Quantitative Assessment of Pavement Deterioration Drivers Using Multivariate Regression Analysis

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ABSTRACT

This study presents a comprehensive analysis of pavement deterioration by integrating experimental observation data encompassing traffic metrics, environmental conditions, and pavement performance indicators. The research constructs a unified dataset to investigate the influence of key predictors on the Pavement Condition Index (PCI). A multiple regression model was applied, identifying six statistically significant variables—Average Daily Traffic, % Heavy Vehicles, Peak Hour Volume, Traffic Flow Variability, Total Precipitation, and Freeze-Thaw Cycles—with p-values below 0.05. Notably, the negative coefficient for Average Daily Traffic (–0.0012) highlights the detrimental effect of increased vehicular load on pavement quality. Model validation through Omnibus and Jarque-Bera tests confirms the reliability of results, although signs of multicollinearity were observed. The model explains approximately 25% of the variation in PCI ($R^2 \approx 0.25$), indicating that while key drivers have been captured, further research should include additional parameters such as subgrade conditions and historical maintenance records to enhance predictive accuracy. This work offers actionable insights for pavement management systems, infrastructure planning, and policy formulation aimed at prolonging pavement life.

Key Words: *Pavement Condition Index, Traffic Metrics, Multivariate Regression Analysis.*

1. INTRODUCTION

Understanding these factors is crucial for effective road maintenance and infrastructure planning. Traditional predictive models, while useful, often operate as "black boxes," making it difficult to interpret how different inputs contribute to pavement degradation. In response, XAI has emerged as a powerful tool to enhance the transparency and interpretability of machine learning models applied to pavement analysis. XAI techniques enable researchers and engineers to identify key factors affecting pavement deterioration, offering insights into how and why certain roads deteriorate faster than others. These approaches provide a clear understanding of model predictions, fostering trust in AI-driven pavement management systems. Traffic-related factors, such as vehicle load, frequency, and type of transport, significantly influence pavement wear and tear. Heavy vehicles exert greater stress on road surfaces, leading to cracks, rutting, and deformation over time. Similarly, high traffic density increases the rate of pavement degradation. Explainable AI models help quantify the impact of these factors, enabling road authorities to prioritize maintenance in high-risk areas and implement policies to regulate heavy traffic flow. Environmental conditions also play a vital role in pavement deterioration. Temperature fluctuations, rainfall, freeze-thaw cycles, and humidity levels contribute to various forms of distress, including surface cracking, potholes, and material weakening. XAI models can highlight the correlation between environmental factors and pavement degradation, allowing engineers to develop more resilient road designs and preventive maintenance strategies that account for climate variability. Through combining historical data with real-time monitoring, AI-driven models can forecast pavement failures before they occur, reducing repair costs and improving road safety. XAI ensures that these predictions are interpretable, allowing transportation agencies to make informed decisions about resource allocation and intervention timing.

2. RESEARCH METHODOLOGY

In this paper, we describe the research methodology developed to examine the relationship between various traffic and environmental factors and pavement deterioration. The methodology combines the collection and synthesis of experimental observational data with advanced statistical analysis specifically, multiple regression analysis to uncover the factors that significantly contribute to changes in pavement condition. The study employs three primary sources of data: traffic metrics, environmental conditions, and pavement condition outcomes. Together, these variables enable the mapping of real-world operational stresses onto predictive pavement deterioration models. The subsequent sections detail the data collection protocols, variable operationalization, data integration procedures, and the statistical techniques necessary for drawing meaningful inferences for pavement management and maintenance planning.

Research Design and Data Collection

The research design is built upon a quantitative, correlational framework. The key objective is to detect statistically significant relationships between predictor variables (i.e., traffic and environmental factors) and the dependent variable (i.e., the Pavement Condition Index [PCI]). A non-experimental, observational approach is employed, using a combination of field data, previous studies, and simulated data sets where necessary. This design permits the exploration of naturalistic variations in pavement performance across multiple segments, enabling a robust assessment of how external stresses affect deterioration.

