AI-Driven Predictive Maintenance Frameworks For Asphalt Pavement Distress Identification And Repair Prioritization

Xiaochen Ruan

School of Water Transport and Land Transpotation Engineering, Wuhan Technical College of Communications, Wuhan, Hubei Province, 430065, China

Corresponding author. E-mail: ryanrxc@163.com

Received: May 09, 2026; Accepted: August 01, 2026

Accurate road pavement condition monitoring plays an important role in safe driving and pavement maintenance; while traditional methods depend only on images or tables independently, which can reduce accuracy and decision-making capability. In this paper, a joint approach based on image-based distress detection and tabular data mining is proposed to promote the pavement maintenance prediction and ranking. By utilizing the YOLOv11 object detection model to detect various road distresses including potholes, cracks, manholes and so on, a high detection performance is achieved with a mean Average Precision (mAP)@0.5, precision, recall, F1-score and Intersection over Union (IoU) at 0.9681, 0.9520, 0.9147, 0.9330 and 0.9681 respectively. The detection-derived features: Pothole Count (PC), Crack Density (CD), and Severity Metrics (SM), are then fused withtabular data: Pavement Condition Index (PCI), Annual Average Daily Traffic (AADT), International Roughness Index (IRI) and rainfall to predict maintenance demands, using the Light Gradient Boosting Machine (LightGBM) model, the results achieved a high performance with accuracy, precision, recall, F1-score, and Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) at 0.9914, 0.9962, 0.9867, 0.9914 and 0.9999 respectively. In the repair ranking module,road segments are prioritized according to prediction probability, damage severity and traffic conditions. Finally, the experiment has verified that multimodal feature fusion model could achieve higher accuracy and stronger robustness compared with tradition Random Forest (RF), Extreme Gradient Boost (XGBoost) and hybrid method.

Keywords: Pavement Maintenance; You Only Look Once version 11; Light Gradient Boosting Machine; Feature Fusion; Predictive Analytics; Repair Prioritization; Distress Identification

http://dx.doi.org/10.6180/jase.202612_35.028

1. Introduction

Infrastructure on roads is crucial for the development of the economy, the efficiency of transport, and for safety of people [1]. The asphalt on roads will be continually subjected to heavy loads of traffic and to the effects of weather, thus causing all kinds of deterioration; and deterioration will lead eventually to failure [2]. Therefore, it is important to identify and repair various forms of pavement deterioration in a timely manner so that further damage could be avoided, repair costs could be reduced, and road safety could be preserved [3]. Inspections of pavements using traditional methods are typically manual, take a long time, and there is always the risk for human error to occur, all of which limit the effectiveness of traditional inspection methods when applied on a large scale [4]. However, as artificial intelligence has developed and matured, there has been much interest in utilizing automated and data-based methods to improve the monitoring and maintenance of pavements [5]. The combination of computer vision and predictive analytics provides a means of detecting pavement damage in real-time and providing a proactive mechanism for making decisions related to road conditions.

Several limitations are evident in current pavement maintenance systems [6]. The manual traditional methods of inspection are labor intensive, and can be prone to human error. Many solutions have been suggested; however, this study integrates detection, prediction, and repair prioritization.

The main contribution is given as follows:

- Design a hybrid pavement distress detection and maintenance prediction system leveraging Road Damage Dataset and Pavement Condition Dataset.
- Implement a structured workflow comprising data acquisition, preprocessing, YOLOv11-based distress detection, feature extraction, feature mapping, and feature-level fusion with tabular attributes (PCI, AADT, IRI, rainfall).
- Apply advanced machine learning techniques by combining YOLOv11, LightGBM, and repair prioritization modules.
- Evaluate the performance using mAP, Precision, Accuracy, F1-score, ROC-AUC, and prioritization assessments.

The rest of the paper is organized as follows. The related works are reviewed in Section 2. Section 3 presents the proposed methodology. Section 4 discusses experimental results, and Section 5 concludes with future work.

More recently, Machine Learning has been applied with several disciplines for the purpose of better predicting pavement performance and fostering sustainable infrastructure development. Shuvo [7], applied AI and predictive models to identify factors affecting pavement performance, demonstrating that machine learning outperformed traditional statistical methods integrated IoT, attention-based deep learning, and digital twins for real-time monitoring and maintenance. However, most studies rely on large-scale datasets and lack integrated detection and prioritization frameworks for limited-data environments.

The present-day research on pavement engineering and infrastructure management needs to integrate artificial intelligence together with digital twin technology and sustainable materials to achieve better performance and maintenance solutions. Lu et al. [8], Sikhakhane-Nwokediegwu [9] and Kashesh et al. [10], demonstrated AI-driven digital twins and predictive maintenance, but their approaches require extensive datasets, complex integration, limiting deployment in low-resource environments.

Furthermore, researchers evaluated and developed methods for predicting friction based on machine learning and detecting objects in real-time via highlighting improvements in safety assessments and infrastructure monitoring. Various techniques such as cross-validation and feature importance analysis and adaptive learning methods have been applied to enhance both model robustness and performance. The research studies face two main challenges because they depend on small datasets which result in limited model generalization and because the high computational demands together with the absence of standardization make it impossible to use their models in large-scale applications.

