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Genetic Algorithm-Enhanced Gradient Boosting for Transverse Cracking in CRCP

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ABSTRACT

Transverse cracking represents a significant level of distress in Continuously Reinforced Concrete Pavement (CRCP), which is damaging to the pavement's functionality and durability. This study intends to construct a state-of-the-art hybrid machine learning algorithm that accurately predicts transverse cracking in CRCP by integrating a Gradient Boosting Machine (GBM) with a Genetic Algorithm (GA). The analysis comprised 33 CRCP sections using the Long-term Pavement Performance (LTPP) database with 20 dependent variables covering traffic, structural, climatic, and performance aspects. The longitudinal and hybrid GA-GBM model was found superior to baseline models, including standard GBM, Random Forest, Support Vector Regression (SVR), Linear Regression, and Artificial Neural Network (ANN), with RMSE of 0.034 and R^2 of 0.98926. Annual Average Daily Truck Traffic (AADTT), Kilo Equivalent Single Axle Load (KESAL), and Temperature were found to be the most impactable, sensitive structural variables, such as Concrete Layer Thickness (L4 Thickness), and Total Thickness. Precipitation and Freeze Index as climatic factors were also identified to have moderate significance. These results demonstrated the significant effects of traffic, structural, and climatic elements on transverse cracking. The findings highlight the GA-GBM model's potential to direct data-driven pavement management strategies and show how robust and dependable the model is for predictive modeling. To further improve prediction accuracy and applicability, future research should broaden the scope by examining sophisticated machine learning techniques and adding more variables.

Keywords: Transverse cracking, Continuously reinforced concrete pavement, Genetic algorithm optimization, Gradient boosting machine, Pavement performance, Machine learning applications, Structural distress prediction.

INTRODUCTION

Transverse cracking is one of the most severe types of distress in Continuously Reinforced Concrete Pavement (CRCP), compromising pavement performance, ride quality, and serviceability (Al-Khateeb et al., 2024; Moharekpour et al., 2022). These cracks, which are perpendicular to the pavement's longitudinal axis, are frequently caused by a combination of heat stresses, traffic-induced loads, and material fatigue (Kim et al., 2019; Choi, 2015). If not addressed, transverse cracks can widen and degrade with time, resulting in water infiltration, decreased pavement durability, and higher maintenance expenses (Alnaqbi et al., 2023). As a result, accurate forecasting and good control of transverse cracking are critical for increasing the lifespan of CRCP and assuring cost-effective infrastructure maintenance plans (van Dam et al., 2019; Huang, 2024).

The complicated, non-linear interactions between contributing factors are frequently not adequately captured by empirical and mechanistic-empirical models, two traditional approaches for predicting transverse cracking (Abojaradeh et al., 2011; Zeiada et al., 2024). These methods are less flexible to the variety of conditions found in real-world situations, since they need a lot of calibration and are predicated on assumptions about pavement behavior (Zhao, 2023; Song et al., 2022). In order to handle high-dimensional datasets and reveal hidden patterns among predictor variables, pavement performance modeling has benefited from recent developments in machine learning (ML) (Alnaqbi et al., 2024a; Alnaqbi et al., 2024b). Because of these qualities, machine learning techniques hold great promise for accurately predicting transverse cracking and understanding the fundamental mechanisms guiding its development (Alnaqbi et al., 2024c).

When it comes to capturing complicated interactions and non-linear correlations between variables, ensemble learning models like Gradient Boosting Machine (GBM), have outperformed other machine learning techniques (Babu Nuthalapati & Nuthalapati, 2024). As an iterative ensemble approach, GBM builds a powerful predictive model by combining several weak learners, usually decision trees. However, GBM's performance is heavily dependent on the meticulous adjustment of its hyperparameters, which control the model's overall accuracy, learning rate, and complexity (Lin et al., 2022). Genetic Algorithm (GA), an effective global optimization technique based on natural selection principles, can be used to find the best hyperparameter settings for GBM in order to overcome this difficulty (Bacanin et al., 2022). By integrating GA with GBM, a hybrid GA-GBM model can leverage the strengths of both methods, achieving enhanced predictive accuracy and robustness (Alkanhel et al., 2024).

A great starting point for this study is the Long-term Pavement Performance (LTPP) database, which offers an extensive compilation of high-quality data on CRCP performance under various traffic, structural, and climatic conditions (Alnaqbi et al., 2024d; Al-Samahi et al., 2024). Data-driven predictive models can be developed because of to this dataset, which contains important data on transverse cracking and its contributing factors (Zeiada et al., 2024; Sati et al., 2024; Al-Suleiman & Daoud, 2021; Al-Omari et al., 2022). While earlier research has effectively used the LTPP database to forecast pavement distresses, more effective hybrid models are still required to more precisely forecast transverse cracking and offer useful information for pavement management.

This study aims to develop and evaluate a hybrid GA-GBM model for predicting transverse cracking in CRCP. By utilizing data from the LTPP database, this research seeks to address the limitations of traditional methods and benchmark the GA-GBM model against other baseline machine learning models, including standard GBM, Linear Regression, Random Forest, Support Vector Regression (SVR), and Artificial Neural Network (ANN). In addition, feature importance and sensitivity analyses will be conducted to identify key contributors to transverse cracking and provide practical recommendations for optimizing pavement design and maintenance strategies.

RESEARCH OBJECTIVES

The primary objective of this study is to develop an accurate and robust machine learning model for predicting transverse cracking in CRCP using a hybrid approach that integrates GBM with GA optimization. This research aims to address the limitations of traditional prediction methods by leveraging advanced machine learning techniques to capture the complex interactions among structural, traffic, climatic, and performance-related factors. The specific objectives of this study are as follows:

1. **Model Development and Optimization**: To develop and optimize a GA-GBM model for predicting transverse cracking in CRCP, utilizing the hyperparameter optimization capabilities of GA to enhance the accuracy and robustness of the GBM model.
2. **Comparative Performance Analysis**: To benchmark the GA-GBM model against baseline machine learning models, including standard GBM, Linear Regression, Random Forest, SVR, and ANN, using key performance metrics, such as Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2).
3. **Feature Importance Identification**: To analyze the

importance of predictor variables, including structural, climatic, traffic-related, and performance factors, and identify the key contributors to transverse cracking in CRCP through feature importance rankings.

4. **Sensitivity Analysis**: To conduct sensitivity analysis on the GA-GBM model, quantifying the impact of changes in individual predictor variables on the prediction outcomes and providing insights into their relative influence on transverse cracking.
5. **Practical Insights for Pavement Management**: To provide actionable recommendations for optimizing pavement design and maintenance strategies, informed by the findings of feature importance and sensitivity analyses.

