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Development of an Artificial Intelligence Model for Predicting Flexible Pavement Deterioration under Indian Traffic Conditions

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Abstract
Under such conditions of heterogeneous traffic, the accurate prediction of deterioration of flexible pavement is necessary for proper pavement maintenance on Indian highways. In this study, a public pavement reference data set was used for engineering plausibility assessment and a synthetic data set of Indian pavements with 8,000 observations from 1,000 pavement sections was used for model development and testing to predict future deterioration of flexible pavement. The data is preprocessed, standardized for tabular models, processed for sequential LSTM models, outlier treatment, feature ranking using Mutual Information, and modeled using Random Forest, XGBoost, Gradient Boosting, Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM). The model performance was measured using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). The comparative results demonstrated that the XGBoost model had the best performance in predicting digital weight gain among the main models, having an RMSE of 0.2280, an MAE of 0.0718, a MAPE of 0.9676%, and an R^2 of 0.9950. Importance of features was determined according to the results, which turned out to be the following features: Current International Roughness Index (IRI), Previous Pavement Condition Index (PCI), Longitudinal Cracking, Rut Depth, Pothole Density and Cumulative Equivalent Standard Axle Load (ESAL). The proposed framework offers a controlled and reproducible methodology for validating the deterioration prediction for flexible pavement under simulated Indian traffic and environment, which needs to be validated in the future with actual Indian pavement data.

Keywords: *Flexible Pavement Deterioration; Artificial Intelligence; XGBoost; Pavement Management; Indian Traffic Conditions; Future IRI Prediction.*

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I.Introduction

Road transport plays a major role in the economic development of India, both in terms of enabling the industrial activities and the trade and regional connectivity. In India flexible pavements are widely used due to the following advantages: They can be constructed at a low cost, maintenance is relatively simple, and they can be used for a variety of traffic conditions. But as traffic levels rise and axles become overloaded, and climate changes, the pavement will fail over time and proper prediction is critical to good maintenance planning.

1.1 Background of Flexible Pavement Deterioration

Flexible pavements comprise a bituminous wearing course placed over a layer of granular base, subbase, and subgrade. The flexible pavements experience the effects of traffic loading, exposure to weather, and material degradation, which result in the occurrence of pavement distress such as ruts, fatigue cracks, potholes, and higher roughness. These conditions lead to poor pavement condition and shortened service life.

Deterioration of pavements is affected by a number of factors such as traffic loading, pavement structure, weather conditions, drainage, and maintenance. Since these factors influence each other in complicated ways, they cannot be simply modelled mathematically. Thus, data-based approaches have increasingly been used in predicting pavement deterioration (Hosseini et al., 2022; Marcelino et al., 2021).

1.2 Importance of Pavement Management Systems (PMS)

Pavement Management System (PMS) is used by highway authorities to assess the state of pavements, to predict their deterioration and plan maintenance activities. Deterioration prediction facilitates timely action and optimization of maintenance efforts. With the increasing expansion of highway network in India, pavement management has become more dependent on advanced analysis techniques which can incorporate traffic, pavement, climatic and maintenance data (Gupta et al., 2026).

1.3 Challenges under Indian Traffic Conditions

The Indian highway network works in a traffic environment characterized by considerable heterogeneity due to vehicle mixture, overloaded trucks, and climate variation. Such loading profiles are very different from those considered by most existing models of pavement deterioration.

Increased rainfall in the monsoon season, inadequate drainage, and differences in maintenance policies may further aggravate pavement deterioration and complicate its forecasting. As such, deterioration models should consider the nonlinear relationships between all these parameters (Zhao et al., 2023).

1.4 Limitations of Conventional Deterioration Models

Traditionally, pavement distress models are empirical or mechanistic and usually make certain assumptions based on uniform conditions for traffic and climate. While such models have been instrumental in the development of design and maintenance strategies for pavements, they are unlikely to be able to model the interrelationship between traffic, axle loads, climatic factors, and maintenance conditions effectively.

Furthermore, traditionally used models do not adapt dynamically to changes in pavement conditions that may occur. Such issues have led to the development of intelligent learning models which can efficiently capture non-linear pavement deterioration (Madeh Piryonesi & El-Diraby, 2021).

1.5 Artificial Intelligence in Pavement Prediction

AI represents a robust technique for modelling engineering systems that have nonlinearity and multi-variability in nature. Algorithms based on machine learning and deep learning can extract patterns from past observations and have shown promising results in combining variables like traffic, climate, structure, maintenance, and condition of pavements in their deterioration prediction model.

Availability of databases with information about pavement condition and advancements in computational techniques have made it possible to develop AI-based models for prediction of pavement deterioration and its maintenance.

1.6 Objectives of the Study

The objective of this study is to develop an AI-based approach for predicting flexible pavement deterioration under Indian traffic conditions. The detailed objectives are as follows:

- To create and preprocess an integrated pavement deterioration dataset for Indian traffic, climate, structure, and maintenance conditions.
- To construct and compare Random Forest, XGBoost, Gradient Boosting, ANN, and LSTM models for pavement deterioration prediction.
- To validate the models constructed on the basis of MAE, MSE, RMSE, R^2 Score, and MAPE.
- To determine the best suited prediction model for pavement maintenance planning under Indian traffic conditions.

These objectives provide a systematic basis for pavement deterioration prediction and support improved maintenance decision-making by highway agencies.

1.7 Contributions of the Proposed Model

This research establishes an AI-based prediction framework for assessing the deterioration of flexible pavements in India by leveraging a Python-powered pipeline and artificial pavement deterioration data.

Five AI techniques, namely Random Forest, XGBoost, Gradient Boosting, ANN, and LSTM, have been designed and compared based on an experimental framework.

In this context, the methodology involves combining Indian traffic data simulation with pavement data, climate data, structural data, maintenance data, and distress data. The pipeline consists of preprocessing, feature analysis, model development, and performance evaluation steps to establish the optimal predictive model.

II. Literature Review

Prediction of pavement deterioration using flexible pavements has developed from traditional empirical models to AI-based models due to increased availability of pavement data and computational technology. Recent research work in this area has been centered around the development of intelligent models that can analyze various interrelationships between traffic, environment, structure, and maintenance parameters.

2.1 Flexible Pavement Deterioration

The flexible pavement deterioration is a gradual process due to the effects of loading, environment, aging, and structure. The common forms of deterioration observed include fatigue cracks, ruts, pot holes, ravelling, and roughness of the pavement surface. The forms of pavement deterioration are known to be results of various interrelated parameters and for this reason, there have been several efforts in applying AI in predicting these deteriorations.

Recent research studies have found that machine learning models can be utilized in predicting parameters associated with pavement deterioration. Alnaqbi et al. (2024b) applied machine learning algorithms in predicting flexible pavement fatigue cracking. Adeke et al. (2025) created an intelligent model to predict deterioration using traffic and pavement parameters, whereas Ehsani et al. (2025) applied metaheuristics and machine learning in predicting rutting deterioration. Additionally, Kaur and Kumar (2025) have effectively employed soft computing techniques for predicting fatigue and rutting deteriorations. The studies are clear indications of the shift from traditional modelling methods towards data-based modelling techniques which are more capable of capturing complex pavement behaviour. Many of the existing studies focus on region-specific data sets.