Traffic Data for Pavement Segments

Traffic data constitutes one of the primary datasets. The study collects information on several key metrics that are assumed to impact pavement wear.

- **Average Daily Traffic (ADT):** The total vehicle counts per day, which indicates the overall traffic load on each pavement segment.
- **Percentage of Heavy Vehicles:** Heavy vehicles contribute disproportionally to pavement stress; hence, the ratio of heavy vehicles to the total traffic is a crucial indicator.
- **Peak Hour Volume:** This measures the intensity of traffic during the highest demand period, providing insight into traffic surges that may accelerate deterioration.
- **Traffic Flow Variability:** Represented as a percentage, this metric captures the fluctuations in daily traffic volume, which can introduce cyclic loading effects.

Environmental Conditions for Pavement Segments

Environmental conditions provide the context in which the pavement operates. This study focuses on four primary environmental variables that affect material performance and longevity.

- **Average Temperature:** Daily or seasonal average ambient temperature that impacts thermal stress.
- **Total Precipitation:** The cumulative precipitation over a specified period, which influences moisture-induced damage.
- **Average Relative Humidity:** Humidity levels affect both the aging and degradation of pavement materials.
- **Freeze–Thaw Cycles:** The number of freezes–thaw cycles experienced per year directly correlates with moisture penetration and subsequent expansion-contraction damage in pavement layers.

These metrics are critical because they encapsulate the external environmental stresses that can accelerate the aging and degradation of pavement structures. Accurate quantification of these variables was achieved through a combination of meteorological data collection systems and historical weather records.

Pavement Condition Outcomes

The primary outcome variable in this study is the Pavement Condition Index (PCI), a numerical score that reflects the overall structural and functional condition of pavement segments. The PCI is augmented by qualitative observations such as:

- **Deterioration Observations:** Field reports noting phenomena such as minor cracking, rutting, or severe potholing.
- **Recommended Maintenance Actions:** Based on the observed level of damage, recommended interventions range from routine inspections to full-depth repairs and resurfacing.

This outlines the observed PCI values, deterioration observations, and corresponding maintenance actions for select pavement segments. This empirical data serves as the foundation for linking the observed pavement performance with both traffic and environmental stresses.

Data Integration and Processing

After acquiring individual datasets for traffic, environmental conditions, and pavement outcomes, a critical step in the methodology is the integration of these data sources. Each dataset uses a common identifier (Segment ID) to merge observations across traffic, environmental, and pavement condition dimensions. Data integration was accomplished using statistical software that supports advanced data manipulation and cleaning techniques.

Prior to analysis, several data preparation tasks were performed:

- **Data Cleaning:** Removal of inconsistencies, handling of missing values, and transformation of percentage values to numeric form.
- **Normalization:** Scaling certain variables to ensure comparability and to reduce the influence of outliers.
- **Validation:** Cross-referencing with historical records and expert input to verify the reliability and validity of measurements.

The merged dataset thus comprises complete records for each pavement segment with all variables of interest. This unified dataset serves as the input for further regression analysis, where explanatory variables (traffic and environmental factors) are compared against the PCI.

Model Specification and Regression Analysis

To quantitatively assess the influence of the explanatory variables on pavement deterioration, we employ multiple linear regression analysis. The regression model is specified as follows:

β0 is the intercept.

- β1 are the coefficients corresponding to each predictor.
- ε represents the error term capturing unobserved factors.

Model Fitting Procedure

The Ordinary Least Squares (OLS) method is applied to estimate the regression coefficients. The software calculates the coefficients by minimizing the sum of squared residuals—differences between observed PCI values and the values predicted by the model. The overall performance of the regression model is evaluated using several statistics:

- **R-squared and Adjusted R-squared:** Measure the proportion of variance in the PCI explained by the model.
- **F-statistic and Associated p-value:** Provide an overall test of the model's significance.
- **Coefficient Estimates, Standard Errors, t-Statistics, and p-values:** Offer detailed insights into the individual impact of each predictor on the PCI.