METHODOLOGY

Data Description

The data utilized in this study was extracted from the LTPP database, a globally recognized resource for pavement performance data extensively used in research. This study focuses on 33 CRCP sections, comprising 395 observations carefully selected to ensure diversity across climate, traffic, and structural conditions. The target variable for this study is the occurrence of transverse cracking, a critical pavement distress type that impacts the structural integrity and serviceability of CRCP.

The independent variables include 20 predictors grouped into four main categories: structure, climate, traffic, and performance, all of which are key factors influencing the formation of transverse cracking. Structure-related variables consist of age (years), construction number, and layer types and thicknesses for Layer #2 (sub-base), Layer #3 (base), and Layer #4 (Portland cement concrete or PCC), along with the total pavement thickness. Layer #1 (sub-grade) was removed from the study because, in pavement engineering, the sub-grade is often supposed to be infinitely thick and cannot be precisely measured in thickness-based structural evaluations. Climatic variables contain the climatic zone (categorical), yearly average precipitation (mm), annual average temperature (°C), annual average freeze index (C-degree days), and relative humidity (minimum and maximum percentages). Traffic-related variables have the number of lanes (categorical), Equivalent Single Axle Loads (ESALs), Annual Average Daily Traffic (AADT), and Annual Average Daily Truck Traffic (AADTT), which are all numerical. The performance-related variable is the initial International Roughness Index (IRI, m/km), which is also numerical.

These variables offer a comprehensive understanding of the structural composition, climate conditions, applied traffic loads, and baseline performance of the pavement, which are significant for modeling transverse cracking in CRCP. By capturing the intricate interactions among these factors, the dataset ensures robust model development and accurate predictions of transverse cracking under different conditions.

Table 1. Summary of the collected data

Data Type	Data Attribute	Number / Categorical
Structure	Age (years)	Number
	Construction Number	Number
	Layer #2 Type	Categorical
	Layer #2 Thickness (mm)	Number
	Layer #3 Type	Categorical
	Layer #3 Thickness (mm)	Number
	Layer #4 Type	Categorical
	Layer #4 Thickness (mm)	Number
	Total Thickness (mm)	Number
Climate	Climate Zone	Categorical
	Annual Average Precipitation (mm)	Number
	Annual Average Temperature (°C)	Number

	Annual Average Freeze Index (°C-Days)	Number
	Min. Relative Humidity (%)	Number
	Max. Relative Humidity (%)	Number
Traffic	Number of Lanes	Categorical
	ESALs	Number
	Annual Average Daily Traffic (AADT)	Number
	Annual Average Daily Truck Traffic (AADTT)	Number
Performance	Initial IRI (m/km)	Number
	Transverse Cracking (Ocuurances)	Number

The geographic distribution of the 33 selected CRCP sections is shown in Figure (1). These sections are located across various regions in the United States, representing a diverse range of climate zones, structural designs, and traffic conditions. The dataset includes sections from four distinct climate classifications—dry freeze, dry non-freeze, wet freeze, and wet non-freeze—ensuring that the model is trained on pavement conditions that span a wide spectrum of environmental settings. The map distinguishes between active sections (13 sections) and out-of-study sections (20 sections) recorded in the LTPP database, reinforcing the dataset's representativeness. The inclusion of climate classification as an input variable allows the GA-GBM model to learn patterns across different pavement exposure conditions, enhancing its potential applicability to regions beyond the original study area.

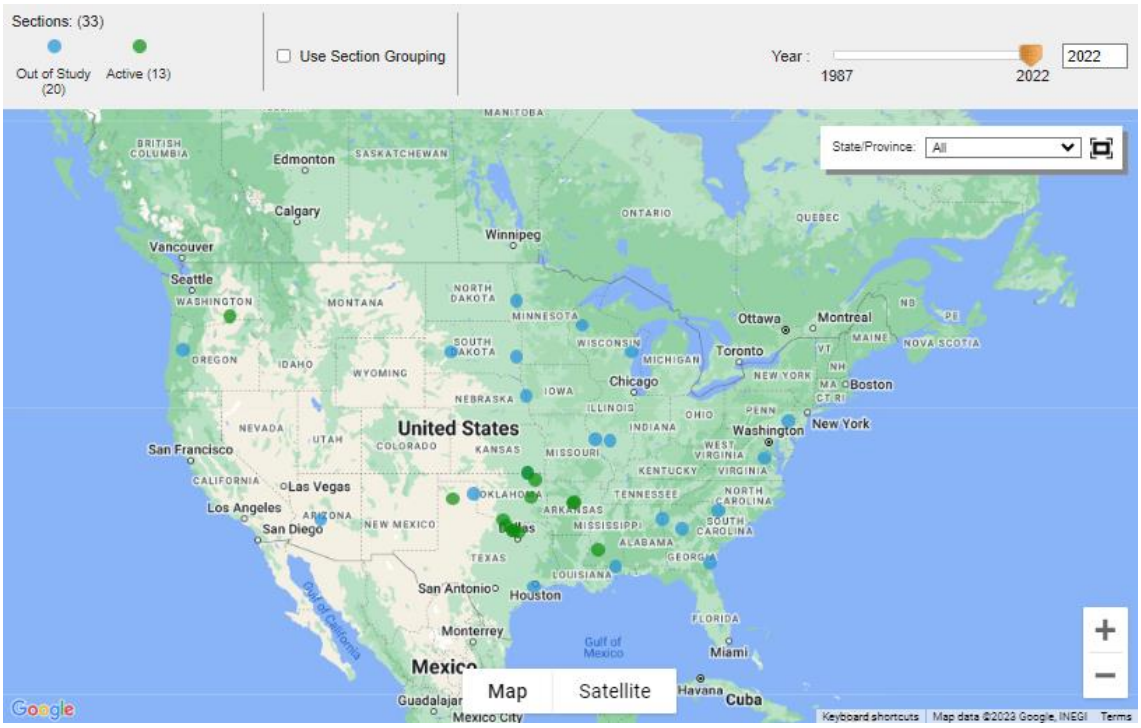

Figure (1): Mapping the geographic locations of the chosen asphalt pavement sections

Table 2 shows a summary of the descriptive statistical analysis for the numerical variables used in the study, offering insights into their central tendencies, variability, and distribution characteristics. The mean age of CRCP sections is 18.51 years, with a moderate standard deviation (SD) of 10.2 years, indicating variability in pavement lifespans. Structural variables, such as the thickness of layers (L2, L3, and L4) and total thickness, show important diversity, with L2 thickness showing the highest mean (169.78 mm) and positive skewness (1.08), suggesting occasional extreme values. Climatic variables, such as annual precipitation and temperature display varied ranges, with precipitation showing a high mean (1044.5 mm) and a moderate variability, while the freeze index is highly skewed (3.78), reflecting the impact of extreme conditions in some sections. Traffic-related variables, including AADT and ESAL, demonstrate important variability and positive skewness, indicating diverse traffic patterns across the sections. Notably, the output, transverse cracking, has a low mean (3.68 occurrences), but shows a high variability (SD = 17.15) and a pronounced skewness (6.96), highlighting its infrequent, yet severe, occurrence. In general, the diversity and variability within these variables underline the robustness of the dataset for developing predictive models of transverse cracking under varied real-world conditions.