2.2 Factors Affecting Flexible Pavement Deterioration

Pavement distress is due to the interaction between factors such as vehicle load, environmental factors, pavement structure, and maintenance, not due to one single factor alone. Higher loads, overloads, and repeated loads lead to fatigue failure and plastic flow, whereas rainfall, temperature variations, and poor drainage may cause rapid degradation of pavements. Gao et al. (2023) have shown that using more distress measures and maintenance factors will help predict pavement performance better. Mansour et al. (2023) showed how climatic factors affect long-term performance of pavements, especially in the case of high temperatures and humidity. Lv et al. (2025) have further pointed out the significance of using traffic, structural, and environmental factors in assessing pavement distress.

2.3 Artificial Intelligence for Pavement Deterioration Prediction

AI-based approaches have proved to be more useful for pavement deterioration prediction since they can capture complicated nonlinear relations from the past data. While previous approaches utilized ANN based models, recently, studies have been conducted using ensemble learning approaches and deep learning techniques. Deneko et al. (2024) showed the effectiveness of ANN in pavement surface condition prediction. Chen et al. (2025) integrated engineering know-how into the model by using physics-guided ANN to increase the prediction accuracy whereas Li et al. (2025) integrated physics into a deep learning technique to enhance prediction accuracy and stability.

The tree-based ensemble learning techniques have also attracted significant interest owing to their superior predictive power and computational efficiency. For instance, Chen and Guestrin (2016) presented an algorithm called XGBoost, which has since become among the most frequently used algorithms for the regression tasks. Based on these ensemble learning techniques, Lei et al. (2026) developed a multimodel approach for predicting the degradation of structural components, while Tamagusko and Ferreira (2025) showed the potential of tree-based supervised learning algorithms in predicting pavement performance. More recently, Tamagusko et al. (2026) further expanded these applications by combining machine learning with pavement maintenance optimization. Advances in deep learning have further expanded the capacity to model pavement deterioration and temporal behaviour. According to Gao et al. (2025), the transformer model has been capable of modelling the temporal degradation behavior. According to Xiao et al. (2025), the Bayesian neural network model has been capable of improving the robustness of the predictions, while Xiao et al. (2026) used LSTM networks to detect anomalies in sequential data.

2.4 Research Gap

From the reviewed literature, there is considerable advancement in AI pavement deterioration prediction. Many of the current studies have used prediction models or datasets that are limited to a particular region or prediction models. It is evident that most of the literature has not addressed the problem with Indian highways, which experience heavy traffic, overloaded axles, climatic variations, and diverse maintenance practices. In addition, it is important to note that few studies have systematically compared the performance of different AI models using the same dataset. This study adopts the use of synthetic Indian pavement deterioration dataset.

III.Materials and Method

The current study develops an AI system based on Python programming for prediction of flexible pavements' deterioration in Indian traffic. The proposed method involves the use of a publicly available dataset and the artificial Indian pavements' dataset along with the steps of data pre-processing, modeling of AI, and performance of the developed models.

3.1 Research Framework

The research methodology includes a chain of related steps that start from collecting data and end with predicting pavement deterioration. Two sources were used to collect pavement data that was then processed in order to use it in modelling. In the next step, five AI models were created and evaluated on the basis of their performance. The best model was then selected for pavement deterioration prediction under Indian traffic conditions. Figure 1 below shows the process followed in this study.

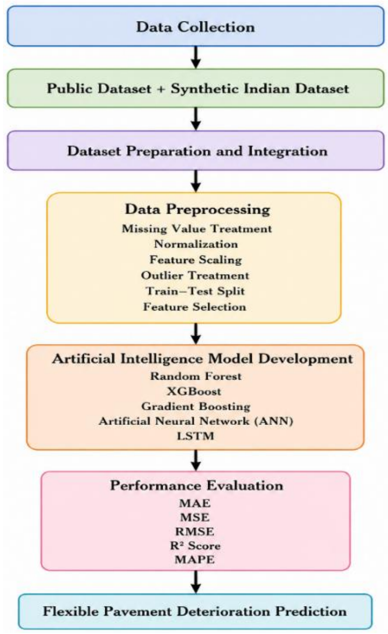

Figure 1. Overall Research Framework

Figure 1 illustrates the sequential workflow from data collection and preprocessing through model development, evaluation, and prediction.

3.2 Data Sources

Two different types of data sets were used in the study, each serving different purposes in the modeling phase. The public data set helped define the engineering ranges whereas the Indian synthetic data set helped develop the AI models. This method allowed the Indian synthetic data set to have Indian pavement attributes in engineering-plausible ranges.

The characteristics of datasets used in this research are listed in Table 1.

Table 1. Summary of Datasets Used for Model Development

Dataset	Purpose	Description
Public pavement dataset	Engineering validation	Approximately 1,050,000 pavement records containing standard pavement variables including PCI, IRI, Annual Average Daily Traffic (AADT), rutting, rainfall, road type, asphalt type, maintenance history, and maintenance requirement.
Synthetic Indian pavement dataset	AI model development	8,000 observations collected from 1,000 pavement sections over eight consecutive years, representing Indian traffic characteristics, climatic conditions, structural properties, maintenance information, pavement distress indicators, and Future IRI as the target variable.

The public pavement dataset was used just for reference only to evaluate the engineering plausibility and distribution ranges of the selected pavement variables, while the synthetic Indian pavement dataset was used for development and testing of AI models. The synthetic dataset reflects the traffic, weather, pavement structure, pavement maintenance conditions, and pavement distress development in a heterogeneous Indian traffic environment. Therefore, reported predictive performance here is on a controlled synthetic data set and should not be construed as field-validation performance on observed Indian highway sections.

The public pavement reference data set for this study is the ESC 12 Pavement Dataset created by Sulay (2023) and made publicly available on Kaggle. The dataset includes about 1.05 million pavement-segment records, and includes variables like Pavement Condition Index (PCI), International Roughness Index (IRI), Annual Average Daily Traffic (AADT), road type, asphalt type, rutting, rainfall, and maintenance status. This dataset was only used as an engineering-reference dataset to investigate possible ranges and distributions of pavement variables in the present study, and was not used to train the final AI models or generate the reported Future IRI predictions (Sulay, 2023).

3.3 Synthetic Indian Pavement Dataset Generation and Target Construction

The synthetic Indian pavement dataset consisted of 8,000 observations corresponding to 1000 pavement sections from 8 annual periods between 2017 and 2024. The observations were created as longitudinal pavement records, where each section has a pavement-condition history for each year. The traffic, cumulative ESAL, climatic, pavement, drainage, maintenance, and distress variables were populated within specified engineering parameters that were suggested by the public ESC 12 pavement reference database. The one-year-ahead pavement condition was determined for each pavement section iand year t, using a pavement deterioration relationship:

$$\mathrm{FutureIRI}_{i,t} = \mathrm{CurrentIRI}_{i,t} + \Delta\mathrm{IRI}_{i,t} + \epsilon_{i,t}$$

where $\mathrm{CurrentIRI}_{i,t}$is the current pavement roughness, $\Delta\mathrm{IRI}_{i,t}$is the annual deterioration increment (or degradation) caused by traffic loading, pavement distress, climate, pavement structure, drainage, and maintenance, and ϵ_(i,t)is a stochastic error term to account for the uncontrolled variability in pavement deterioration. To ensure physically realistic pavement-condition values, the Future IRI values generated were limited to the pre-defined engineering limits in the synthetic dataset. Future IRI was then defined as the Current IRI of the same pavement section in the next year for observations 2017-2023:

$$\mathrm{FutureIRI}_{i,t} = \mathrm{CurrentIRI}_{i,t+1}$$

So, the target is not an independently derived response variable but rather a true measure of a longitudinal deterioration over a one-year period. The lack of an annual observation for 2024 meant that Future IRI was created as a fake (synthetic) one-year-ahead projection using the same deterioration formula. The following 2024 values were not considered as measured in the field but as synthetic values only. In the synthetic-generation procedure, it is assumed that pavement deterioration is affected by traffic loading and existing pavement condition, distress, environmental exposure, structural characteristics, drainage, and maintenance, with some random variation from section to section and year to year. The resulting data set then offers a controlled and repeatable setting for comparing AI benchmarks. It is important to note that, since the target is being generated as part of this structured synthetic deterioration process, the extremely high predictive performance should be seen as an ability to perform in this synthetic environment and not as a field-level accuracy check. It is advisable to validate practically using the longitudinal observations from real Indian pavement sections.