2. Materials and methods

This Artificial Intelligence system combines computer vision and machine learning to evaluate pavement condition and perform predictive analysis of potential maintenance requirements. YOLOv11 detects pavement distress, while fused image and tabular data are classified using LightGBM to predict maintenance priorities, supporting data-driven infrastructure management, as shown in Fig. 1.

The proposed framework is multimodal, integrated and scalable system for Intelligent Pavement Management. The framework can be extended for autonomous infrastructure inspection via vehicle/road-based imaging, integrating road distress detection, predictive maintenance, repair prioritization, HDDT updates, and smart pavement monitoring for continuous large-scale roadway surveillance.

The research makes use of a Road Damage Dataset: Potholes, Cracks and Manholes [11] contain labeled road images enabling accurate YOLOv11 training for robust pavement distress detection. Roadway images for both Rome and Sacrofano were captured with the same cameras, namely the GoPro HERO7 and Samsung Galaxy A14, that are also different in characteristics, road appearance, and environmental conditions. Training YOLOv11 on diverse samples improves generalized pavement distress recognition across various roadway environments. In this work, predictive maintenance model for urban infrastructure systems was developed using Pavement Dataset [12].

The framework utilizes 3,150 road images and 2,800 tabular pavement records. The image dataset includes potholes (1,215), cracks (1,487), and manholes (448), while the tabular dataset contains 49.50% maintenance-required and 50.50% no-maintenance-required samples. Both datasets were divided into training (70%), validation (15%), and testing (15%) subsets. The image data were collected from Rome and Sacrofano to provide spatial diversity. YOLOv11 was trained only on the training subset, and image-derived

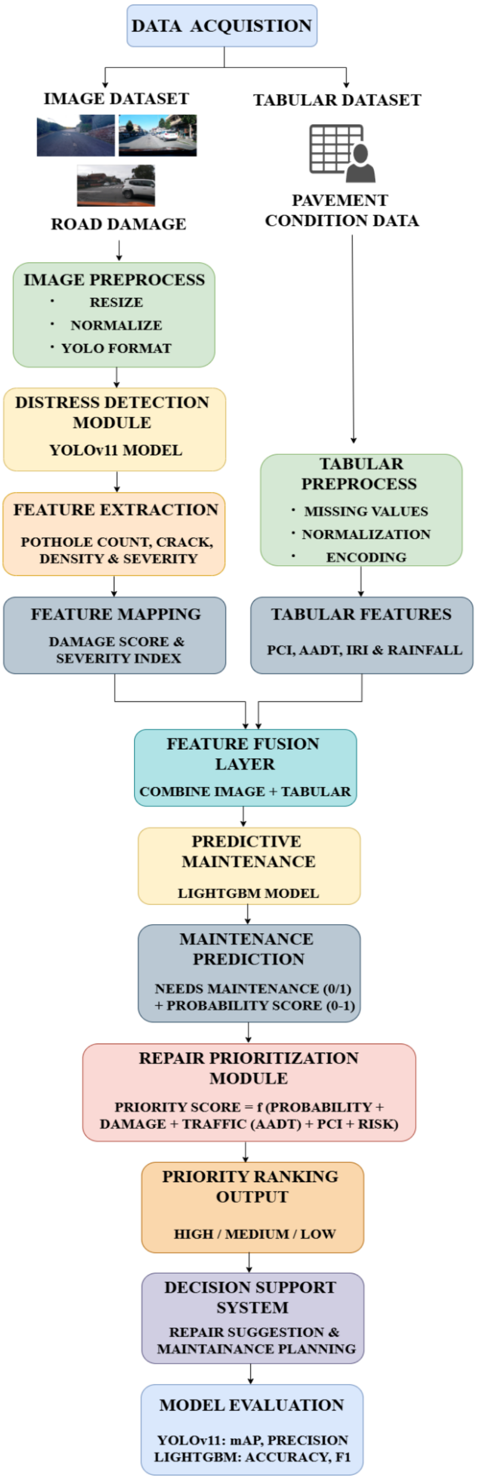

Fig. 1. Proposed Multimodal Framework for Pavement Condition Assessment and Maintenance Prediction.

features for the validation and testing subsets were extracted independently before LightGBM prediction. This ensured that no information was shared across dataset partitions, preventing potential data leakage.

Data preprocessing is an initial part involving resizing, normalization, missing-value handling, and feature encoding. The standardization of image size to 640×640 ensures uniform YOLOv11 input and efficient batch processing, represented by Eq. (1).

$$I_{resized} = Resize(I, H, W) \tag{1}$$

Where, I denotes original input image, W and H image width, height, output $I_{resized}$ refers transformed image resized to a fixed dimension.

Two alternative strategies for dealing with missing values in a structured data set are median replacement and KNN imputation. Median replacement reduces outlier effects, KNN imputes from neighbouring samples, while mean imputation ensures a simple, consistent preprocessing pipeline before feature fusion and LightGBM prediction.