Table 2. Summary of descriptive statistical analysis

Variable	Mean	SD	Min.	Q1	Median	Q3	Max.	IQR	Skewness
Age, years	18.51	10.2	0	11	18	26	47	15	0.34
Number of Lanes	2.24	0.52	1	2	2	3	3	1	0.24
L2 Thickness, mm	169.78	69.35	71	112	152	198	366	86	1.08
L3 Thickness, mm	155.95	73.8	41	102	140	216	325	114	0.27
L4 Thickness, mm	142.61	117.82	0	0	203	236	295	236	-0.28
Total Thickness, mm	468.33	109.07	264	376	475	549	694	173	0.3
Precipitation, mm	1044.5	389.3	62	779.3	1104.4	1324.7	2209.2	545.4	-0.25
Temperature, °C	15.52	3.78	3	13.7	16.1	17.9	22.8	4.2	-0.78
Freeze Index, °C-Days	112.7	252.9	0	4	24	89	1763	85	3.78
Min. Humidity, %	16.24	6.93	2	12	16	20	43	8	0.62
Max. Humidity, %	116.65	5.59	102	113	116	119	145	6	0.81
AADT	7991	6929	784	3400	5121	11933	51030	8533	2.48
AADTT	1251.9	1147	104	524	900	1544	8249	1020	2.31
ESAL	644	693.9	22	165	410	827	4305	662	2.12
initial IRI, m/km	1.33	0.4	0.58	1	1.24	1.67	2.31	0.67	0.4
Transverse Cracking	3.682	17.152	0	0	0	0	155.3	0	6.96

The data pre-processing phase was essential to ensure the integrity and usability of the dataset for machine learning model development. The derived dataset had 20 independent variables and one dependent variable (transverse cracking in CRCP). The pre-processing procedures involved handling missing data, encoding categorical variables, normalizing continuous variables, managing outliers, and preparing the data for model training.

The derived dataset contained very few missing values, which were carefully assessed and imputed where necessary to maintain data completeness. The high quality and well-maintained nature of the LTPP database ensured that most variables were fully populated, providing a strong foundation for reliable analysis.

Categorical variables were converted into numerical representations, so that they could be used with machine learning methods. Climate zones were assigned number values based on their categorization. One represents "Wet, freeze," two means "Wet, non-freeze," three means "Dry, freeze," and four means "Dry, non-freeze." Also, pavement layer types were encoded as follows: The numbers 1 through 8 represent the following terms: "Asphalt concrete layer (AC)," "Portland cement concrete layer (PC)," "Bound (treated) base (TB)," "Bound (treated) sub-base (TS)," "Unbound (granular) base (GB)," "Unbound (granular) sub-base (GS)," "Sub-grade (untreated) (SS)," and even "Rigid Layer used for backcalculation (RB)." These encodings eliminated false ordinal connections while keeping the categorical variables interpretable.

Continuous variables were normalized using z-score normalization to ensure uniform scaling. This transformation adjusted each variable to have a mean of zero and a standard deviation of one, preventing variables with larger scales, such as AADT or AADTT, from disproportionately influencing the model training process. By standardizing the data, all variables contributed fairly to the predictive models.

Outliers were recognized using the interquartile range (IQR) rule, where values exceeding 1.5 times the IQR above the third quartile or below the first quartile were identified. While unrealistic or erroneous outliers were eliminated, meaningful outliers were retained to capture the full range of real-world conditions, thus improving the model's generalizability.

The dataset was then separated into training and testing sub-sets by k-fold cross-validation with 5 folds. This approach offers a robust model evaluation by allowing the model to be trained and validated on different sub-sets of data, reducing the risk of overfitting. Cross-validation also ensured reliable performance estimation on unseen data. To confirm the quality of pre-processing, descriptive statistics were recalculated after normalization and encoding, verifying that the dataset was ready for modeling.

These pre-processing steps ensured that the data was clean, consistent, and properly formatted, supporting the accurate prediction of transverse cracking in CRCP. The rigorous procedures enhanced the robustness and reliability of the analysis across diverse conditions, setting a strong foundation for the development of predictive models.

MODEL DEVELOPMENT

The primary goal of this study was to develop and evaluate machine learning models to predict transverse cracking of CRCP. A total of six models were developed and compared, including a GA-GBM, a baseline GBM, Linear Regression, Random Forest, SVR, and ANN. These models were selected to capture varying levels of complexity, interpretability, and predictive performance. The steps for model development are outlined below:

GA-GBM

The GA-Optimized GA-GBM is an advanced predictive modeling approach that combines the GBM algorithm with the hyperparameter optimization capabilities of GA. This hybrid approach enhances the accuracy and robustness of predictions by systematically optimizing critical hyperparameters in the GBM model. Below, we detail the methodology, equations, and steps involved in developing the GA-GBM model.

GBM is an ensemble learning method that combines the predictions of multiple weak learners, typically decision trees, to build a strong predictive model. The GBM algorithm minimizes a differentiable loss function L(y,ŷ) by sequentially adding decision trees, where each tree corrects the residual errors of the previous ensemble. The model prediction is updated iteratively as follows:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta \cdot h\,(x_i;\, \theta_t) \tag{1}$$

where:

$\hat{y}_i^{(t)}$: Prediction for observation i at iteration t.

$\hat{y}_i^{(t-1)}$: Predection from the previous iteration.

η: Learng rate (controls the contribution of each tree).

$h\,(x_i;\, \theta_t)$: Weak learner (decision tree) fitted to the negative gradient of the loss function.

θ_t: Parameter of the decision tree at iteration t.

The loss function L(y, ŷ) used in this study is the Least Squares Error, defined as:

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

where:

y_i: True value for observation i.

$\hat{y}_i$: Predicted value for observation i.

n: Total number of observations.

The GBM hyperparameters optimized in this study include the number of learning cycles (T), which determines the total number of trees in the ensemble; the learning rate (η), which controls how much each tree contributes to the final prediction; and the maximum number of splits (S), which defines the depth of each decision tree.