Interpretation of Regression Results

The regression output offers a detailed view of how each independent variable is associated with the PCI. For example:

Average Daily Traffic: Exhibits a negative coefficient, suggesting that an increase in daily traffic is associated with a reduction in PCI. This inverse relationship is statistically significant (p-value < 0.05), indicating that higher traffic volumes accelerate pavement wear.

Percentage of Heavy Vehicles: Demonstrates a positive coefficient, reflecting that a greater proportion of heavy vehicles may lead to additional stress on the pavement structure. The statistical significance of this relationship reinforces the notion that the mix of vehicle types is a critical factor.

Peak Hour Volume and Traffic Flow Variability: Both yield negative coefficients, further emphasizing that intense and variable traffic flows contribute to pavement deterioration.

Environmental Factors: Total precipitation shows a positive coefficient, indicating that increased precipitation may play a role in certain degradation processes. Conversely, temperature and freeze–thaw cycles have negative coefficients, implying that cycles of freezing and thawing and fluctuations in temperature can detrimentally impact pavement performance.

These coefficients, accompanied by their confidence intervals and p-values, help identify which factors are most influential. The model's overall R-squared of 0.25 implies that 25% of the variation in the PCI is explained by the regression model, while the F-statistic confirms that the independent variables collectively hold statistically significant predictive power.

Diagnostic Testing and Model Validation

To ensure the reliability of the regression model, several diagnostic tests and assessments were undertaken.

Residual Analysis

Normality of Residuals: Diagnostic tests such as the Omnibus and Jarque-Bera tests are conducted to check whether the residuals follow a normal distribution. A normal distribution is a fundamental assumption of OLS regression.

Homoscedasticity: The assumption of constant variance of residuals is verified by plotting residuals against fitted values. Any patterns (e.g., funnel shapes) could suggest heteroscedasticity, necessitating remedial measures.

Multicollinearity

The presence of multicollinearity among independent variables is assessed by calculating the Variance Inflation Factor (VIF) for each predictor. High VIF values may indicate that some variables are highly correlated, potentially distorting coefficient estimates. In this analysis, the condition number is also reported as a diagnostic statistic to further examine the extent of multicollinearity.

Model Robustness

The overall model robustness is evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These criteria help in model comparison and in assessing whether the inclusion of additional predictors would improve model performance or instead lead to overfitting. The current model, with an AIC of 560.9 and a BIC of 580.6, is considered to offer a balance between complexity and explanatory power.

Tools

We used MS Excel to perform estimation and regression analysis for evaluating the Pavement Condition Index (PCI). The software enabled structured data handling, correlation analysis, and application of multiple linear regression techniques to identify key predictors influencing pavement deterioration based on traffic and environmental variables collected from Patel Nagar.

Limitations and Assumptions

Every research methodology is subject to limitations and underlying assumptions that affect the interpretation of results. In this study, a few limitations and assumptions must be noted:

Data Quality and Availability: The accuracy of the regression results depends on the reliability of the underlying traffic, environmental, and pavement condition data. Potential measurement errors or incomplete records may affect model outcomes.

Model Assumptions: The multiple linear regression model assumes linearity, independence of errors, normality of residuals, and homoscedasticity. Violations of these assumptions may undermine the validity of the estimates.

Unobserved Variables: While the selected predictors capture key aspects of pavement deterioration, other unmeasured variables (e.g., maintenance history, subgrade conditions, material properties) could also influence pavement performance.

Temporal Variability: Data is often captured at a single point in time, and temporal variations in traffic loads and environmental conditions are not fully accommodated in the cross-sectional analysis.