The proposed framework takes into account environmental and structural pavement factors and their interactions in the prediction of maintenance. The prediction model integrates traffic loading, rainfall, pavement conditions, and image-derived distress characteristics for reliable pavement maintenance prediction and repair prioritization.

YOLOv11 was selected for effective accuracy-efficiency trade-off, supporting image-based distress detection, multimodal feature fusion, and LightGBM maintenance prediction.

The selection of detection backbone considered state-of-the-art models: YOLOv8 single-stage, Faster R-CNN better localization, transformers computationally intensive, YOLOv11 supporting multimodal LightGBM prediction. YOLOv11 is single-stage, using 640×640 input, CSP-inspired backbone, PAN-FPN for multi-scale fusion.

The backbone network consists of cascaded CSP layers learning pavement texture-to-semantic features, while PAN-FPN fuses multi-scale features detecting different-sized pavement distresses is shown in Fig. 2. The detection head predicts multi-scale bounding boxes, objectness, and class probabilities using bounding box offsets, represented by Eq. (2).

$$b_x, b_y = \sigma(t_x) + c_x, b_w, b_h = p_w e^{t_w}, p_h e^{t_h} \tag{2}$$

Where (t_x, t_y, t_w, t_h) network outputs, (c_x, c_y) gridcell offsets, (p_w, p_h) prior dimensions.

Table 1 demonstrates that CIoU achieved the highest Precision (0.952), Recall (0.915), F1-score (0.933), mAP@0.50 (0.968), and IoU (0.968), confirming its superior localization and detection performance compared with GIoU and DIoU. The confidence threshold was used to keep reliable

Table 1. Comparison of IoU Loss Functions

Loss Function	Precision	Recall	F1-score	mAP@0.50	IoU
GIoU	0.941	0.903	0.922	0.953	0.951
DIoU	0.947	0.910	0.928	0.961	0.960
CIoU (Proposed)	0.952	0.915	0.933	0.968	0.968

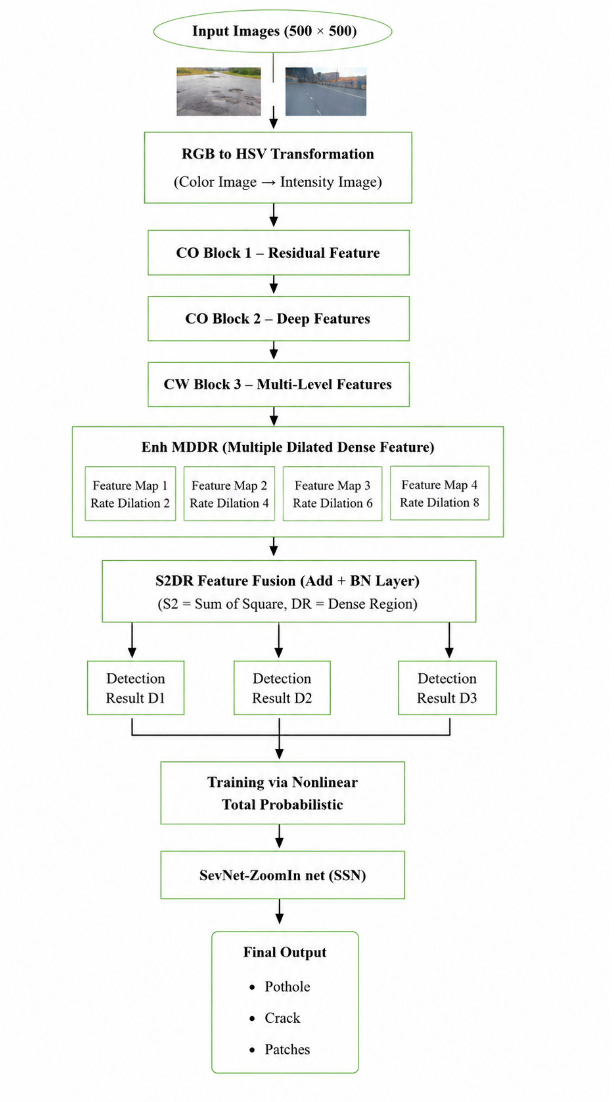

Fig. 2. YOLOv11 Architecture for Multi-Scale Road Damage Detection 1.

pavement distress detections and reject low-confidence predictions when making inferences. Then, Non-Maximum Suppression (NMS) removes redundant bounding boxes, retaining highest-confidence detections and providing consistent feature extraction inputs. The model YOLOv11 used Mosaic, Mixup, and Close Mosaic augmentations, with confidence threshold and Non-Maximum Suppression, improving generalization, localization reliability, feature extraction, and multimodal feature fusion. The diversity of pavement distress samples is further enhanced by small angle image rotation, brightness adjustment, motion blur simulation during training to handle camera orientation, lighting, enhancing YOLOv11 robustness across pavement inspection scenarios.