To ensure reproducibility, the parameter selection process for GA was carefully designed based on best practices and empirical evaluations. The population size was set to 20, striking a balance between diversity in solutions and computational efficiency. A total of 10 generations was used, as trial runs indicated that additional iterations yielded diminishing improvements in predictive performance. Tournament selection was employed to ensure that stronger candidate solutions had a higher probability of being selected while maintaining genetic diversity in the population.

The cross-over strategy utilized was Blend Cross-over (BLX-α), which helps maintain a balance between exploration and exploitation by blending parent solutions to generate new offspring. The mutation rate, managed internally by MATLAB's ga function, introduced small random perturbations in hyperparameters to avoid premature convergence to local minima. The termination criteria were defined as either completion of 10 generations or stagnation in RMSE improvements.

The GA optimization workflow followed a structured process. Initially, a random population of candidate solutions was generated, with each individual representing a unique combination of the hyperparameters T, η, and S. The fitness function was then applied to evaluate each individual based on its Root Mean Square Error (RMSE) across 5-fold cross-validation. The top-performing solutions were selected using the tournament selection method, and new offspring were generated *via* BLX-α cross-over. To maintain population diversity, mutation was applied to a sub-set of the offspring. The process iterated until the termination criteria were met.

$$\text{Fitness}=\text{RMSE}= \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2} \quad (3)$$

The search space for hyperparameters was defined as follows:

- Number of Learning Cycles (T): [50,200];
- Learning Rate (η): [0.01,0.1];
- Maximum Splits (S): [1,20].

These bounds were determined based on a combination of literature review, prior experimental results, and empirical tuning. The final GA-optimized GBM model was trained using the best-performing hyperparameters obtained from the optimization process and was subsequently evaluated using cross-validation.

Linear Regression

Linear regression is one of the simplest predictive models, assuming a linear relationship between the predictors and the target variable. The mathematical formulation of the model is:

$$y = \beta_0 + \sum_{j=1}^{p}\beta_j x_j + \epsilon \quad (4)$$

where:

y: Target variable (transverse cracking).
β_0: Intercept.
β_j: Coefficients for predictor x_j.
ϵ: Random error term.
p: Number of predictors.

The model minimizes the Residual Sum of Squares (RSS):

$$\text{RSS} = \sum_{i=1}^{n}(y_i-\hat{y}_i)^2. \quad (5)$$

Linear regression provides interpretable results, as the coefficients (βj) indicate the contribution of each predictor to the target variable. However, it is limited in handling non-linear relationships and interactions between variables.

Random Forest (RF)

The Random Forest model is an ensemble method that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. Unlike GBM, RF constructs trees independently by randomly selecting sub-sets of features and data. The final prediction is the average (for regression) of all tree predictions:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_i^{(t)} \quad (6)$$

where:

$\hat{y}_i^{(t)}$: Prediction from tree t.
T: Total number of trees.

The RF model uses bootstrap aggregation (bagging) to reduce variance and improve generalization. The default parameters included:

- Number of Trees: 100;
- Maximum Splits: Unrestricted.

Random Forest calculates feature importance by evaluating the reduction in impurity for each feature across all trees.

SVR

SVR is a kernel-based machine learning algorithm that aims to find a hyperplane within a tolerance margin (ϵ) to predict the target variable. SVR minimizes the following loss function:

$$L(y, \hat{y}) = \sum_{i=1}^{n} \max(0, |y_i - \hat{y}_i| - \epsilon) + \frac{1}{2}\left||w|\right|^2 \tag{7}$$

where:

w: Weight vector defining the hyperplane.

ϵ: Margin of tolerance.

$\left||w|\right|^2$: Regularization term to prevent overfitting.

For non-linear relationships, SVR uses the Radial Basis Function (RBF) kernel, defined as:

$$K(x_i, x_j) = \exp\left(-\gamma \left||x_i - x_j|\right|^2\right) \tag{8}$$

where γ is the kernel scale parameter. Default hyperparameters included:

- Regularization Parameter (C): 1;
- Kernel Scale (γ): Auto;
- Epsilon (ϵ): 0.1.

ANN

ANNs are powerful models designed to capture complex, non-linear relationships. The ANN developed in this study consisted of:

- **Input Layer**: 20 neurons (one for each predictor).
- **Hidden Layer**: A single layer with 10 neurons.
- **Output Layer**: A single neuron for the target variable (transverse cracking).

Each neuron in the hidden layer applied a non-linear activation function (σ):

$$zj = \sigma\left(\sum_{i=1}^{p} w_{ij}x_i + b_j\right) \tag{9}$$

where:

- zj: Output of neuron j.
- wij: Weight connecting input iii to neuron j.
- bj: Bias for neuron j.
- σ: Activation function (ReLU was used in this study).

The network minimizes the Mean Squared Error (MSE) loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2. \tag{10}$$

The ANN was trained using the back-propagation algorithm with the Adam optimizer, and default hyperparameters included:

- Learning Rate: 0.01;
- Number of Epochs: 100.

Model Evaluation

To ensure the reliability and generalizability of the developed models, 5-fold cross-validation was employed. The dataset was randomly partitioned into five equal-sized sub-sets. For each fold:

- Four sub-sets were used as the training data.
- The remaining sub-set was used as the testing data.
- This process was repeated five times, and the performance metrics were averaged across all folds.

The training and testing sub-sets were rotated in each iteration, ensuring that all data points were used for both training and testing. This technique mitigates overfitting and provides robust estimates of model performance on unseen data.

Two key metrics were used to evaluate model performance across each fold:

1. **RMSE**: measures the average magnitude of prediction errors, penalizing larger deviations.
2. **R²**: indicates the proportion of variance in the dependent variable explained by the model. It is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{11}$$

where:

$\bar{y}$: Mean of the actual values.

R^2 ranges from 0 to 1, with a higher value indicating a better model performance.

The RMSE and R^2 values were computed for each fold, and the mean values were calculated to summarize the model's overall performance.

RESULTS AND DISCUSSION

Figure (2) displays a heatmap of the relationships between the predictors themselves, as well as between the dependent variable (transverse cracking) and the independent variables. Visual representations of the correlation coefficients, which vary from -1 to 1, show blue for negative correlations and yellow and green for positive correlations. Transverse cracking is complex, as evidenced by its weak-to-moderate connection with a number of factors. For instance, there is a moderately positive association between traffic-related variables like AADT and AADTT, indicating that rising traffic loads leads to more transverse cracking incidents. Similar to this, there are different degrees of correlation between structural variables like total thickness and layer thicknesses; certain layers have negative associations, suggesting that they may help prevent cracking. Climate variables, such as precipitation, temperature, and freeze index, show minimal associations, indicating that they have a lower direct impact on transverse cracking than traffic and structural factors. Furthermore, the heatmap demonstrates a considerable interdependence between numerous independent variables, such as AADT and KESAL, emphasizing their common influence on the pavement system. These heatmap insights highlight the need of taking into account the combined effects of traffic, structural, and climatic variables for predicting transverse cracking and developing data-driven pavement management methods. The heatmap's visual clarity makes it easier to identify essential variables, which helps prioritize features for model building and interpretation.

