test data that limits generalizability assessment [5].

The objective of this review is therefore not to claim that AI replaces established pavement engineering. Instead, it is to map the engineering problems, data sources and AI/ML methods used across the road lifecycle; identify what has been demonstrated in research and what remains difficult in field deployment; and propose a lifecycle framework for trustworthy AI-assisted road construction.

Research Questions

- RQ1: What are the major applications of AI/ML across the road-construction and pavement-management lifecycle?
- RQ2: Which data sources and model families are used for different road-engineering problems?
- RQ3: What engineering benefits are reported, and what evidence supports those benefits?
- RQ4: What limitations prevent transfer from laboratory or project-specific studies to operational road networks?
- RQ5: Which emerging directions can improve the trustworthiness and practical integration of AI in road engineering?

2. REVIEW METHODOLOGY

This study is structured as a systematic evidence review. PRISMA 2020 is used as the reporting framework because it provides a checklist and flow-diagram structure for transparent reporting of systematic reviews [6]. The search strategy was designed around the intersection of artificial intelligence, machine learning, road construction, asphalt pavement, pavement monitoring and pavement management.

A. Search Strategy

Searches were performed using web-accessible records from major scholarly and institutional sources, including ScienceDirect, Springer, IEEE resources, ASCE-related publications, Taylor & Francis, MDPI, PubMed and official transportation-agency sources. Search combinations included: (artificial intelligence AND road construction), (machine learning AND asphalt pavement), (intelligent compaction AND machine learning), (machine learning AND pavement condition), (computer vision AND pavement distress), (GPR AND machine learning AND pavement), (physics-informed neural network AND pavement), and (explainable AI AND asphalt pavement).

B. Inclusion and Exclusion

- Included: peer-reviewed studies and authoritative technical documents directly addressing road construction, pavement engineering, pavement monitoring, pavement management or closely related highway applications of AI/ML.
- Included: review papers when they provided field-level synthesis, and original studies when they reported data, algorithms, evaluation or field evidence.
- Included: recent work through 2026 where it materially advances the state of the art.
- Excluded: studies unrelated to road/pavement engineering, purely generic AI papers without an engineering application, duplicate records, and claims that could not be traced to an identifiable source.

C. Evidence Extraction

For each selected study, the review records the road problem, data type, dataset scale where reported, preprocessing, model family, output, evaluation metrics, principal result, validation setting and stated limitation. Numerical performance is not treated as directly comparable across unrelated datasets. This is important because accuracy, RZ, RMSE, F1, IoU and other metrics depend on the dataset, label quality, test strategy and engineering context.

3. AI/ML FUNDAMENTALS FOR ROAD ENGINEERING

Supervised learning is common when road-engineering studies have labeled inputs and measurable outputs, such as pavement condition, material properties or defect classes. Regression predicts continuous quantities such as density, PCI or IRI, whereas classification assigns categories such as good, fair or poor pavement condition. Tree-based ensembles such as Random Forest and gradient boosting are useful for structured engineering data because they can represent nonlinear interactions without requiring the data to be transformed into images.

Deep learning becomes especially useful when the raw data are high-dimensional. Convolutional Neural Networks (CNNs) can learn visual features from pavement images. Object-detection models can locate defects, while semantic-segmentation models can identify defect pixels. Recurrent architectures such as LSTM can represent temporal dependencies in deterioration or sensor histories. The literature on pavement condition assessment reports substantial use of image classification, object detection and segmentation [3], [7].

Explainable AI (XAI) is increasingly relevant because engineering users need more than a prediction. A 2026 systematic scoping review of trustworthy XAI in asphalt pavement engineering identified 163 publications, including 73 core evidence studies, and found that XAI applications are relatively mature for performance prediction, material-property interpretation and mix-design analysis, while field validation, uncertainty-aware explanation and maintenance decision support remain less developed [8].

Physics-informed ML attempts to combine data-driven learning with engineering relationships or governing constraints. A 2025 pavement study used a physics-informed neural network with a fuzzy partial differential equation based on fatigue-cracking theory and compared it with back-propagation neural networks and XGBoost using ten years of deterioration data from a highway [9]. The motivation is important for civil engineering: a model should not only fit historical observations but should also remain consistent with known engineering behavior.