The total number of detected potholes PC for pavement damage assessment, shown in Eq. (3).

$$PC = \sum_{i=1}^{N} 1 \tag{3}$$

Here, (PC) represents total number of potholes detected, N denotes number of detected potholes bounding boxes from the YOLOv11 model.

Damage severity (DS) constructs several damage markers into one score denoted as Eq. (4).

$$DS = \alpha \cdot PC + \beta \cdot CD \tag{4}$$

Where, DS is combined metric, weighted combination of (PC) and (CD), where α and β are weighting factors. The weighting coefficients are applied to balance the relative impact of pothole severity and crack density on the severity score, because these distress types balance overall pavement condition without assuming different distress contribution weights.

The weighting coefficients were tried and tested during the process of designing the proposed framework to give a balanced contribution from potholes and crack density, ensuring consistent severity scores for feature fusion and LightGBM prediction.

The Severity Index standardizes damage scores for pavement assessment, shown in Eq. (5).

$$SI = \frac{DS_{score}}{DS_{\max}} \tag{5}$$

Where, (SI) is normalized damage score, DS_{score} is computed damage score, $DS_{\max}$ is maximum damage score. The normalization approach allows that the Severity Index can be compared between roadway segments having different pavement conditions and geographic characteristics, normalized severity enables generalizable, practical roadway implementation.

Feature fusion combines image-based and tabular features for accurate predictive maintenance. The distresses are computed and assembled into a structured image feature vector prior to the integration with the pavement attributes. This feature-level representation maintains YOLOv11 visual-features contextual-pavement-information supporting predictive maintenance.

The objective is to join both features to a single vector, an extension that allows the model to learn having more types of data (both visual and contextual) can be represented as Eq. (6).

$$F_{\text{fusion}} = \left[F_{\text{image}} \| F_{\text{tabular}}\right] \tag{6}$$

Where, the image feature vector and tabular feature vector into a single combined vector F_{fusion}. YOLOv11 detection outputs are converted into numerical pavement descriptors by computing pothole count, crack density, damage score, and severity index. These image-derived features are mapped to the corresponding pavement records and combined with PCI, AADT, IRI, and rainfall to form a unified feature vector, which is subsequently used as the input to the LightGBM maintenance prediction model. The image-derived features and tabular pavement attributes were aligned for each corresponding pavement record to provide a consistent representation integrating YOLOv11 potholes, crack-density, damage-score, severity-index, PCI, AADT, IRI, rainfall fused features for LightGBM maintenance predictions. The feature representation integrates pavement condition, traffic, environment, image-derived distress, enabling LightGBM learning fused multivariate relationships for maintenance prediction prioritization. The rainfall attribute was also preserved as part of the pavement through the multi modal data integration, providing same geographical context maintaining rainfall, PCI, AADT, IRI and image-derived distress features for reliable predictive maintenance modelling.

Random Forest (RF), Logistic Regression (LR), and Decision Tree (DT) used identical fused features and dataset partitions for comparison. RF employs ensemble learning, LR estimates maintenance probability using a linear decision function, DT performs recursive feature partitioning, and LightGBM applies leaf-wise gradient boosting. Model configurations, hyperparameter settings, and training procedures were consistently applied for fair comparison.

LightGBM is efficient, scalable, handling high-dimensional fused image-tabular data for accurate pavement maintenance prediction, as illustrated in Fig. 3.

The objective function combines predict Eq. (7).