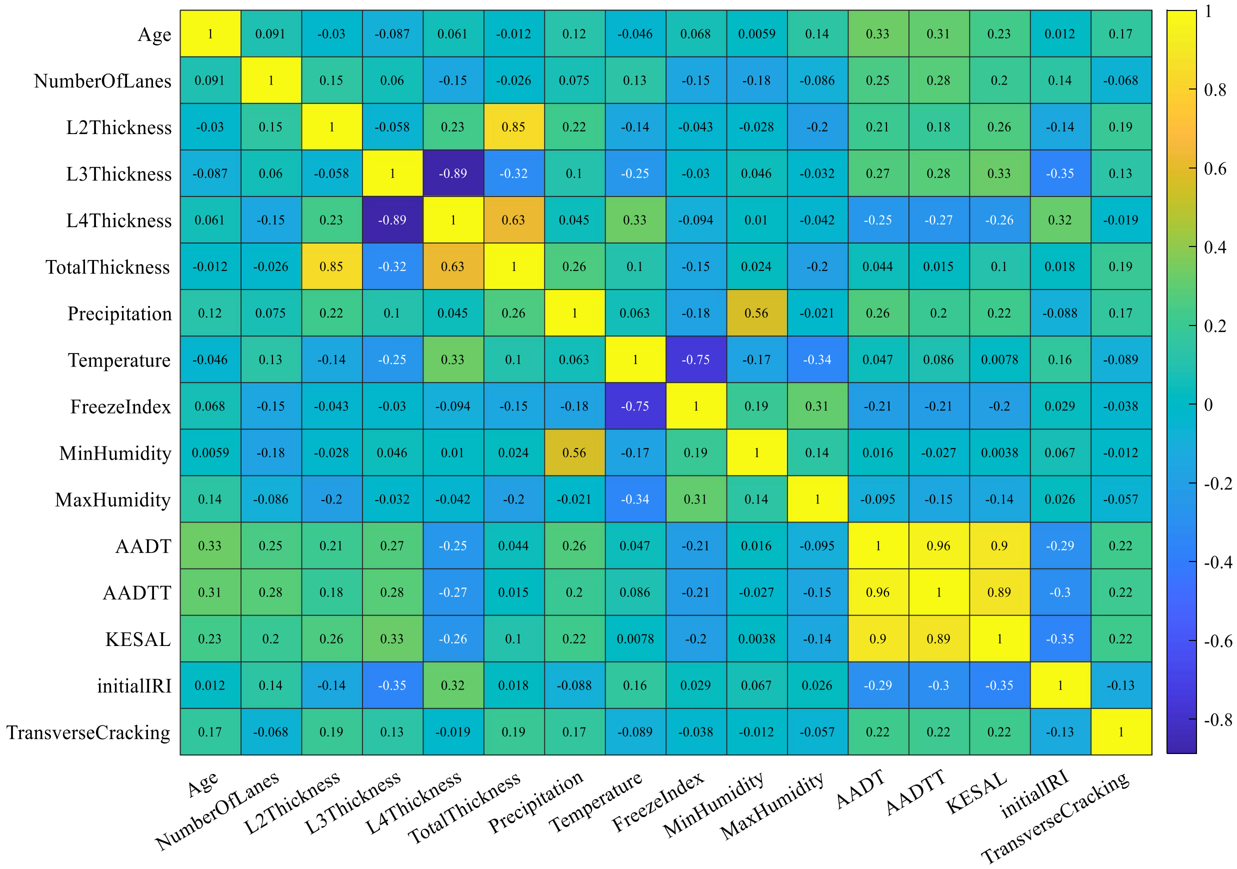

Figure (2): Heatmap of dependent variables *versus* independent variables

The GA was successful in adjusting important parameters to enhance model performance, as demonstrated by Table 3, which shows the ideal hyperparameters found for the GBM model. The best number of learning cycles (NumLearningCycles) was determined to be around 107, resulting in a fair trade-off between underfitting and overfitting by providing a suitable number of iterations to capture patterns in the data. The learning rate (LearnRate) was set to 0.09685, allowing the model to produce consistent and incremental updates throughout training without exceeding the ideal answer. Also, the maximum number of splits (MaxNumSplits) was set to approximately 19, allowing decision trees within the GBM ensemble to discover complex interactions among predictor variables while avoiding unnecessary depth that could lead to overfitting. These hyperparameter values reflect the systematic exploration and optimization abilities of GA, confirming that the GBM model achieves high predictive accuracy and generalization across diverse data conditions. The optimized hyperparameters lay a strong foundation for robust and reliable predictions of transverse cracking in CRCP.

Table 3. Optimal hyperparameters identified by GA

Hyperparameter	Optimal Value
NumLearningCycles	106.7824
LearnRate	0.09685
MaxNumSplits	19.2111

Table 4 shows, through a five-fold cross-valuation for six different machine learning models, a thorough comparison of model performance measures including RMSE and R^2. With the lowest mean RMSE (1.6955) and highest R^2 (0.98926), the GA-GBM model routinely outperformed all other models to show its better predictive capacity for transverse cracking in CRCP. With a mean RMSE of 15.7082 and an R^2 of -0.2676, the baseline GBM model without hyperparameter optimization fared much worse, underscoring the significance of GA-driven optimization in adjusting tree depth, learning rate, and increasing iterations. With an RMSE of 15.9642 and an R^2 of -0.3419, Linear Regression fared the poorest, demonstrating its incapacity to capture the intricate non-linear interactions that underlie transverse cracking. The Random Forest model outperformed Linear Regression, with a mean RMSE of 14.6839 and an R^2 of -0.0109. However, it fell short of GA-GBM due to its lack of sequential learning and dynamic feature selection, which are key features of gradient boosting models. The marginal difference between GA-GBM and Random Forest suggests that bagging-based ensemble methods (Random Forest) are somewhat effective, but boosting-based models like GBM optimize error reduction more efficiently, particularly when enhanced through Genetic Algorithm (GA)-based hyperparameter tuning. The Support Vector Regression (SVR) model, with a mean RMSE of 16.1702 and a slightly negative R^2 (-0.0015), struggled to capture the complexity of the dataset, likely due to its sensitivity to high-dimensional data and the presence of both categorical and continuous variables, which can affect the generalization of kernel-based models. Artificial Neural Networks (ANNs) showed a marginally better performance than SVR, with a mean RMSE of 14.5730 and an R^2 of -0.0885, yet exhibited inconsistent predictions, possibly due to the limited dataset size (395 observations across 33 sections), which can hinder the effective convergence of neural networks. While ANN's performance was close to that of Random Forest, its variability suggests that its weight updates may not have fully converged, reinforcing the advantage of structured hyperparameter tuning in GA-GBM. The GA-GBM model not only demonstrated a superior accuracy, but also maintained a remarkable consistency, as evidenced by its low variance in RMSE and R^2 across all folds. The combination of gradient boosting and GA-driven hyperparameter optimization allowed the model to effectively balance bias and variance, making it the most reliable choice for predicting transverse cracking in CRCP.