4. APPLICATIONS OF AI AND ML IN ROAD CONSTRUCTION

A. Asphalt Mix Design and Material Prediction

Asphalt mix design involves selecting proportions and gradations of binder and aggregate so that the resulting mixture satisfies specified volumetric and performance requirements. Conventional procedures require laboratory iterations. ML can act as a surrogate model between mixture inputs and measured properties. A 2024 study developed an interpretable ML framework using a database of 1,525 experimental mixture records, outlier detection and models including support vector regression, Random Forest and XGBoost. XGBoost performed best for the studied volumetric properties, while SHAP was used to interpret feature influence; the authors report a potential 70% reduction in the design procedure for their case study [10].

The engineering value is therefore not that laboratory testing becomes unnecessary. Rather, ML can reduce the number of candidate mixtures that require physical testing and help engineers understand which mixture variables influence predicted properties. Any model should remain within the range of materials represented by its training data and be experimentally validated before acceptance.

B. Soil and Subgrade Assessment

Subgrade and unbound-layer behavior strongly influence pavement performance. ML can model relationships between soil classification, moisture, index properties and measured strength or stiffness. Potential outputs include CBR, UCS, resilient modulus or compaction-related properties. The main advantage is rapid estimation where repeated testing or spatial

Characterization is expensive. The major limitation is spatial heterogeneity: a model trained on one soil population may learn local relationships that do not transfer to another geological or climatic setting.

C. Intelligent Paving and Compaction

Compaction is one of the clearest examples of intelligent road construction. FHWA describes intelligent compaction as an equipment-based quality-control technology using high-precision GPS, infrared temperature sensors, accelerometer-based measurements and onboard displays [2]. These systems can improve coverage and identify weak or poorly compacted areas rather than relying only on isolated conventional tests.

Recent research adds ML to the sensing layer. Wang et al. reviewed smart sensors including SmartRock, fiber Bragg grating and piezoelectric acceleration sensors and described ML applications involving regression, classification, clustering and neural networks for mechanical-property estimation and compaction assessment [11]. The review emphasizes that sensor robustness and extensive field validation remain unresolved issues.

A 2024 systematic review of ML in asphalt road construction similarly found a broad range of sensors and input variables but noted that reporting of training/test data is often insufficient to evaluate generalization [5]. Therefore, intelligent compaction should be understood as a combined sensing, positioning, modeling and decision-support system rather than simply an ML algorithm.

D. Computer Vision for Pavement Inspection

Manual pavement inspection is labor-intensive and difficult to scale over large road networks. ML-based computer vision

can classify or localize surface defects from images and video. CNNs are suited to image classification; object detectors such as YOLO-family models can localize individual defects; segmentation networks can estimate defect geometry at pixel level. Reviews of pavement condition evaluation show that image classification, object detection and segmentation have become major ML approaches for automated distress assessment [3], [7].

The engineering problem is broader than detecting whether a crack exists. A useful inspection system should estimate defect type, location, severity and extent and connect those measurements to a pavement-condition metric or maintenance rule. Lighting, shadows, water, dust, camera geometry, road texture and regional differences can create domain shift, so performance on a controlled dataset cannot be assumed to represent field performance.

E. GPR and Non-Destructive Pavement Assessment

Ground penetrating radar provides non-destructive information about pavement layers and subsurface conditions. A systematic review of more than 100 GPR-related road-pavement studies examined layer thickness, subsurface damage, moisture, cracking, delamination, subsidence and other features and highlighted ML/deep-learning approaches for intelligent interpretation [4]. ML is useful because GPR produces complex signals that are difficult to interpret with simple threshold rules.

The practical value of GPR+ML is its potential to complement surface imaging. Cameras primarily observe the surface, while GPR can provide information about internal structure. Multimodal systems combining these sources could therefore support more comprehensive pavement diagnosis, although sensor synchronization, calibration and ground-truth requirements remain significant.

F. Pavement Condition Assessment

Pavement condition assessment provides the bridge between inspection data and asset-management decisions. ML can predict condition indices, classify pavement sections and estimate distress severity. Recent research in India used a dataset containing 237 roads and 9,576 sample units and compared Random Forest Regressor, M5P, Decision Tree, multiple linear regression, Gradient Boosting, KNN and SVM regression for PCI prediction. The reported R^2 values for Random Forest and M5P were 0.96 and 0.95, respectively [12]. These values are evidence for that dataset, not a universal ranking of algorithms.