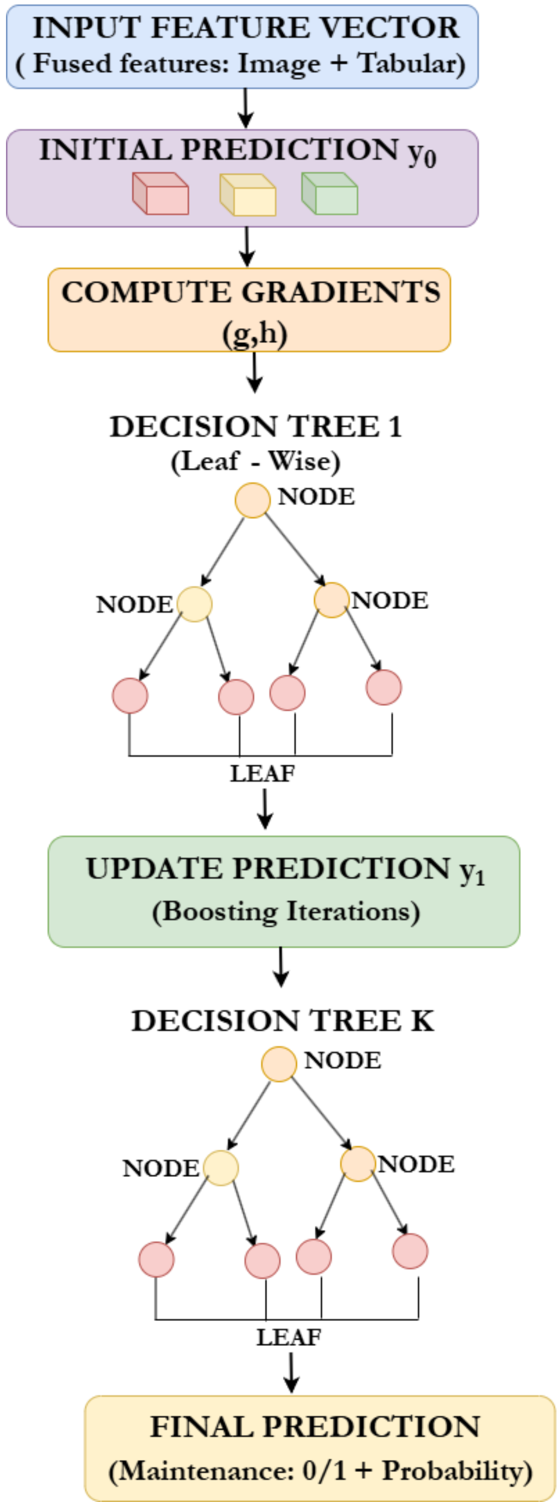

Fig. 3. LightGBM Architecture for Predictive Maintenance using Feature Fusion.

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{7}$$

Table 2. Priority Score Weight Configuration and Sensitivity Analysis

Parameter	Description	Weight	Accuracy (+10%)	Priority Stability
α	Maintenance Prediction Probability	0.35	0.9381	98.80%
β	Damage Severity	0.25	0.9362	98.10%
γ	Traffic Volume (AADT)	0.20	0.9347	97.60%
δ	Pavement Condition Index	0.15	0.9339	97.30%
ϵ	Environmental Risk	0.05	0.9360	99.10%

The loss function $L(y_i, \hat{y}_i)$ prediction error, regularization $\Omega(f_k)$, controls model complexity.

The binary loss function was selected because maintenance prediction classifies pavement segments requiring or not requiring maintenance, enabling LightGBM objective optimizing repair-prioritization outputs. The computed feature importance scores give a clear indication of the relative impact of each fused feature on the maintenance classification process. For this proposed framework integrates pavement-condition indicators, rainfall, image-derived distress, AADT, IRI, classifying transparent predictive maintenance decisions.

This priority score is calculated by the following: Maintenance Probability, Damage Severity, (AADT), PCI, Risk Factors determine High, Medium, or Low priorities shown as Eq. (8).

$$PS = \alpha \cdot P + \beta \cdot DS + \gamma \cdot AADT + \delta \cdot (1 - PCI) + \epsilon \cdot R \quad (8)$$

The parameters, $\alpha, \beta, \gamma, \delta, \epsilon$ represent tunable weights. The term $(1 - PCI)$ is inversely relate pavement condition to priority, where lower PCI (poor condition), higher PCI (good condition)

The weighting coefficients $\alpha, \beta, \gamma, \delta$, and ϵ in Eq. (8) regulate the relative contribution of maintenance prediction probability, damage severity, traffic volume, pavement condition, associated risk during repair-prioritization. The weighting strategy manually assigns coefficients based on maintenance prediction probability, damage severity, traffic volume, pavement condition, and environmental risk. Table 2 shows Accuracy of 0.9339–0.9381 and Priority Stability of 97.30%–99.10%, confirming robustness.

By predicting priority level, the decision support system provides repair recommendations and maintenance planning for efficient pavement resource allocation represented as Eq. (9).

$$\text{Action} = \begin{cases} \text{Immediate Repair,} & PS \geq T_2 \\ \text{Scheduled Maintenance,} & T_1 \leq PS < T_2 \\ \text{Routine Monitoring,} & PS < T_1 \end{cases} \quad (9)$$

Where, T_1, T_2 describes predefined thresholds, the system assigns repair actions-based priority score (PS) using threshold values. The predefined threshold categories were chosen to give a approach to maintenance prioritization using the integrated priority score. The three categories (Immediate Repair, Scheduled Maintenance, and Monitoring), allow maintenance actions to increasingly represent the interaction of maintenance prediction probability, pavement distress severity, pavement condition, traffic demand, and other considerations.

3. Results & discussion

The proposed YOLOv11 model trained 160 epochs, 640×640, batch 8, SGD, 0.01 learning rate, 0.937 momentum, 0.0005 decay, cosine scheduling, augmentations; LightGBM: 350 estimators, depth 9, 70 leaves, 40 samples, 0.8 subsample/colsample, 0.6 regularization, state 42. Parameters of LightGBM used 350 estimators and maximum depth 9, optimizing learning reliability and image-tabular pavement feature relationships. Real-time deployment performance was evaluated using an NVIDIA RTX 4090 GPU. The complete pipeline achieved an average inference time of 20.0 ms per image, including 18.7 ms for YOLOv11 distress detection and 1.3 ms for LightGBM maintenance prediction, corresponding to a throughput of 50 FPS. Memory usage remained at 2.3 GB with an average CPU utilization of 34%, demonstrating efficient latency, inference speed, and reliable operation for intelligent pavement management applications.