Table 4. Model performance metrics

Fold	GA-GBM		GBM		Linear Regression		Random Forest		SVR		ANN	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
1	1.0474	0.9952	15.645	0.25135	17.544	0.058562	14.972	0.31435	18.252	-0.018914	14.976	0.31396
2	2.6712	0.9789	11.875	0.37861	15.417	-0.047271	13.054	0.24916	15.049	0.0021324	16.392	-0.18404
3	2.2380	0.9837	18.222	0.0049029	15.53	0.27714	15.801	0.2517	18.497	-0.025431	13.31	0.46903
4	1.0459	0.9966	23.12	0.010442	21.382	0.15366	21.665	0.13107	23.65	-0.035428	19.636	0.28625
5	1.4750	0.9920	9.6792	-1.9832	9.9483	-2.1514	7.9273	-1.001	5.4032	0.070385	8.5501	-1.3278
Mean	1.6955	0.98926	15.7082	-0.2676	15.9642	-0.3419	14.6839	-0.0109	16.1702	-0.0015	14.5730	-0.0885

Figure (3) depicts the GA convergence plot, which shows the optimization process for selecting the optimum hyperparameters of the GBM model over ten generations. The red triangles reflect the highest fitness values obtained in each generation, while the blue circles represent the population's average fitness values at that time. The first generation reflects the variety in the randomly generated population with a high mean fitness value of about 15. The mean fitness value clearly decreases as the optimization runs, suggesting notable increases in the general quality of the candidate solutions. The best fitness value settles at about 14.3 by the third generation, indicating that the GA has essentially converged to almost ideal hyperparameters. The narrowing gap between the mean and best fitness values in later generations suggests a well-refined population with reduced variability among solutions. This plot underscores the efficiency of GA in systematically exploring the hyperparameter space, achieving substantial performance improvements within a limited number of iterations. The convergence pattern confirms that the GA-GBM model is robustly optimized for high predictive accuracy in modeling transverse cracking in CRCP.

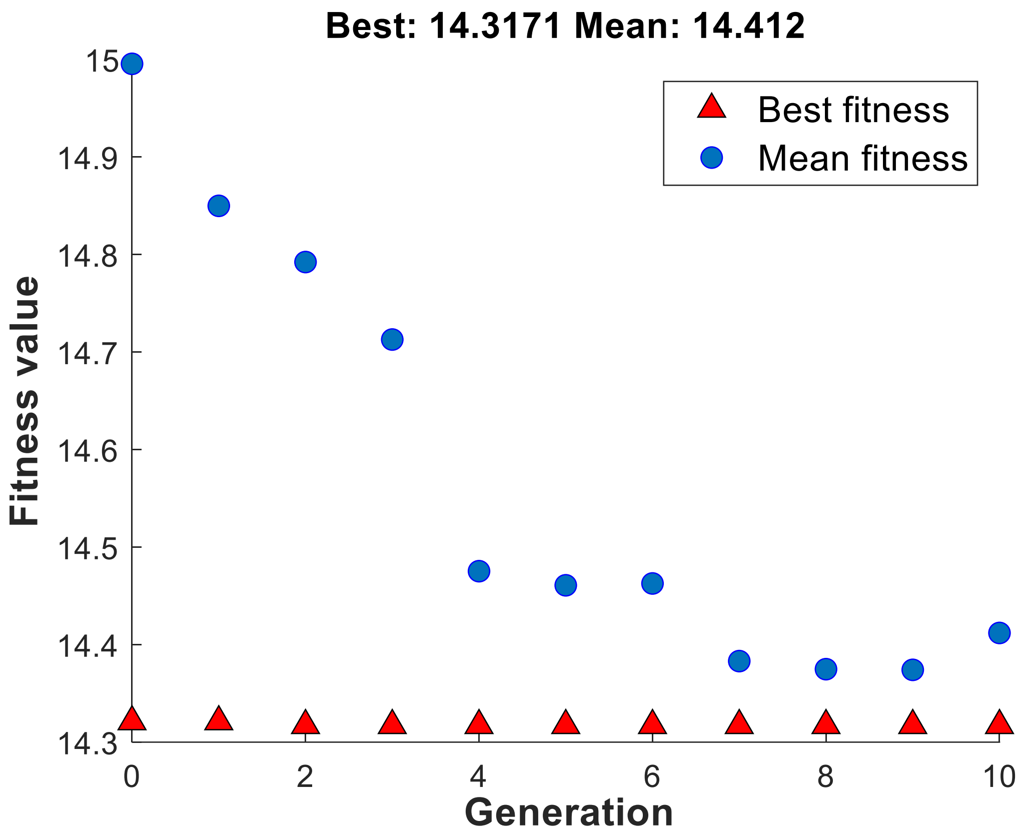

Figure (3): GA convergence plot

Figure (4) compares predicted and actual values for transverse cracking using six machine learning models: (a) GA-GBM, (b) GBM, (c) Linear Regression, (d) Random Forest, (e) SVR, and (f) ANN. Among these models, the GA-GBM (Figure 4a) makes the most accurate predictions, with points closely aligning along the red dashed line, reflecting the ideal case in which anticipated and observed values match. In contrast, the normal GBM (Figure 4b) has more scatter around the line, indicating lower precision without hyperparameter modification. Particularly at higher measured values, Linear Regression (Figure 4c) and Random Forest (Figure 4d) show notable deviations, so stressing their shortcomings in modeling the non-linear relationships in the dataset. With most predictions grouping close to zero, SVR (Figure 4e) performs poorly and indicates extreme underfitting. Analogous to this, ANN (Figure 4f) suffers with erratic predictions, especially at higher measured values, which reflects its incapacity to sufficiently capture intricate interactions among variables. Given better alignment with real values than other models, the GA-GBM model stands out as the most dependable and strongest method for forecasting transverse cracking in CRCP.