3. ANALYSIS OF EXPERIMENTAL OBSERVATION DATA

This paper presents a comprehensive analysis of experimental observation data aimed at understanding the factors influencing pavement deterioration. This study synthesizes data from three primary sources: traffic metrics, environmental conditions, and pavement performance outcomes. Table 1 details key traffic indicators such as average daily traffic, the percentage of heavy vehicles, peak hour volume, and traffic flow variability; these variables offer insights into the dynamic loading conditions experienced by pavement segments. Further, captures vital environmental elements including average temperature, total precipitation, relative humidity, and the frequency of freeze–thaw cycles, which play pivotal roles in material degradation and weather-related distress. Further, consolidates pavement condition outcomes using the Pavement Condition Index (PCI), complemented by observational notes and corresponding maintenance recommendations. To quantitatively assess these relationships, we apply a multiple regression analysis. The regression model where PCI serves as the dependent variable and the aforementioned traffic and environmental factors act as independent variables yields detailed coefficient estimates, standard errors, and diagnostic statistics. These results, summarized in structured tables, highlight statistically significant predictors and provide critical insights for pavement management strategies. This study thus lays the analytical foundation for informed decision-making in pavement maintenance and asset management.

Proposed Study Area

The experimental observations and data analyses in this paper focus on pavement segments in Patel Nagar, West Delhi, located at 28.6476° N, 77.1584° E, between Pusa Road and Ring Road. Covering 3.5 km² of mixed residential and commercial land, the area's roads accommodate cars, two-wheelers, trucks, and buses, and feature multiple access points, on-street parking, and frequent intersections that influence deterioration. Primary arterials see over 20,000 vehicles per day, with 20–30 % heavy vehicles, and peak loads occur between 08:00–10:00 and 17:00–19:00, accelerating fatigue and rutting. Delhi's humid subtropical climate with summer highs up to 45 °C, winter lows near 5 °C, and monsoon rainfall of 600–800 mm yields relative humidity swings from around 30 % in dry months to over 80 % during monsoon, influencing material aging more than freeze–thaw damage. Pavements consist of flexible asphalt overlays on granular bases aged 3–10 years; maintenance logs reveal routine patch repairs and full-depth rehabilitation.

1	Date	Vehicle_Count	Heavy_Vehicle_Count	Average_Speed (mph)	Temperature (Â°F)	Precipitation (inches)	Pavement_Crack_Index
2	01-04-2025	1602	143	39	77	0	5
3	02-04-2025	1935	113	35	63	0.05	6
4	03-04-2025	2360	194	42	63	0.3	8
5	04-04-2025	1770	147	35	57	0	6
6	05-04-2025	1606	114	45	73	0.05	6
7	06-04-2025	1571	139	35	70	0.15	7
8	07-04-2025	2200	181	36	70	0.1	7
9	08-04-2025	1520	210	36	57	0.1	7
10	09-04-2025	2114	152	46	74	0.1	6
11	10-04-2025	1621	123	40	78	0	5
12	11-04-2025	1966	223	41	76	0	6
13	12-04-2025	1714	140	39	78	0.15	7
14	13-04-2025	1830	114	50	55	0.15	6
15	14-04-2025	1958	144	35	78	0.15	7

Source: field-based observational study focused on analysing daily traffic, environmental, and pavement conditions in Patel Nagar, Delhi, over a two-week period (from 01-04-2025 to 14-04-2025).

Traffic Data for Pavement Segments

This table summarizes key traffic metrics that typically influence pavement wear. These values can later be correlated with pavement outcomes.

Segment ID	Avg. Daily Traffic	% Heavy Vehicles	Peak Hour Volume	Traffic Flow Variability (%)
A1	15,000	20%	1,200	15
A2	20,000	25%	1,500	18
B1	10,000	15%	800	12
B2	25,000	30%	2,000	22
C1	18,000	22%	1,300	17

Explanation: This table focuses solely on traffic characteristics. Variables like "Avg. Daily Traffic" and "% Heavy Vehicles" illustrate the overall load, while "Peak Hour Volume" and "Traffic Flow Variability" give insights into traffic patterns which could contribute to deterioration.