Fig. 4 depicts YOLOv11 manholes (0.87), potholes (0.90), minimizing false positives.

Fig. 5 presents the overall YOLOv11 detection performance across the three distress classes, achieving Precision of 0.9520, Recall of 0.9147, F1-score of 0.9330, mAP@0.5 of 0.9681, and IoU of 0.9681. The corresponding class-wise, macro-average, and weighted-average detection metrics are summarized in Table 3.

Preprocessed data achieved higher performance than the original dataset in Table 4, improving accuracy from 0.9080 to 0.9367, precision from 0.9010 to 0.9280, recall from 0.8940 to 0.9215, and F1-score from 0.8970 to 0.9247.

Table 3. Class-wise YOLOv11 Detection Performance

Class	Precision	Recall	F1-score	AP@0.50
Pothole	0.950	0.918	0.934	0.966
Crack	0.957	0.913	0.934	0.970
Manhole	0.949	0.918	0.933	0.968
Macro Average	0.952	0.916	0.934	0.968
Weighted Average	0.952	0.915	0.933	0.968

Table 4. Original vs. Preprocessed Data Performance

Dataset	Accuracy	Precision	Recall	F1-score
Original Dataset	0.9080	0.9010	0.8940	0.8970
Preprocessed Dataset	0.9367	0.9280	0.9215	0.9247

Table 5. Robustness Validation of the Proposed YOLOv11–LightGBM Framework

Validation Method	Accuracy	Precision	Recall	F1-score	ROC-AUC
Five-Fold Cross-Validation (Mean $\pm$ Std)	0.936 ± 0.003	0.929 ± 0.003	0.923 ± 0.003	0.925 ± 0.003	—
Repeated Experiments (10 Runs, Mean $\pm$ Std)	0.9365 ± 0.0024	0.9288 ± 0.0028	0.9226 ± 0.0025	0.9257 ± 0.0026	0.9989 ± 0.0004

Fig. 4. Road Infrastructure and Hazard Detection using YOLOv11.

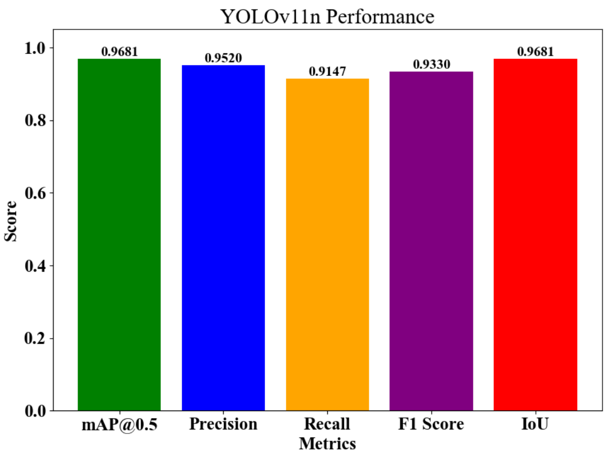

Fig. 5. Performance Summary Metrics for YOLOv11.

The reported Accuracy (0.9914), Precision (0.9962), Recall (0.9867), F1-score (0.9914), and ROC-AUC (0.9999) consistently demonstrate excellent classification performance is shown in Fig. 6.

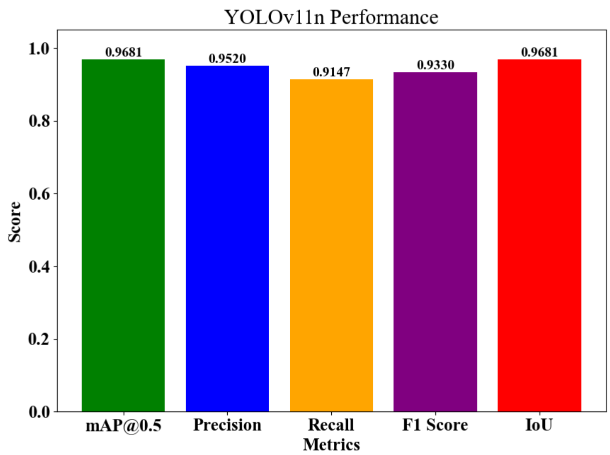

Fig. 6. Performance Summary Metrics for YOLOv11.

The confusion matrix is primarily due to the fact that the pavement deterioration characteristics of potholes and cracks are similar, as cracked asphalt surfaces, irregular boundaries, and pavement distress patterns create similar visual representations, complicating distress-stage classification, while manholes show least misclassifications shows in Fig. 7; YOLOv11 performs well overall. The proposed

YOLOv11 model showed good detection results, but there is still a risk of false pothole detection due to shadows, confidence thresholding, Non-Maximum Suppression, and multi-scale feature learning minimize false detections reliably.