3.4 Dataset Preparation and Integration

Both of the datasets were constructed independently in relation to their roles in the research. The publicly available ESC 12 data set was analyzed for determining the plausible values for the pavement parameters such as IRI, PCI, AADT, annual precipitation, and rutting depth. The engineering values determined based on this analysis were used in creating the synthetic data set for India. This data set consisted of traffic, ESAL, pavement structure, climatic, drainage, maintenance, distress, and future pavement condition data sets. These distributional comparisons were made to determine the engineering plausibility and not to prove that both data sets belong to the same statistical population.

Comparison of IRI between the two datasets is shown in Figure 2.

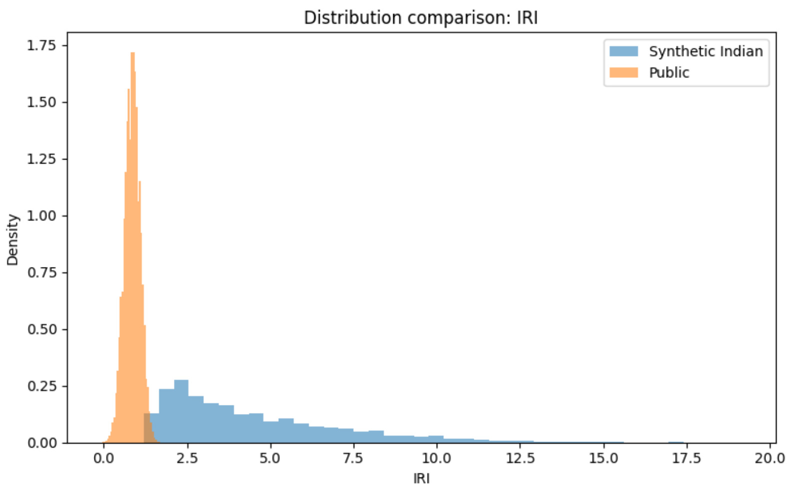

Figure 2. Distribution Comparison of International Roughness Index (IRI)

The distribution of PCI in both the datasets is shown in Figure 3.

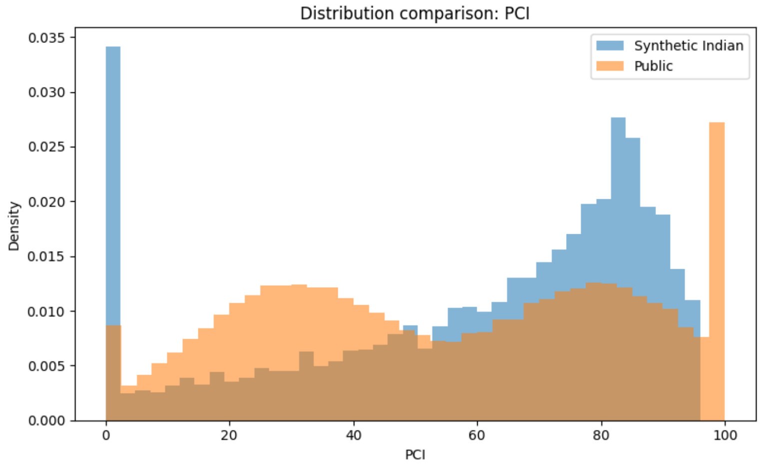

Figure 3. Distribution Comparison of Pavement Condition Index (PCI)

Distribution of AADT Used for Engineering Comparison is Shown in Figure 4.

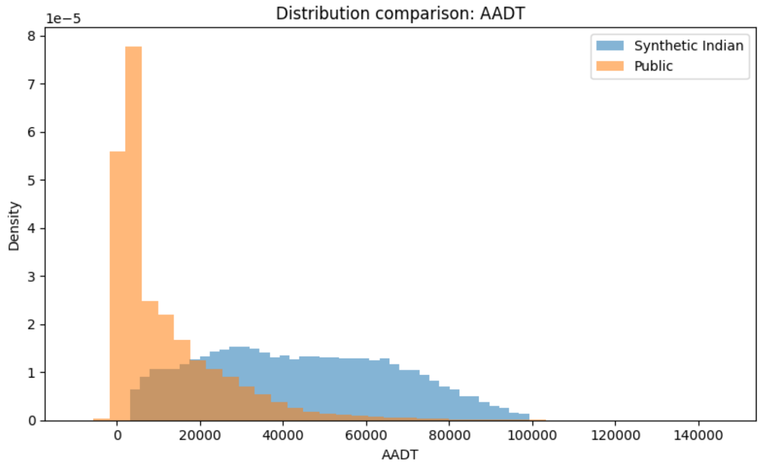

Figure 4. Distribution Comparison of Annual Average Daily Traffic (AADT)

The annual rainfall measured from the two data sets is presented in Figure 5 below.

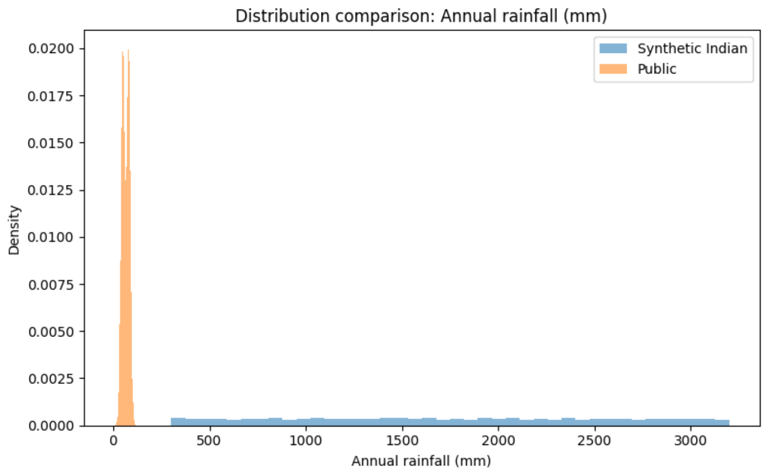

Figure 5. Distribution Comparison of Annual Rainfall

The final section is devoted to the rut depth comparison of the public and synthetic data, which can be seen in Figure 6.