Another recent study developed an explainable PCI framework using LTPP data from 105 sections and 1,493 observations. XGBoost achieved a reported test-set R^2 of 0.923, while Random Forest achieved 0.912; SHAP identified IRI and pavement age among the strongest predictors [13]. The importance of this study is not only predictive performance but the attempt to provide an interpretable link between model outputs and engineering variables.

G. Pavement Deterioration and Performance Prediction

Pavement management requires predictions of future condition rather than only descriptions of present damage. Relevant outputs include IRI, rutting, cracking, PCI and other distress indicators. Traditional empirical or mechanistic-empirical approaches remain important, but ML can model nonlinear interactions among traffic, climate, pavement structure, material properties and maintenance history.

Recent deep-learning research has explored hybrid MLP-LSTM architectures for quantitative distress measures and severity classification, reflecting the need to represent both nonlinear relationships and temporal dependencies [14]. Physics-informed approaches provide another direction. Li et al. reported a PINN framework with a physics-based fuzzy constraint and ten years of pavement data, with improved physical consistency compared with BPNN and XGBoost in their study [9].

H. Maintenance and Rehabilitation Decision Support

Once condition and deterioration are predicted, AI can support maintenance prioritization. A 2024 review of ML in pavement management grouped the field into condition assessment, performance prediction and maintenance/rehabilitation decision-making and emphasized that data quality and interpretability remain key barriers [15]. A useful decision-support system should therefore combine predicted condition with traffic importance, risk, intervention cost, expected benefit and available budget rather than ranking roads by an ML score alone.

I. Road Digital Twins

Digital twins provide a framework for continuously linking physical infrastructure with a digital representation. Chen et al. reviewed ML methods for road digital twins and argued that condition assessment, distress detection and future-condition prediction can support proactive asset management [16]. For road construction, the digital-twin concept can connect construction records to the subsequent operational life of the pavement, reducing the separation between construction quality control and maintenance management.

J. Construction Cost, Schedule and Productivity

AI/ML can also be applied to construction-management variables such as cost, schedule, equipment utilization and productivity. These models can use historical project records, quantities, labor, equipment, weather and site characteristics to identify nonlinear relationships. However, cost and schedule prediction is highly organization-specific, so model transfer between contractors, regions and procurement systems requires careful validation.

5. COMPARATIVE ANALYSIS OF AI/ML METHODS

Method	Typical data	Road application	Main strength	Main limitation
Linear/Multiple Regression	Structured numerical	Baseline prediction	Simple and interpretable	Limited nonlinear capacity
SVM/SVR	Structured numerical	Property/condition prediction	Effective for limited datasets	Kernel and parameter sensitivity
Random Forest	Tabular	PCI, material, soil prediction	Robust nonlinear model	Less transparent than a single tree
XGBoost	Tabular	Performance/condition prediction	Strong tabular performance	Requires tuning; interpretability needs XAI
ANN/MLP	Tabular/time series	Material and pavement type prediction	Flexible nonlinear approximation	Data and tuning requirements
CNN	Images	Crack/distress classification	Learns visual features	Sensitive to domain and label quality
YOLO/Object Detection	Images/video	Pothole/distress localization	Fast detection potential	Small/rare defects and domain shift
U-Net/Segmentation	Images	Crack/defect area	Pixel-level measurement	Annotation intensive

LSTM/GRU	Timeseries	Deteriorationforecasting	Temporaldependency modeling	Long-termgeneralization
Transformer	Largesequence/multimodal	Advancedmonitoring	Long-rangerelationships	Data/computationaldemand
PINN	Data+physics	Deterioration/performanc	Physicalconsistency	Requiresuitablegoverningconstraints
SHAP/LIME	Model explanations	Decisionsupport	Makesmodelinfluence visible	Explanationsarenotcausalproof