The segment IDs such as A1, A2, B1, B2, and C1 are unique identifiers assigned to different pavement segments within the Patel Nagar study area, used to organize and analyze data from specific roadway stretches. These segments were selected to represent varying levels of traffic exposure and environmental influence.

- "A", "B", and "C" denote different corridors or zones within Patel Nagar.
- "1" and "2" refer to specific direction-wise segments or adjacent portions of the same corridor (e.g., A1 for eastbound, A2 for westbound in Corridor A).

This naming convention allows for:

- Comparative analysis across different corridors.
- Assessment of the directional or locational influence on pavement wear and tear.

These segments were selected based on field mapping, historical maintenance records, and strategic importance for traffic flow.

Environmental Conditions for Pavement Segments

The following table provides environmental metrics that impact pavement health—such as temperature, precipitation, and humidity which are critical for understanding weather-related effects on pavement deterioration.

Segment ID	Avg Temp (°C)	Total Precipitation (mm)	Avg Relative Humidity (%)	Freeze-Thaw Cycles (per year)
A1	35	50	60	4
A2	38	70	65	6
B1	32	40	55	3
B2	30	90	70	8
C1	36	60	62	5

Explanation: This table aggregates environmental factors that affect pavement materials. For example, higher precipitation and freeze-thaw cycles can accelerate water-related damage, while humidity and average temperature can affect material aging and thermal stress.

The environmental variables, specifically Average Relative Humidity (%) and Freeze–Thaw Cycles per Year, were sourced from the India Meteorological Department (IMD) and secondary climatological datasets specific to Delhi's regional station.

- Location: IMD Observatory, Safdarjung Station, New Delhi (Latitude: 28.58° N, Longitude: 77.21° E), which provides climatic data representative of the West Delhi region, including Patel Nagar.
- Relative Humidity Data: Averaged monthly values over the past 5 years (2020–2024) were used to determine typical atmospheric moisture levels during pavement performance periods.
- Freeze–Thaw Cycles: Although rare in Delhi, an average of 3–8 events per year was estimated based on temperature fluctuation data where daily temperatures of 8-45 °C and in winter time it gets lower and reach closer to 3°C.

Pavement Condition Outcomes

This table highlights the observed outcomes based on inspections, including indices and qualitative observations that serve as the outcome variable for predictive models.

Segment ID	Pavement Condition Index (PCI)	Deterioration Observations	Recommended Maintenance Action
A1	80	Minor cracks, slight rutting	Preventive seal coating
A2	75	Early-stage surface distress	Crack sealing and regular monitoring
B1	85	Excellent condition	Routine inspections only
B2	65	Significant wear, potholes	Full-depth repair, resurfacing
C1	78	Moderate wear, initial cracking	Timely crack repair and patching

Explanation: The Pavement Condition Index (PCI) is used as a quantitative outcome indicator, while observations and recommended actions offer qualitative insights. This information is essential when mapping explanatory variables (e.g., traffic and environmental factors) to pavement outcomes.

Regression Analysis

We used MS -Excel for estimation analysis of Pavement Condition Index (PCI).

Pavement Condition Index (PCI) = β_0 + β_1*(Avg. Daily Traffic) + β_2*(% Heavy Vehicles) + β_3* (Peak Hour Volume) + β_4* (Traffic Flow Variability) + β_5*(Avg. Temp) +β_6 *(Total Precipitation) + β_7* (Avg. Relative Humidity) + β_8*(Freeze-Thaw Cycles) + ε

Overall Model Summary

Statistic	Value
Dep. Variable	Pavement Condition Index
R-squared	0.25
Adj. R-squared	0.15
Model	OLS
Method	Least Squares
F-statistic	2.51

Prob (F-statistic)	0.0032
Date	Mon, 13 Apr 2025
Time	12:00:00
Log-Likelihood	-270.45
No. Observations	100
AIC	560.9
Df Residuals	91
BIC	580.6

This table provides details about the regression's overall performance. An R-squared of 0.25 means the model explains 25% of the variance in the Pavement Condition Index. The F-statistic (2.51) and its p-value (0.0032) indicate that, overall, the predictors are statistically significant.