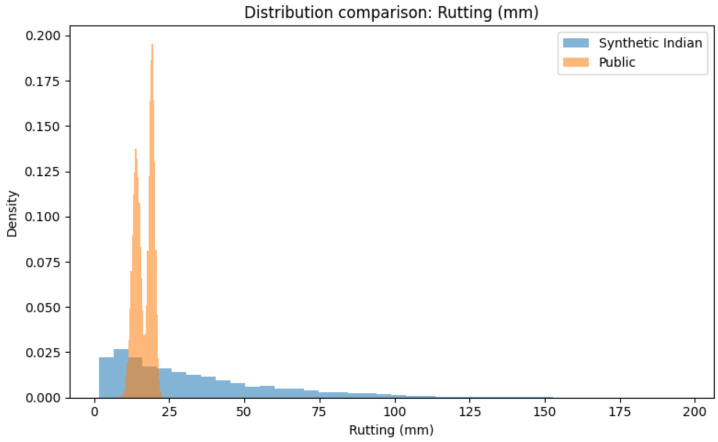

Figure 6. Distribution Comparison of Rut Depth

From the above analysis, the two datasets have shown that the synthetic Indian dataset and the publicly available reference data set are clearly different empirical distributions rather than being the same populations. The range of traffic, rainfall, IRI, and rutting values for the synthetic dataset are broader, since they need to account for the varying conditions in India, while the public reference dataset has its own unique distribution of values. Hence, these analyses are meant to act as plausibility tests in engineering.

3.5 Data Preprocessing and Model Validation

Any missing numerical data were imputed through median imputation. The training and test datasets were created by using GroupShuffleSplit method where 20 percent of the observations were used for testing while the random state was fixed to 42. Pavement Section ID was used for creating the groups so that no observation from the same section could be present in both the train and test datasets.

For the tabular models, the numerical features were standardize using StandardScaler after median imputation. Outlier threshold was calculated using the training dataset with 1.5*IQR criterion and then applied on the test dataset. In case of LSTM model, Min-Max scaling was used on sequential input variables.

Five models namely Random Forest, XGBoost, Gradient Boosting, Artificial Neural Network and LSTM were trained and evaluated using the same section-wise train-test split. The fixed hyperparameter settings of all the five models are described in Table 2. No automatic hyperparameter tuning or any grid search strategy was adopted. The performance of these models were analyzed using the section-wise 80:20 train-test split where random state is set to 42. Thus, the reported results are based on this particular experiment only.

3.6 Artificial Intelligence Models

After the preprocessing stage, there were five artificial intelligence algorithms used to predict future pavements degradation based on the Indian traffic environment. This included three ensemble learning algorithms; Random Forest, XGBoost, and Gradient Boosting and two deep learning algorithms; ANN and LSTM. All the algorithms were built on the prepared data set.

The relation between the predictor variables and the future deterioration of pavements can be mathematically described by Eq. (1).

$$\hat{Y} = f(X) \tag{1}$$

Where $\hat{Y}$ denotes the predicted Future IRI, X represents the selected predictor variables, $f(\cdot)$ and denotes the corresponding AI model.

The Random Forest approach was used to build several decision trees and produce predictions via ensemble averaging. Both XGBoost and Gradient Boosting have been used as methods of sequential boosting, whereby the prediction errors are sequentially minimized at each model fitting step. ANNs have been utilized to capture the non-linear interactions between the pavement degradation factors, while the LSTM network has been applied to find the sequence relationships within the prepared pavement data. Models have been trained and tested under the same experimental settings in order to make their comparative analysis fair.

The fixed sets of hyperparameters of the five main AI models have been presented in Table 2. They have been specified in the experimental procedure and remained unchanged for both training and testing of the models; there has been no automatic hyperparameter tuning or parameter grid searching involved. The ANN and LSTM models have also used an additional 15% validation split inside the training stage for early stopping and learning rate adjustment. It is not cross-validation.

Table 2. Fixed Hyperparameter Configurations Used for the Five Primary AI Models

Model	Hyperparameter / Configuration	Fixed value
Random Forest	Number of estimators	350
	Maximum depth	None
	Minimum samples for split	2
	Minimum samples per leaf	1
	Maximum features	sqrt
	Random state	42
	Number of jobs	-1
XGBoost	Number of estimators	600
	Learning rate	0.035
	Maximum depth	6
	Minimum child weight	2
	Subsample	0.85
	Column subsample by tree	0.85
	L1 regularization (reg_alpha)	0.05
	L2 regularization (reg_lambda)	1.0
	Objective	reg:squarederror
	Random state	42
	Number of jobs	-1
Gradient Boosting	Number of estimators	350
	Learning rate	0.04
	Maximum depth	3
	Minimum samples for split	4
	Minimum samples per leaf	2
	Loss function	Huber
	Random state	42
ANN	Hidden-layer architecture	128–64–32
	Hidden-layer activation	ReLU
	Dropout rates	0.20, 0.15
	Output layer	1 neuron
	Optimizer	Adam
	Learning rate	0.001
	Loss function	MSE
	Batch size	64
	Maximum epochs	180
	Internal validation split	15%
	Early stopping patience	18 epochs
	Learning-rate reduction factor	0.5
	Learning-rate reduction patience	7 epochs
	Minimum learning rate	1×10^{-6}
LSTM	Sequence window	3 years
	LSTM architecture	64–32 units
	First LSTM layer	return_sequences=True
	Dense layer	16 neurons, ReLU
	Dropout rates	0.20, 0.15
	Output layer	1 neuron
	Optimizer	Adam
	Learning rate	0.001
	Loss function	MSE
	Batch size	64
	Maximum epochs	180
	Internal validation split	15%
	Early stopping patience	18 epochs
	Learning-rate reduction factor	0.5
	Learning-rate reduction patience	7 epochs
	Minimum learning rate	1×10^{-6}

Apart from these five main models, Support Vector Regression (SVR) was considered as an additional optional baseline for the purpose of creating another non-linear benchmark. The SVR model considered was that of radial basis function (RBF) kernel with $C = 50$, $\varepsilon = 0.03$ and γ = "scale". In order to cut down the computational cost of regression with kernels, SVR was applied on a reproducible random sample of 5,000 training samples. Hence, SVR was only considered as an additional baseline.

3.7 Performance Evaluation

Performance of the model was assessed based on five measures of regression: MAE, MSE, RMSE, R^2, and MAPE. Such measures describe the difference between observed and predicted Future IRI values.
The MAE is the average absolute difference between actual and predicted values and is given as per Eq. (2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

MSE measures the average squared prediction error and is denoted in Eq. (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

The RMSE is derived from the square root of MSE using Eq. (4).

$$RMSE = \sqrt{MSE} \tag{4}$$

The $\mathcal{R}^2$ measures the proportion of variance explained by the prediction model and is computed using Eq. (5).

$$\mathcal{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

where $\bar{y}$ represents the mean of the observed values.

MAPE measures the prediction error as a percentage using the equation provided in Eq. (6).

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{6}$$

The smaller the MAE, MSE, RMSE, and MAPE values, the lesser the error in predictions; and the larger the (R^2) value, the better is the fit of the future IRI values. These performance metrics were applied to evaluate the five main AI models, where the SVR model was considered separately.

IV.Results and Discussion

The five AI models mentioned above and the baseline SVR model were analyzed using the synthetic Indian pavement dataset that was generated. The following section provides descriptive statistics, correlation analysis, feature importance, model comparison, and XGBoost prediction analysis. The results include the descriptive analysis of the dataset, relations between predictor variables, feature importance analysis, and comparison of developed AI models.

4.1 Dataset Statistics

Prior to the analysis of the performance of the predictive models, the characteristics of the data set after processing was done were evaluated. Descriptive statistics were used to describe the distribution and variability of the predictor and target variables.