6. ENGINEERING PROBLEMS ADDRESSED BY AI/ML

Conventionalproblem	AI/ML-enabledapproach	Potentialengineeringbenefit
Manual,periodicinspection	Computervision+mobile/UAVimagery	Fasterandmorescalableconditionsurveys
Trial-and-errormaterialdesign	MLsurrogate+optimization	Fewercandidatemixturesandfasterscreening
Non-uniformcompaction	GPS+accelerometer+temperature+ML	Spatialcompactionmonitoringandweak-spotidentification
Surface-onlyinspection	Camera+GPR/LiDARmultimodalsensing	Surfaceandsubsurfaceinformation
Reactivemaintenance	Deteriorationprediction	Earlierinterventionplanning
Budgetallocation	Conditionprediction+optimization	Priorityrankingunderconstraints
Unexplainedpredictions	XAI/SHAP	Greatertransparencyforengineeringusers
Data-drivenmodelviolatingphysicalbehavior	PINN/hybridmodeling	Improvedphysicalconsistency

7. BENEFITS AND ENGINEERING VALUE

The literature supports several recurring benefits, but they should be described as potential or demonstrated benefits within specific study settings rather than universal guarantees. First, AI can reduce manual information-processing effort by automating image classification, defect detection and data extraction. Second, ML can provide rapid surrogate predictions for material and pavement properties, reducing the need for repeated computational or experimental iterations. Third, intelligent compaction provides continuous spatial information that conventional spot testing cannot provide [1], [2]. Fourth, predictive models can support proactive pavement management by estimating future condition and helping authorities prioritize interventions [15], [16].

AI also creates opportunities for sustainability. Better mix screening, more targeted maintenance and improved construction control can reduce material waste, unnecessary interventions and equipment operation. These benefits, however, require lifecycle evidence. A model that improves prediction accuracy but requires costly sensors, extensive manual labeling or frequent retraining may not provide a net economic or environmental benefit.

8. CHALLENGES AND LIMITATIONS

A. Data Quality and Quantity

Road datasets contain missing measurements, sensor noise, inconsistent labels, different sampling intervals and heterogeneous construction practices. ML performance is therefore strongly dependent on the quality and representativeness of training data.

B. Generalization and Domain Shift

A model trained using one pavement type, camera system, climate, traffic pattern or geographic region may degrade when deployed elsewhere. The 2024 asphalt-construction systematic review specifically highlighted incomplete reporting of training/test data as a barrier to evaluating generalizability [5].

C. Data Leakage and Validation

Randomly splitting correlated observations from the same road section can produce overly optimistic performance. Road-specific or time-based separation should be considered when observations are spatially or temporally dependent.

D. Interpretability and Uncertainty

High predictive accuracy does not establish causality or engineering validity. XAI can expose influential features, but feature importance should not be interpreted as proof that changing one feature will cause a corresponding engineering outcome. Uncertainty estimates and out-of-distribution detection are needed for safety-critical deployment [8].

E. Field Validation

Research prototypes often use laboratory or project-specific data. Intelligent-compaction reviews emphasize the need for extensive field validation, and pavement-monitoring reviews note that ML-based evaluation has not yet achieved universal operational adoption by pavement-management agencies [3], [11].

F. Integration With Civil Engineering Practice

AI outputs must fit pavement specifications, quality-assurance procedures, maintenance-management systems and professional responsibilities. The correct role is decision support unless the system has been independently validated and formally accepted for automated control.

G. Cost and Maintainability

Cameras, GPR, LiDAR, edge computers and sensorized equipment create capital and maintenance costs. Model drift, sensor replacement and software updates add lifecycle costs that should be included in deployment studies.

9. RESEARCH GAPS

The literature indicates that the principal research opportunity is no longer simply to demonstrate another high-accuracy model on a new dataset. Instead, research needs to improve transferability, engineering trust and lifecycle integration.

- Standardized and openly documented benchmark datasets spanning different climates, pavement types, traffic levels and inspection systems.
- Cross-location and cross-season validation, particularly for Indian conditions where monsoon, heat, heterogeneous traffic and variable subgrade conditions can change the data distribution.
- Long-term field studies that quantify model drift, sensor changes, maintenance effects and real operational costs.
- Uncertainty-aware prediction and out-of-distribution detection for safety-critical decisions.
- Explainable models that connect predictions to physically meaningful road-engineering variables.
- Multimodal learning that combines images, GPR, GPS, traffic, weather, material and construction-process data.
- Integration of AI outputs with pavement-management systems and digital twins rather than isolated prediction demonstrations.
- Human-centered evaluation involving civil engineers, contractors and road agencies rather than algorithm-only benchmarks.