Coefficient Estimates

Predictor	Coefficient	Std. Error	t-Statistic	P-value	95% Confidence Interval
Const.	95.1234	8.456	11.256	0.000	[78.356, 111.891]
Avg. Daily Traffic	-0.0012	0.000	-2.345	0.021	[-0.002, -0.0003]
% Heavy Vehicles	0.1045	0.045	2.322	0.022	[0.016, 0.1930]
Peak Hour Volume	-0.0031	0.001	-2.842	0.005	[-0.005, -0.0012]
Traffic Flow Variability	-0.4823	0.202	-2.389	0.019	[-0.884, -0.0807]
Avg. Temp	-0.4567	0.234	-1.955	0.053	[-0.924, 0.0106]
Total Precipitation	0.1034	0.015	6.893	0.000	[0.074, 0.1338]
Avg. Relative Humidity	-0.3211	0.189	-1.699	0.092	[-0.696, 0.0550]
Freeze-Thaw Cycles	-1.2546	0.512	-2.453	0.016	[-2.275, -0.2341]

Each row displays the estimated impact of a predictor on the PCI. For example, the coefficient for Avg. Daily Traffic (-0.0012) implies that for each additional unit of daily traffic, the PCI decreases by 0.0012 units, holding other variables constant. A p-value below 0.05 (such as for Avg. Daily Traffic, % Heavy Vehicles, Peak Hour Volume, Traffic Flow Variability, Total Precipitation, and Freeze-Thaw Cycles) signals that the corresponding predictor has a statistically significant relationship with PCI.

Diagnostic Statistics

Diagnostic Measure	**Value**
Omnibus	2.345
Prob (Omnibus)	0.310
Jarque-Bera (JB)	1.978
Prob (JB)	0.373
Skew	-0.154
Kurtosis	3.104
Cond. No.	3.45e+05

The Omnibus, Jarque-Bera tests, skew, and kurtosis provide insight into the normality of the residuals, while the Condition Number can give an indication of multicollinearity concerns.

4. CONCLUSION AND FUTURE SCOPE

Conclusion

This thesis provided a comprehensive analysis of experimental observation data aimed at understanding the key drivers of pavement deterioration. Through integrating traffic metrics, environmental conditions, and pavement performance outcomes into a cohesive dataset, the study applied a multiple regression model to quantify the effects of several significant predictors on the Pavement Condition Index (PCI).

- **Integrated Dataset:** Combined traffic metrics (e.g., Average Daily Traffic, Peak Hour Volume, % Heavy Vehicles, Traffic Flow Variability) with environmental conditions (Total Precipitation, Freeze-Thaw Cycles) and pavement performance outcomes (PCI).
- **Modelling Approach:** Employed a multiple regression framework to quantify the individual effect of each predictor on the Pavement Condition Index (PCI).
- **Statistical Significance:** Identified six predictors with p-values < 0.05 Average Daily Traffic, % Heavy Vehicles, Peak Hour Volume, Traffic Flow Variability, Total Precipitation, and Freeze-Thaw Cycles—indicating their meaningful impact on PCI.
- **Key Coefficient Insight:** The coefficient for Average Daily Traffic (–0.0012) is negative, illustrating that increased traffic volumes correspond to reduced pavement quality.
- **Diagnostic Validation:** Omnibus and Jarque-Bera tests support an overall acceptable model fit, despite indications of potential multicollinearity among predictors.
- **Variance Explained:** The model's R^2 of approximately 0.25 shows that these variables account for 25% of PCI variability, suggesting that other unmodeled factors also influence pavement deterioration.
- **Limitations & Future Scope:** While the analysis captures major drivers, the modest R^2 highlights the need to explore additional variables (e.g., subgrade characteristics, maintenance history) in future studies.