Descriptive statistics of the study variables is shown in Table 3.

Table 3. Descriptive Statistics of the Study Variables

Variable	Count	Mean	Std. Dev.	Minimum	25th Percentile	Median	75th Percentile	Maximum	Missing Values
Year	8000	2020.50	2.29	2017.00	2018.75	2020.50	2022.25	2024.00	0
Pavement Age	8000	4.50	2.29	1.00	2.75	4.50	6.25	8.00	0
Surface Age (Years)	8000	3.65	2.17	1.00	2.00	3.00	5.00	8.00	0
AADT	8000	44272.98	23009.62	3091.00	25570.75	42986.00	62249.00	99249.00	0
Commercial Vehicle (%)	8000	25.05	8.71	10.00	17.55	25.03	32.63	40.00	0
Mixed Traffic Index	8000	0.63	0.19	0.30	0.46	0.63	0.79	0.95	0
Overloading Factor	8000	1.40	0.23	1.00	1.20	1.40	1.60	1.80	0
Annual ESAL	8000	18.14	17.71	0.18	5.89	12.16	24.33	138.11	0
Cumulative ESAL	8000	77.25	68.12	0.18	24.19	57.84	110.05	484.36	0
Annual Rainfall (mm)	8000	1733.36	829.15	300.80	1026.88	1726.45	2444.72	3199.30	0
Mean Temperature (°C)	8000	24.55	5.50	15.00	19.76	24.63	29.36	34.00	0
Maximum Temperature (°C)	8000	37.45	5.49	28.00	32.70	37.40	42.22	47.00	0
Climate Severity Index	8000	0.85	0.42	0.09	0.53	0.84	1.14	1.98	0
Surface Thickness (mm)	8000	140.15	34.46	80.00	110.70	139.90	170.20	200.00	0
Base Thickness (mm)	8000	235.32	49.22	150.00	192.88	234.60	278.40	320.00	0
Sub-base Thickness (mm)	8000	250.06	57.67	150.00	200.58	249.90	300.23	350.00	0

Subgrade CBR	8000	9.01	3.46	3.00	6.04	9.02	11.99	15.00	0
Deflection (mm)	8000	3.79	1.62	0.63	2.63	3.59	4.71	12.53	0
Drainage Score	8000	3.00	1.15	1.00	1.98	3.00	3.99	5.00	0
Maintenance Score	8000	3.02	1.16	1.00	2.01	3.04	4.04	5.00	0
Maintenance Cost (INR Lakh)	8000	13.09	6.97	1.00	6.91	13.20	19.12	25.00	0
Traffic Loading Index	8000	17.35	20.47	0.11	4.23	10.00	22.14	185.86	0
Rut Depth (mm)	8000	32.91	27.25	1.49	11.68	25.10	46.07	196.55	0
Fatigue Cracking (%)	8000	79.98	29.12	2.82	59.85	100.00	100.00	100.00	0
Longitudinal Cracking	8000	332.00	278.32	6.26	116.79	254.20	468.88	1969.49	0
Transverse Cracking	8000	7.00	2.70	1.01	5.03	7.03	8.99	12.99	0
Pothole Density	8000	10.58	6.47	0.52	5.36	10.02	14.21	44.31	0
Current IRI	8000	4.51	2.71	1.20	2.40	3.72	5.90	19.22	0
Previous PCI	8000	59.66	28.43	0.00	42.15	68.82	82.74	96.00	0
Future IRI (Target Variable)	**8000**	**5.49**	**3.22**	**1.33**	**2.99**	**4.58**	**7.16**	**23.08**	**0**

The final dataset, as shown in Table 3, consists of 8,000 data points drawn from 1,000 pavement sections over eight years, with no missing data points following the preprocessing phase. The dataset shows high variation in traffic, climatic, structural, maintenance, and pavement distress factors. AADT varies between 3,091 and 99,249 vehicles/day, while annual rainfall is between 300.80 and 3,199.30 mm, indicating varied traffic and environmental conditions within India. On the other hand, the target variable, Future IRI, is between 1.33 and 23.08 m/km, thus showing variation in terms of both good and poor pavement conditions. In general, the dataset is highly variable for the purpose of developing the AI model.

To further investigate pavement properties within different traffic environments, the dataset was analyzed according to road type. The road-type summary is shown in Table 4.

Table 4. Road-Type Summary

Road Type	Observations	Mean AADT	Mean Overloading	Mean Current IRI	Mean Future IRI	Mean Rutting
MDR	2600	44408.25	1.400	4.550	5.544	33.397
NH	2712	42543.14	1.401	4.352	5.287	30.981
SH	2688	45887.42	1.406	4.617	5.632	34.385

The difference in pavement condition features is presented in Table 4. The mean future IRI of State Highways (SH) is the highest (5.632), as well as the mean rut depth (34.385 mm), while in the case of National Highways (NH), these indicators are at their minimum (5.287 and 30.981 mm, respectively). The MDR value lies between SH and NH.

4.2 Correlation Analysis

Correlation analysis was used to establish the interrelationships between the predictor variables and their relationship with the Future IRI. The matrix obtained through the correlation analysis of the prepared data is presented in Figure 7.

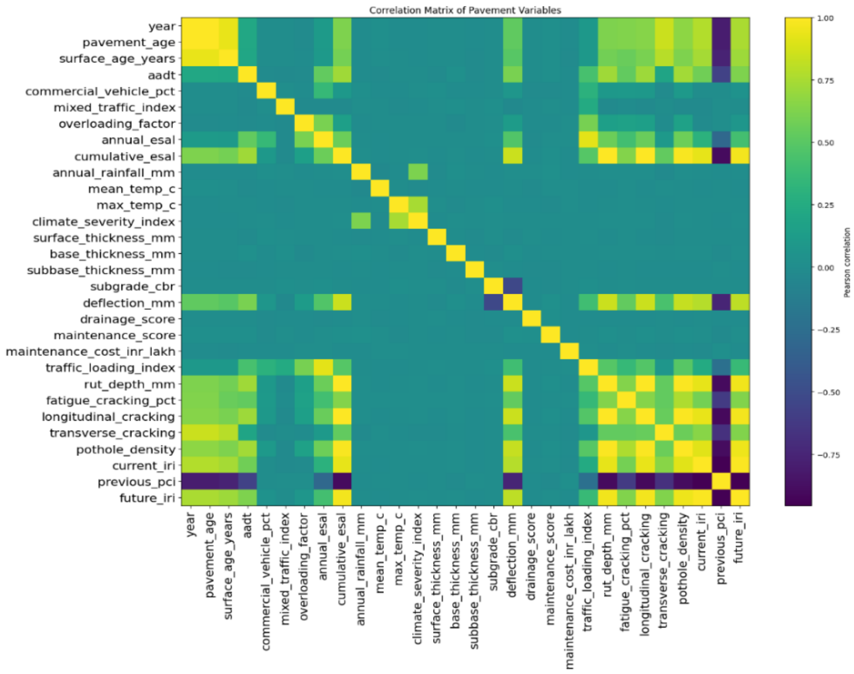

Figure 7. Correlation Matrix

From Figure 7, it is evident that there are strong positive correlations between Current IRI, Rut Depth, Fatigue Cracking, Cumulative ESAL, and Future IRI. These relationships have shown that future IRI increases when there is higher traffic loading as well as pavement distress. The above relationship justifies the use of the above variables as part of the predicting process. Correlation analysis thus forms a foundation from which predictor importance will be analyzed in the next step.