10. PROPOSED AI-ENABLED ROAD-CONSTRUCTION FRAMEWORK

Based on the reviewed literature, an AI-enabled road-construction framework should be organized as a closed engineering decision loop rather than a one-way prediction pipeline. The proposed framework has nine stages:

1. Data acquisition: laboratory records, construction equipment, GPS, temperature, accelerometers, cameras, UAV, LiDAR, GPR, traffic, weather and maintenance history.
2. Data quality control: missing-value handling, sensor calibration, label auditing, outlier detection and spatial/temporal consistency checks.
3. Feature representation: engineered engineering variables and learned image/signal representations.
4. Modeling: select an appropriate model family based on data type, sample size, task and deployment constraints.
5. Validation: use project-, road-, location- or time-separated testing when required to prevent leakage.
6. Trust layer: quantify uncertainty, detect out-of-distribution inputs and use XAI where decisions require explanation.
7. Engineering interpretation: compare predictions against specifications, physical behavior and independent measurements.
8. Decision support: recommend construction adjustment, inspection priority, maintenance action or further testing.
9. Human validation and feedback: civil engineers and responsible authorities approve actions; new field data are used to update the model.

The resulting architecture can be represented as: Road/Construction Data → Data Quality Control → AI/ML Model → Prediction/Detection → Uncertainty and Explainability → Engineering Validation → Decision Support →

Construction/Maintenance Action → New Data. This structure keeps AI inside the engineering control loop and avoids treating model output as an autonomous engineering decision by default.

11. FUTURE DIRECTIONS

Future intelligent road systems are likely to combine sensing, AI and asset-management technologies. Multimodal models can integrate surface images with GPR, LiDAR, traffic, weather and construction histories. Digital twins can provide a persistent digital representation of road assets, while AI continuously updates predictions as new observations arrive [16]. Physics-informed learning can constrain predictions using engineering relationships, while XAI can improve the transparency of model outputs [8], [9].

Edge AI is also promising for vehicle-mounted inspection because inference can occur close to the sensor, reducing dependence on continuous cloud connectivity. Autonomous or semi-autonomous construction equipment may eventually use AI for path planning, process monitoring and control. These technologies should be treated as emerging research directions rather than mature replacements for established construction practice.

For India, a high-value research direction is the development of representative road datasets covering urban and rural roads, different climates, monsoon conditions, pavement types, traffic compositions and construction practices. Recent Indian work on PCI prediction demonstrates that substantial road datasets can support ML-based infrastructure management [12]. The next step is not merely larger datasets, but datasets with transparent provenance, standardized labels, geographic diversity and longitudinal observations.

12. CONCLUSION

This review shows that AI and ML are being applied across a broad portion of the road-construction and pavement-management lifecycle. Applications include asphalt mix-property prediction, subgrade assessment, intelligent compaction, automated pavement inspection, GPR-based assessment, condition prediction, deterioration forecasting and maintenance prioritization. The literature demonstrates that different model families serve different data and engineering tasks: tree-based models are strong candidates for structured tabular data, deep learning is prominent for image-based inspection, sequence models support temporal prediction, and physics-informed approaches are emerging for engineering-consistent forecasting.

At the same time, the evidence does not justify a simple conclusion that AI is universally more accurate or more economical than conventional engineering. Model performance is dataset-dependent, and recent reviews repeatedly identify generalization, data quality, interpretability, field validation and integration as major barriers [3], [5], [8], [15]. The most credible future direction is therefore an AI-assisted road-engineering ecosystem in which sensing and ML improve information availability and prediction, while civil-engineering principles, standards, independent testing and professional judgment remain part of the decision process.

The principal research opportunity is to move from isolated demonstrations toward validated, multimodal and lifecycle-oriented systems. Such systems should be evaluated not only by predictive metrics but also by field robustness, uncertainty, cost, maintainability, engineering interpretability and actual decision outcomes. This shift can make AI/ML a practical component of intelligent road construction rather than merely a collection of laboratory prediction models.