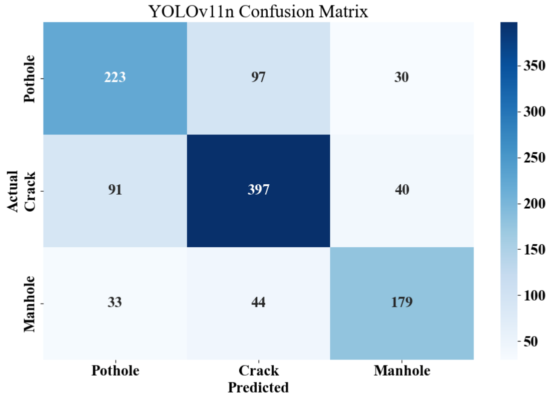

Fig. 7. Multi-Class Confusion Matrix for Road Feature Classification.

Fig. 8 demonstrates that the Top-K Accuracy (0.9367) Spearman Correlation (0.9755) confirm reliable strong agreement between predicted actual maintenance priorities.

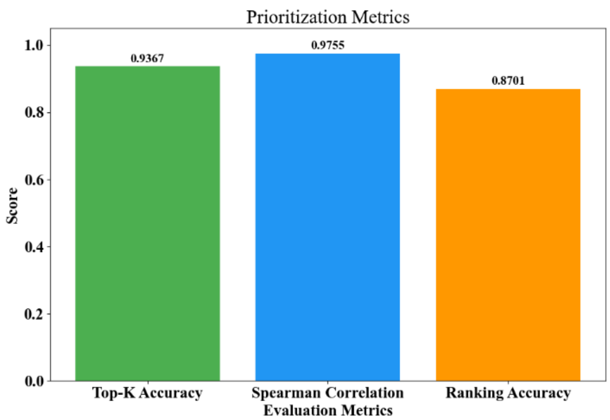

Fig. 8. Evaluation of Automated Repair Prioritization Metrics.

Table 6 presents the feature importance scores using original feature values. PCI ranked highest (0.284), followed by Average Rainfall (0.173), AADT (0.141), IRI (0.123), Crack Density (0.101), Pothole Count (0.089), and Severity Score (0.056).

To evaluate the classifier discrimination power, Fig. 9 shows LightGBM nearest the optimal corner with AUC 0.9999, while RF achieved AUC 0.8559 with higher false positives.

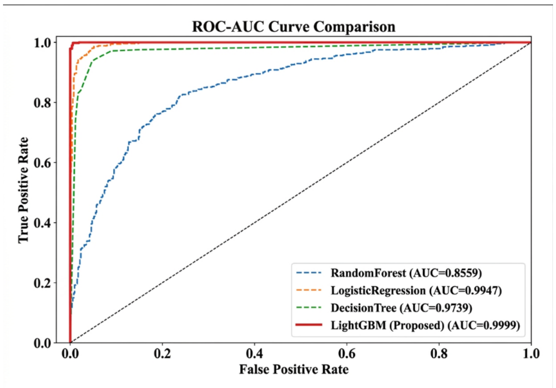

Fig. 9. ROC-AUC Curve Comparison for Classifier Discrimination.

The proposed YOLOv11 + LightGBM framework achieved 0.9367 accuracy, 0.999 ROC-AUC; Table 7 confirms superior predictive performance.

The complete model achieved the highest accuracy (0.9914) and ROC-AUC (0.9999), Table 8 shows removing YOLO features reduced accuracy to 0.8573, YOLO-only achieved 0.4913.

4. Conclusion

The present work developed a multi-modal system comprising YOLOv11 distress detection and LightGBM predictive maintenance using the features extracted from the images (i.e., PC, crack density and severity) and table (i.e., PCI, AADT, IRI and rainfall). The result of the ablation study also found significant evidence about the gain by using multi-modal fusion and the prioritization module was able to generate a ranking scheme. Additionally, the framework provides an increase in the accuracy, reliability, and quality of maintenance decision making; therefore, it is a viable and scalable solution for the intelligent management of infrastructure.

Future studies might develop this framework by adding different types of data (for example, data obtained from sensor-based real-time monitoring or data from non-linear changes in pavement deterioration over time) to provide better long-term predictions. In addition, adding explainable AI techniques can help bridge any potential transparency gaps in the models, thereby improving transparency and trust for decision makers. Testing this framework with large-scale deployment in smart city projects may further improve the framework and find its true potential and effectiveness in various real-world settings.

Table 6. Feature Importance Using Original Feature Values

Rank	Original Feature	Importance
1	PCI	0.284
2	Average Rainfall	0.173
3	AADT	0.141
4	IRI	0.123
5	Crack Density	0.101
6	Pothole Count	0.089
7	Severity Score	0.056

Table 7. Performance Comparison of Proposed YOLOv11 + LightGBM Model with Baseline Methods

Model / Method	Accuracy	Precision	Recall	F1-Score	ROC-AUC
RF [13]	0.842	0.835	0.828	0.831	0.861
XGBoost Model [14]	0.874	0.865	0.858	0.861	0.889
RF–XGBoost Hybrid [15]	0.931	0.918	0.910	0.914	0.942
Proposed (YOLOv11 + LightGBM Fusion)	0.9367	0.9280	0.9215	0.9247	0.999

Table 8. Ablation Study Results of the Proposed Multimodal Framework

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Full Model (Proposed)	0.9914	0.9962	0.9867	0.9914	0.9999
No YOLO Features	0.8573	0.8437	0.8547	0.8373	0.8679
Only YOLO Features	0.4913	0.4912	0.52	0.5052	0.5082
Without preprocessing	0.902	0.9146	0.9093	0.9192	0.9081
No Traffic (AADT)	0.976	0.9811	0.9707	0.9759	0.9984
No PCI	0.9561	0.9476	0.9653	0.9564	0.9928

Acknowledgement

The author would like to express gratitude for the support and resources provided during this research.