4.3 Feature Importance

The analysis of feature importance was later on conducted to find the variables with high correlation with predicting Future IRI. The methods utilized for analyzing the variables in terms of significance of prediction from two perspectives, which are dependency between variables and contribution of the variable in the model. Figure 8 shows the ranking of features using Mutual Information analysis.

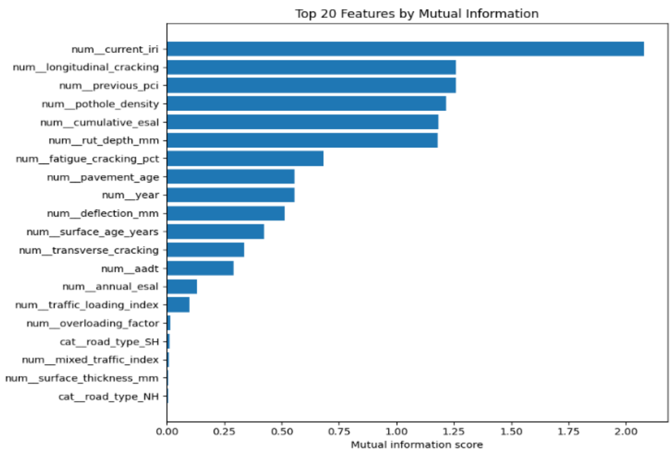

Figure 8. Top 20 Predictors Ranked by Mutual Information

As illustrated in Figure 8, Current IRI is the most important feature for determining Future IRI, followed by Longitudinal Cracking, Previous PCI, Pothole Density, Cumulative ESAL, and Rut Depth. It indicates that pavement condition at present along with traffic loading are the most important factors for predicting the future deterioration condition. Further to investigate this relationship, XGBoost based feature importance was carried out. Feature importance is shown in Figure 9.

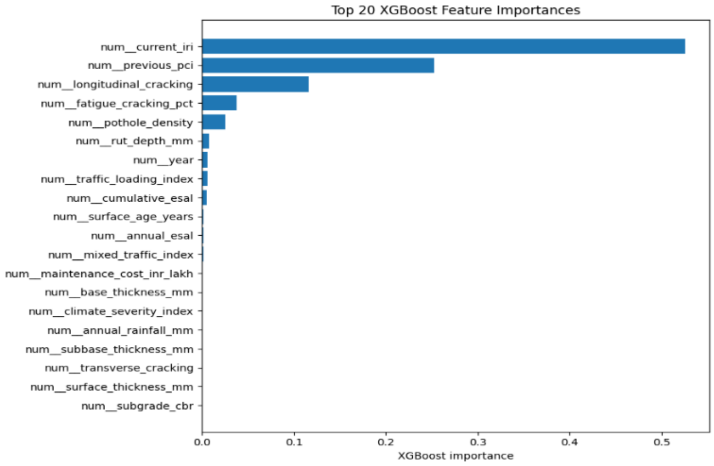

Figure 9. XGBoost Feature Importance

The feature rankings of XGBoost and Mutual Information techniques, as illustrated in Figure 9, have a high level of correlation. The most influential variables to the outputs are: Current IRI, Previous PCI, Longitudinal Crackings, Fatigue Crackings, Potholes per Unit Length, Rut Depth, Traffic Load Index, and ESALs accumulated. The consistency of the ranking achieved through both methodologies is additional evidence for the significance of the variables in the suggested predictive model.

4.4 AI Model Comparison

There were six models under evaluation including five primary artificial intelligence algorithms namely, Random Forest, XGBoost, Gradient Boosting, ANN and LSTM along with SVR which was used as an auxiliary nonlinear algorithm. The performance comparison of all these models is provided in Table 5.

The highly accurate predictions of the models could not be directly regarded as indicators of the models' performance as the synthetic target has an intrinsic connection with the longitudinal variables of pavement condition used as predictor variables.

Table 5. Performance Comparison of Artificial Intelligence Models

Model	MAE	MSE	RMSE	R^2	MAPE (%)
XGBoost	**0.0718**	**0.0520**	**0.2280**	**0.9950**	**0.9676**
Gradient Boosting	0.0870	0.0522	0.2285	0.9950	1.3620
Random Forest	0.1862	0.0822	0.2868	0.9921	3.7182
SVR (Baseline)	0.1431	0.0977	0.3126	0.9907	2.3696
LSTM	0.2898	0.1942	0.4407	0.9802	4.1562
ANN	0.3373	0.2341	0.4838	0.9776	7.4126

As seen in Table 5, XGBoost performed best among the five major models with respect to the minimum MAE (0.0718), RMSE (0.2280), and MAPE (0.9676%) values. The R^2 value of 0.9950 was also the same as that of the Gradient Boosting model. Although Gradient Boosting had good predictive accuracy, Random Forest performed better in terms of high prediction errors. Both ANN and LSTM had higher errors compared to the other tree-based ensemble models. This suggests that the predictive performance of the tree-based ensemble models is superior to that of the deep learning models in this artificial data benchmarking scenario. RMSE values of all developed models are shown in Figure 10.

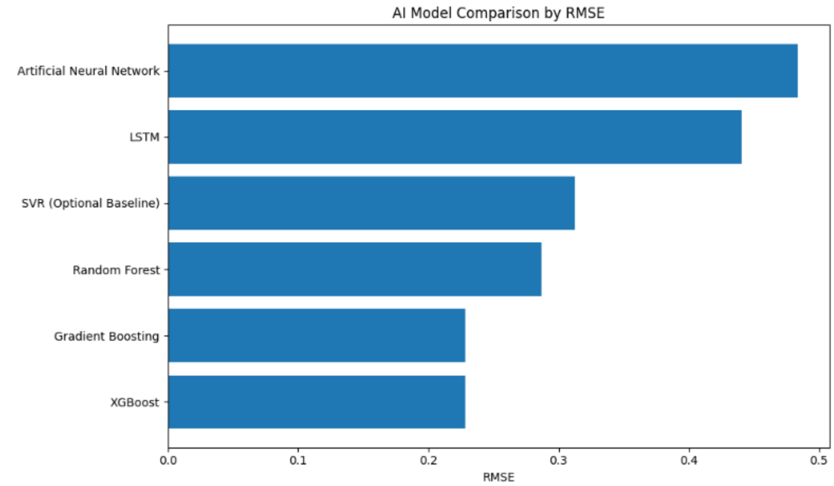

Figure 10. RMSE Comparison of Artificial Intelligence Models

Both XGBoost and GBM had the minimum RMSE scores, while RF was better than ANN and LSTM, which had higher error values, similar to those shown in Table 5.

In a similar manner, the comparison of the R^2 is performed in Figure 11.