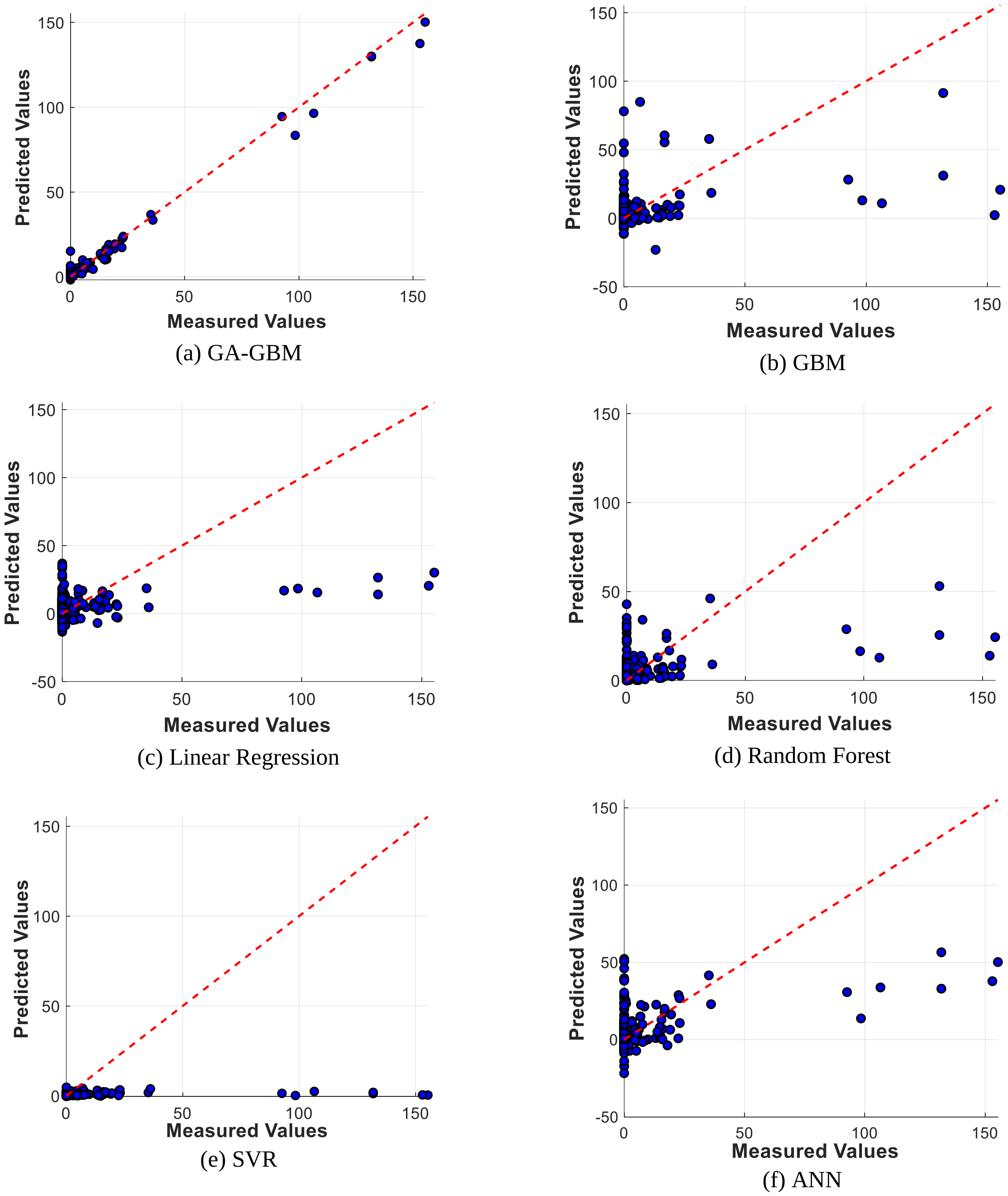

Figure (4): Prediction *vs.* actual values (a) GA-GBM (b) GBM (c) Linear Regression (d) Random Forest (e) SVR (f) ANN

Six machine learning models' residual plots—a) GA-GBM, b) GBM, c) Linear Regression, d) Random Forest, e) SVR, and f) ANN—are shown in Figure (5). Plotting the residuals—that is, the variations between the expected and actual values—against the predicted values yields the GA-GBM (Figure 5a) shows among the models the most homogeneous and tightly spaced residuals around the zero line, so indicating a low bias and a great predictive accuracy. In contrast, the standard GBM model (Figure 5b) shows greater residual scatter, particularly at higher predicted values, reflecting a reduced accuracy compared to its optimized counterpart. Linear Regression (Figure 5c) reveals a clear pattern of increasing residuals with higher predicted values, highlighting its inability to capture the non-linear relationships in the data. The Random Forest model

(Figure 5d) also displays considerable scatter, suggesting moderate underfitting. SVR (Figure 5e) performs poorly, with residuals clustering near zero and sharply increasing for larger predicted values, indicating significant underfitting and bias. Similarly, ANN (Figure 5f) exhibits a significant residual dispersion, particularly at higher projected values, indicating disagreement in predictions. Overall, the GA-GBM model is the most robust and dependable one, with evenly distributed residuals and the lowest level of systematic error when compared to the other models. This demonstrates how the GA-GBM model accurately models transverse cracking in CRCP.