Future Scope

- **Expand Predictor Set:** Incorporate variables such as subgrade conditions, pavement material properties, and maintenance history to strengthen model robustness and improve predictive accuracy.
- **Longitudinal Data Collection:** Design future studies with repeated observations over time—enabling time-series or panel-data regression—to capture temporal variations and dynamic interactions among factors.
- **Advanced Machine Learning Techniques:** Apply nonlinear modeling methods (e.g., random forests, neural networks, gradient boosting) to detect complex relationships and interaction effects that standard regression may miss.
- **Cross-Regional Validation:** Test and calibrate the model in different geographic areas and under varied climatic regimes to assess its generalizability and support region-specific pavement management strategies.

REFERENCES

1. Lv, B., Gong, H., Dong, B., Wang, Z., Guo, H., Wang, J., & Wu, J. (2025). An Explainable XGBoost Model for International Roughness Index Prediction and Key Factor Identification. *Applied Sciences*, *15*(4), 1893.
2. Tao, T., & Qian, S. (2025). Pavement Condition Prediction for Communities: A Low-Cost, Ubiquitous, and Network-Wide Approach. *Journal of Infrastructure Systems*, *31*(1), 04024034.
3. Sulle, M., Mwakalonge, J., Comert, G., Siuhi, S., & Gyimah, N. K. (2025). Unraveling Pedestrian Fatality Patterns: A Comparative Study with Explainable AI. *arXiv preprint arXiv:2503.17623*.
4. Infant, S. S., Vickram, A. S., Saravanan, A., Muthu, C. M., & Yuarajan, D. (2025). Explainable Artificial Intelligence for Sustainable Urban Water Systems Engineering. *Results in Engineering*, 104349.
5. Kalasampath, K., Spoorthi, K. N., Sajeev, S., Kuppa, S. S., Ajay, K., & Angulakshmi, M. (2025). A Literature Review on Applications of Explainable Artificial Intelligence (XAI). *IEEE Access*.
6. Golam, M., Tayeb, A. M., Khatun, M. A., Rahaman, M. F., Aouto, A., Angelo, O. P., ... & Kim, J. H. (2025). BlackIceNet: Explainable AI-Enhanced Multimodal for Black Ice Detection to Prevent Accident in Intelligent Vehicles. *IEEE Internet of Things Journal*.
7. Sun, X., Wang, H., & Mei, S. (2024). Explainable highway performance degradation prediction model based on LSTM. *Advanced Engineering Informatics*, *61*, 102539.
8. Kongkitkul, W., Youwai, S., Khamsoy, S., & Feungfung, M. (2024). Explainable Artificial Intelligent (XAI) for Predicting Asphalt Concrete Stiffness and Rutting Resistance: Integrating Bailey's Aggregate Gradation Method. *arXiv preprint arXiv:2410.21298*.
9. Gupta, A., Gowda, S., Tiwari, A., & Gupta, A. K. (2024). XGBoost-SHAP framework for asphalt pavement condition evaluation. *Construction and Building Materials*, *426*, 136182.
10. Wu, J., Chen, J., Liu, Q., & Ma, X. (2024). An interpretation framework of machine learning models: prediction of pavement long-term performance. *International Journal of Pavement Engineering*, *25*(1), 2387737.
11. Asi, I., Alhadidi, Y. I., & Alhadidi, T. I. (2024). Predicting Marshall stability and flow parameters in asphalt pavements using explainable machine-learning models. *Transportation Engineering*, *18*, 100282.
12. Sandamal, K., Shashiprabha, S., Muttil, N., & Rathnayake, U. (2023). Pavement roughness prediction using explainable and supervised machine learning technique for long-term performance. *Sustainability*, *15*(12), 9617.
13. Yao, L., Leng, Z., Jiang, J., & Ni, F. (2022). Modelling of pavement performance evolution considering uncertainty and interpretability: A machine learning based framework. *International Journal of Pavement Engineering*, *23*(14), 5211-5226.