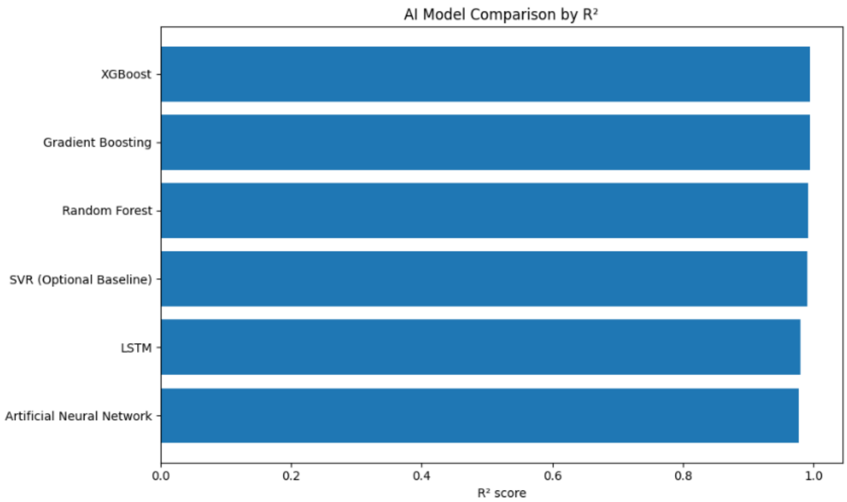

Figure 11. R^2 Comparison of Artificial Intelligence Models

As observed from Figures 11, XGBoost and Gradient Boosting models perform best with the R^2 value which is followed by Random Forest model. The R2 values obtained by ANN and LSTM were approximately lower than the rest of the algorithms, in accordance with their higher prediction errors.
On a combined basis of the numerical and graphical metrics presented, XGBoost emerges as the most accurate prediction technique for deterioration of flexible pavements under Indian traffic conditions.

4.5 Best Prediction Model

The comparative evaluation showed that XGBoost was the best performing model, with the smallest MAE, RMSE, and MAPE and the highest R^2 of 0.9950. To further investigate the learning ability of the developed deep learning models, the curves for training and validation losses of the ANN and LSTM models have been analyzed. Training results of the ANN and LSTM models have been shown in Figures 12 and 13, respectively.

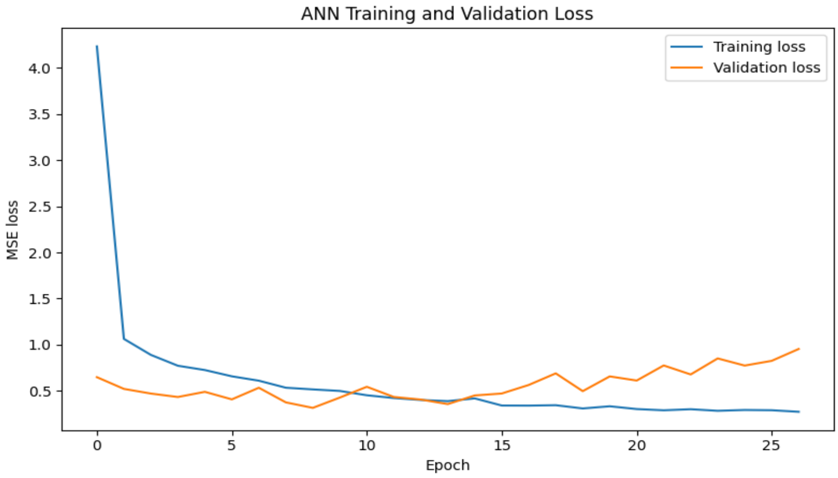

Figure 12. ANN Training and Validation Loss

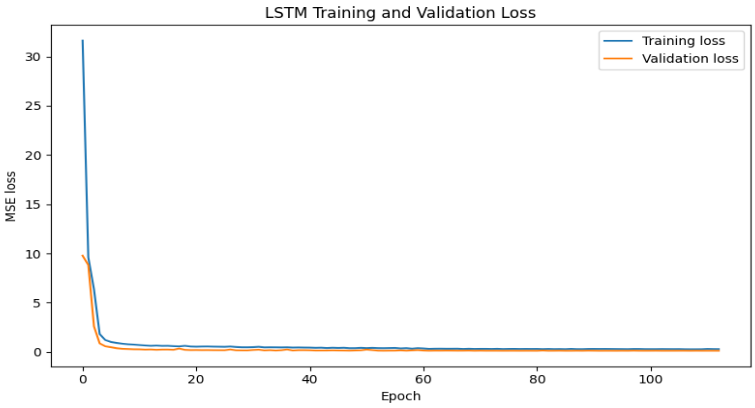

Figure 13. LSTM Training and Validation Loss

As shown in Figures 12 and 13, there is no sign of divergence in both the neural network loss curves and the training and validation loss curves during training, indicating stable convergence. Both models performed well during training, however, the errors from them on the test set was greater than the errors of the ensemble models, especially for XGBoost and Gradient Boosting.

Therefore, XGBoost was chosen as a final predictor of pavement deterioration under Indian traffic conditions.

4.6 Prediction under Indian Traffic Conditions

XGBoost was found to be the best performing model and the predictive performance was assessed using the held out testing data that was the synthetic Indian pavement. To verify the feasibility of the proposed framework, the accuracy and residual error of the predictions and scenario prediction were analyzed. The comparison of observed and predicted values of Future IRI is shown in figure 14.

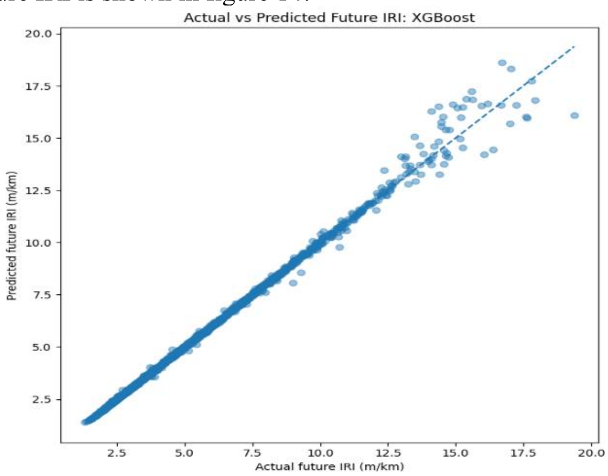

Figure 14. Actual versus Predicted Future IRI Using XGBoost

The close agreement between the observed and predicted Future IRI shown in Figure 14 confirms that XGBoost captures the relationships between the traffic, climatic, structural, maintenance and pavement-condition variables in the synthetic data set. The majority of the prediction points are very close to the ideal prediction line, indicating accurate predictions and good correlation between the observed and predicted pavement deterioration.
To examine the robustness of the developed model, the prediction residuals were considered. The residual error distribution obtained from the XGBoost model is presented in Figure 15.

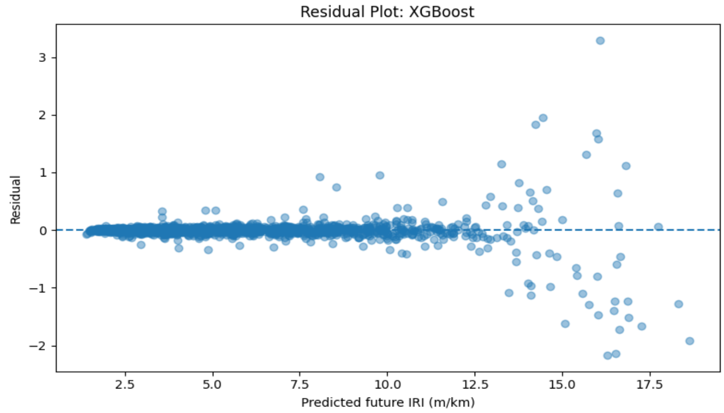

Figure 15. Residual Error Distribution of the XGBoost Model

As seen in Figure 15, the residuals are clustered around zero across the majority of the prediction range, although the spread in the residuals increases at higher predicted values of the IRI and there are several large negative and positive residuals. This pattern suggests that there is heteroscedasticity, and that prediction uncertainty increases with highly deteriorated pavement conditions. The pattern is relevant because the synthetic dataset is much smaller in the extreme conditions of the pavement than it is in the moderate conditions. Thus, the overall predictive agreement is good but the residual plot shows that the overall stability is not as good at the top of the range of deterioration.