Data availability

Image Dataset Availability: https://www.kaggle.com/datasets/lorenzoarcioni/road-damage-dataset-potholes-cracks-and-manholes

Tabular Dataset Availability: https://www.kaggle.com/datasets/gifreysulay/pavement-dataset

Conflicts of interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author contribution

Xiaochen Ruan: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing.

Ethical approval

This study does not involve human participants or animals. Therefore, ethical approval was not required.

Consent to participate

Not applicable.

Consent to publication

Not applicable.

Competing interests

The author declares that there are no competing interests.

References

[1] A. Kadyraliev et al., (2022) *"Investments in Transport Infrastructure as a Factor of Stimulation of Economic Development"* **Transportation Research Procedia** *63*: 1359–1369. DOI: 10.1016/j.trpro.2022.06.146.

[2] A. Almeida and L. Picado-Santos, (2022) *"Asphalt Road Pavements to Address Climate Change Challenges—An Overview"* **Applied Sciences** *12*(24): DOI: 10.3390/app122412515.

[3] A. A. Angelo, K. Sasai, and K. Kaito, (2023) *"Safety Integrated Network Level Pavement Maintenance Decision Support Framework as a Practical Solution in Developing Countries: The Case of Addis Ababa, Ethiopia"* **Sustainability** *15*(11): DOI: 10.3390/su15118884.

[4] A. Azam, A. H. Alshehri, M. Alharthai, M. M. El-Banna, A. M. Yosri, and A. A. A. Beshr, (2023) *"Applications of Terrestrial Laser Scanner in Detecting Pavement Surface Defects"* **Processes** *11*(5): DOI: 10.3390/pr11051370.

[5] R. Bayat, S. Talatahari, A. H. Gandomi, M. Habibi, and B. Aminnejad, (2023) *"Artificial Neural Networks for Flexible Pavement"* **Information** *14*(2): DOI: 10.3390/info14020062.

[6] W. Wang et al., (2025) *"YOLO-RD: A Road Damage Detection Method for Effective Pavement Maintenance"* **Sensors** *25*(5): DOI: 10.3390/s25051442.

[7] M. S. Shuvo, (2022) *"Machine Learning-Based Pavement Condition Prediction Models for Sustainable Transportation Systems"* **AJIS** *3*(1): 31–64. DOI: 10.63125/1jsmkg92.

[8] L. Lu, M. Yin, Y. Xie, Y. Pan, M. Wang, and I. Brilakis, (2025) *"Development of a Trustworthy AI-Supported Digital Twin Framework for Road Operation and Maintenance"* **Smart Construction**: DOI: 10.55092/sc20250001.

[9] A. T. Adetokunbo and Z. Q. Sikhakhane-Nwokediegwu, (2022) *"Conceptual Framework for Performance-Based Design of Pavement Structures Under Variable Loading Conditions"* **SHISRRJ** *5*(5): 436–456. DOI: 10.32628/SHISRRJ225892.

[10] G. J. Kashesh et al., (2025) *"Data-Driven Optimization of Sustainable Asphalt Overlays Using Machine Learning and Life-Cycle Cost Evaluation"* **CivilEng** *7*(1): DOI: 10.3390/civileng7010001.

[11] *Road Damage Dataset: Potholes, Cracks and Manholes*. 2026. URL: https://www.kaggle.com/datasets/lorenzoarcioni/road-damage-dataset-potholes-cracks-and-manholes (visited on 04/21/2026).

[12] *Pavement Dataset*. 2026. URL: https://www.kaggle.com/datasets/gifreysulay/pavement-dataset (visited on 04/21/2026).

[13] N. S. Ahmed, (2024) *"Machine Learning Models for Pavement Structural Condition Prediction: A Comparative Study of Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)"* **Open Journal of Civil Engineering** *14*(4): 570–586. DOI: 10.4236/ojce.2024.144031.

[14] N. S. Ahmed, N. Huynh, S. Gassman, R. Mullen, C. Pierce, and Y. Chen, (2022) *"Predicting Pavement Structural Condition Using Machine Learning Methods"* **Sustainability** *14*(14): DOI: 10.3390/su14148627.

[15] J. Zhang, R. Wang, Y. Lu, and J. Huang, (2024) *"Prediction of Compressive Strength of Geopolymer Concrete Landscape Design: Application of the Novel Hybrid RF–GWO–XGBoost Algorithm"* **Buildings** *14*(3): DOI: 10.3390/buildings14030591.