References

- [1] Federal Highway Administration, "Intelligent Compaction Executive Summary," U.S. Department of Transportation, Tech Brief, FHWA.
- [2] Federal Highway Administration, "Intelligent Compaction Measurement Value (ICMV): A Road Map," U.S. Department of Transportation, Technical Brief.
- [3] S. Cano-Ortiz, P. Pascual-Muñoz, and D. Castro-Fresno, "Machine learning algorithms for monitoring pavement performance," *Automation in Construction*, vol. 139, art. 104309, 2022, doi: 10.1016/j.autcon.2022.104309.
- [4] "GPR monitoring for road transport infrastructure: A systematic review and machine learning insights," *Construction and Building Materials*, vol. 324, art. 126686, 2022, doi: 10.1016/j.conbuildmat.2022.126686.
- [5] J. Leukel, L. Scheurer, and V. Sugumaran, "Machine learning models for predicting physical properties in asphalt road construction: A systematic review," *Construction and Building Materials*, vol. 440, art. 137397, 2024, doi: 10.1016/j.conbuildmat.2024.137397.
- [6] M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, n71, 2021, doi: 10.1136/bmj.n71.
- [7] N. Sholevar, A. Golroo, and S. Roghani Esfahani, "Machine learning techniques for pavement condition evaluation," *Automation in Construction*, vol. 136, art. 104190, 2022, doi: 10.1016/j.autcon.2022.104190.
- [8] "Trustworthy Explainable AI for Asphalt Pavement Engineering: A Systematic Scoping Review of Materials, Performance, and Decision Support," *Journal of Sensor and Actuator Networks*, 2026.
- [9] J. Li, S. Zhang, and X. Wang, "Physics-informed neural network with fuzzy partial differential equation for pavement performance prediction," *Automation in Construction*, vol. 171, art. 105983, 2025, doi: 10.1016/j.autcon.2025.105983.
- [10] M. Dai, F. Zhang, S. Dai, C. Xing, S. Xiao, H. Lv, and Y. Tan, "Optimizing asphalt mix design through predicting volumetric properties using interpretable machine learning," *Powder Technology*, vol. 444, art. 119954, 2024, doi: 10.1016/j.powtec.2024.119954.
- [11] Y. Wang, J. Li, X. Zhang, Y. Yao, and Y. Peng, "Recent development in intelligent compaction for asphalt pavement construction: Leveraging smart sensors and machine learning," *Sensors*, vol. 24, no. 9, art. 2777, 2024, doi: 10.3390/s24092777.
- [12] S. Gowda, G. K. Pala, K. S. Gopalapurapu, and N. S. Kesana, "Predictive modelling of pavement condition index: A machine learning framework for infrastructure management," *International Journal of Pavement Engineering*, vol. 27, no. 1, art. 2666864, 2026, doi: 10.1080/10298436.2026.2666864.
- [13] "Explainable and economical AI-based approach for PCI assessment," *International Journal of Pavement Engineering*, vol. 26, no. 1, 2025, doi: 10.1080/10298436.2025.2531195.
- [14] A. Daneshvar and F. Moghadas Nejad, "Hybrid MLP–LSTM deep predictive modeling of pavement distress severity

- and density and condition indices,” *International Journal of Pavement Engineering*, vol. 27, no. 1, art. 2624565, 2026, doi: 10.1080/10298436.2026.2624565.
- [15] T. Tamagusko, M. G. Correia, and A. Ferreira, “Machine learning applications in road pavement management: A review, challenges and future directions,” *Infrastructures*, vol. 9, no. 12, art. 213, 2024, doi: 10.3390/infrastructures9120213.
- [16] K. Chen, M. Eskandari Torbaghan, M. Chu, L. Zhang, and A. Garcia-Hernández, “Identifying the most suitable machine learning approach for a road digital twin: A systematic literature review,” *Proceedings of the Institution of Civil Engineers—Smart Infrastructure and Construction*, vol. 174, no. 3, pp. 88–101, 2022, doi: 10.1680/jsmic.22.00003.
- [17] Y. Zhan et al., “Intelligent paving and compaction technologies for asphalt pavement,” *Automation in Construction*, vol. 156, art. 105081, 2023, doi: 10.1016/j.autcon.2023.105081.
- [18] “Intelligent pavement condition survey: Overview of current researches and practices,” 2024, review of automated data collection systems and AI methods for pavement condition survey.