The results of the Future IRI predictions for varied traffic cases are provided in Table 6.

Table 6. Prediction under Indian Traffic Scenarios

Scenario	Predicted Future IRI (m/km)
Low Traffic – Good Maintenance	4.420
Moderate Mixed Traffic	4.513
Heavy Monsoon – Poor Drainage	4.600
Heavy Overloaded Highway Traffic	4.756

Graphical comparison for the forecasted future values of IRI is shown in Figure 16.

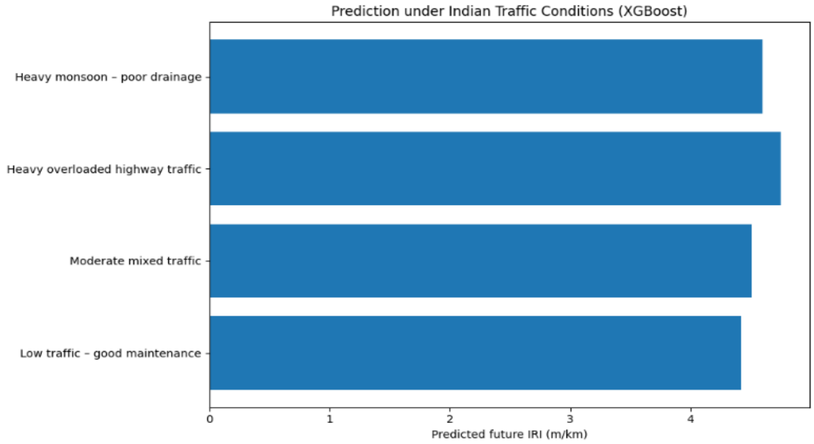

Figure 16. Prediction under Indian Traffic Conditions

There is an increase in the predicted Future IRI when heavier traffic loading and adverse environmental conditions are involved as shown in Table 6 and Figure 16. The highest value of Future IRI (4.756 m/km) in this case was for the Heavy Overloaded Highway Traffic scenario and the lowest was for the Low Traffic-Good

Maintenance scenario (4.420 m/km). Similarly, the Heavy Monsoon-Poor Drainage scenario also resulted in higher level of degradation as compared to the Moderate Mixed Traffic scenario, thus emphasizing the impact of the adverse weather condition and drainage. With these findings, it can be concluded that the XGBoost model can explain the combined effect of the traffic, climatic, and maintenance conditions in the synthetic prediction system.

4.7 Comparison with Existing Studies

Proposed AI framework was benchmarked with the latest research on pavement deterioration prediction, in terms of dataset characteristics, modelling approaches, and main findings. The comparison covers the prediction approach, the characteristics of the data sets, AI methods and main results. Comparison is provided in Table 7.

Table 7. Comparison of the Proposed Framework with Existing Studies

Study	Dataset / Application	AI Models	Major Findings
Marcelino et al. (2021)	Pavement performance dataset	Machine Learning models	Demonstrated that machine learning improves pavement performance prediction compared with conventional empirical approaches.
Madeh Piryonesi and El-Diraby (2021)	Flexible pavement deterioration dataset	Multiple ML algorithms	Showed that prediction accuracy depends on the selected performance indicator and machine learning algorithm.
Alnaqbi et al. (2024b)	Flexible pavement IRI prediction	Machine Learning models	Reported accurate IRI prediction using pavement condition and traffic variables but focused on regional pavement data.
Gao et al. (2023)	Pavement distress dataset	Deep Learning	Improved pavement prediction by incorporating multiple distress indicators and maintenance history.
Tamagusko and Ferreira (2025)	Pavement performance dataset	Random Forest, XGBoost and other tree-based models	Demonstrated that ensemble tree-based algorithms provide reliable pavement performance prediction.
Present Study	**Synthetic Indian pavement dataset (8,000 observations)**	**Random Forest, XGBoost, Gradient Boosting, ANN and LSTM**	**XGBoost achieved the highest prediction performance (RMSE = 0.2280, R^2 = 0.9950). The proposed framework integrates heterogeneous Indian traffic, climatic, structural and maintenance variables within a unified AI prediction workflow.**

As indicated in Table 7, recent research has shown the promise of AI techniques in pavement deterioration forecasting, but many of these have been limited to certain regions and limited models. Five main AI models are compared in the present study based on a common synthetic dataset that contains traffic, climatic, structural, maintenance and pavement-distress variables. XGBoost outperformed all the other models, Gradient Boosting and Random Forest showed the best performance, ANN and LSTM had comparatively higher error of prediction.

4.8 Limitations of the Study

There are several limitations to this study. First, the Indian pavement data is synthetic and hence cannot replace the independent field observations taken from Indian highways. Second, the high predictive performance seen in the models is structurally related to the longitudinal pavement-condition variables used as the Future IRI target, which could be responsible for the high performance. Third, model evaluation was done using a single section-wise train–test split, and not k-fold cross validation, so the reported performance does not reflect variation across the different folds of the cross validation. Repeated or k-fold section-wise cross validation and independent external validation datasets should be used for evaluating the robustness of the model in future studies. Fourth, the public ESC 12 data set was only employed for engineering plausibility and distributional comparison and not as an external validation data set. Lastly, the 2024 Future IRI values are extrapolated synthetic targets, as there are no observed values available for that year. The said proposed framework should therefore be tested using independent longitudinal pavement-condition data from various highway corridors in India and the robustness of the model should be tested by repeating the cross-validation or by using external hold-out dataset.

V.Conclusion and Future Scope

This study has created and validated an artificial-intelligence framework to predict the deterioration of flexible pavements for a year ahead based on a synthetic Indian pavement dataset of 1000 pavement sections with 8 years of observation data, that makes up 8000 observations. The model with the best overall performance was XGBoost, which had an MAE of 0.0718, an RMSE of 0.2280, a MAPE of 0.9676%, and an R^2 of 0.9950. The most important indicators of future pavement condition were determined to be Current IRI, Previous PCI, Longitudinal Cracking, Rut Depth, Pothole Density and Cumulative ESAL.

The results show that the AI pavement degradation prediction was possible in the artificially created Indian pavement environment. The reported R^2 of 0.9950 and sub-1% MAPE, however, should not be taken as a performance in real Indian highway data as the Future IRI target was created in a controlled synthetic longitudinal environment. The framework must be further tested in the field, independently, before it can be adopted for operational pavement-management applications. Future studies involving validation of the models using pavement data collected in India and testing the robustness of the prediction by repeating the validation process along with embedding real-time pavement monitoring with GIS-based pavement-management system are recommended.

Data Availability Statement

The public ESC 12 Pavement Dataset, which was used for engineering-reference comparison, has been made available to the public by Kaggle, and is referenced in this study as Sulay (2023). The synthetic Indian pavement dataset of 8000 observations has been created specifically for this study and is not based on field observations. The synthetic data and accompanying research materials are available from the corresponding author with reasonable request.

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Conflict of Interest Statement

The authors have no conflict of interest or competing interest with this research or its publication.

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