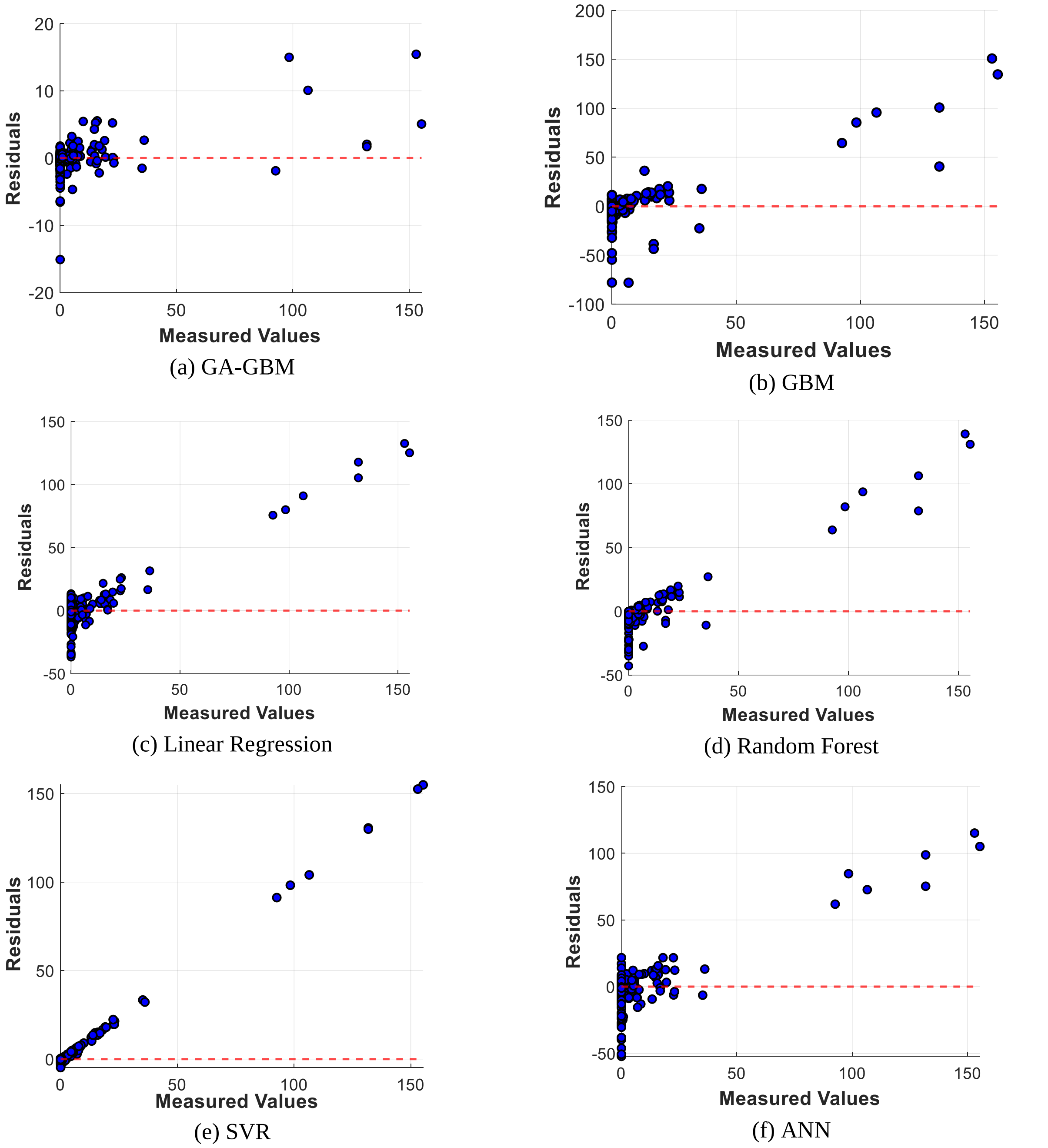

Figure (5): Residual plot (a) GA-GBM (b) GBM (c) Linear Regression (d) Random Forest (e) SVR (f) ANN

Figure (6) shows the importance of predictor variables in the GA-GBM model, measured by their relative contribution to changes in RMSE. The AADTT emerges as the most influential variable, indicating that truck traffic has a crucial role in the formation of transverse cracking in CRCP. This is followed by Age, suggesting that pavement deterioration over time significantly impacts cracking severity. AADT is also highly important, highlighting the cumulative effects of traffic loading. Structural factors, such as Total Thickness and L2 Thickness (Sub-base Thickness), contribute notably, reinforcing the importance of pavement design in mitigating cracking. Climatic factors, including Precipitation and Temperature, further influence transverse cracking, emphasizing the environmental conditions' role in pavement distress. Additionally, KESAL, which quantifies cumulative axle loading, ranks among the key contributors. Other structural parameters, including L4 Thickness and L3 Thickness, also impact the model's predictions, though to a lesser extent. Overall, these results underscore the interplay between traffic, structural design, and climatic conditions in predicting transverse cracking, validating the GA-GBM model's ability to capture complex interactions among multiple pavement-related factors.

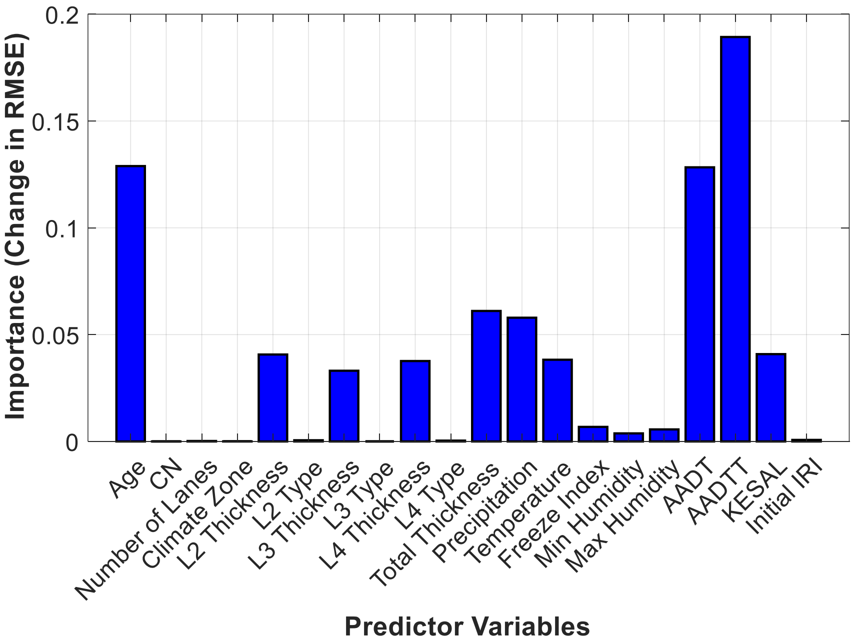

Figure (6): Importance of predictor variables of GA-GBM

Figure (7) displays the normalized sensitivity analysis of predictor variables in the GA-GBM model, ranking their influences on the prediction of transverse cracking in CRCP. AADTT (1) emerges as the most sensitive variable, reflecting its critical role in capturing the impact of truck traffic on pavement deterioration. KESAL (2) follows closely, emphasizing the significance of cumulative traffic loads in driving transverse cracking. Temperature (3) is identified as the most influential climatic factor, highlighting the effects of environmental conditions on pavement performance. Structural factors, such as L4 Thickness (4), and climatic variables like Precipitation (5) and Freeze Index (6), also demonstrate notable sensitivity, indicating their combined impact on the cracking process. AADT (7) and Age (8), while less sensitive than the top predictors, still contribute meaningfully to the model’s accuracy. These rankings provide valuable insights into the dominant factors influencing transverse cracking, emphasizing the importance of traffic and structural variables, along with key environmental factors, in predictive modeling and pavement management strategies.

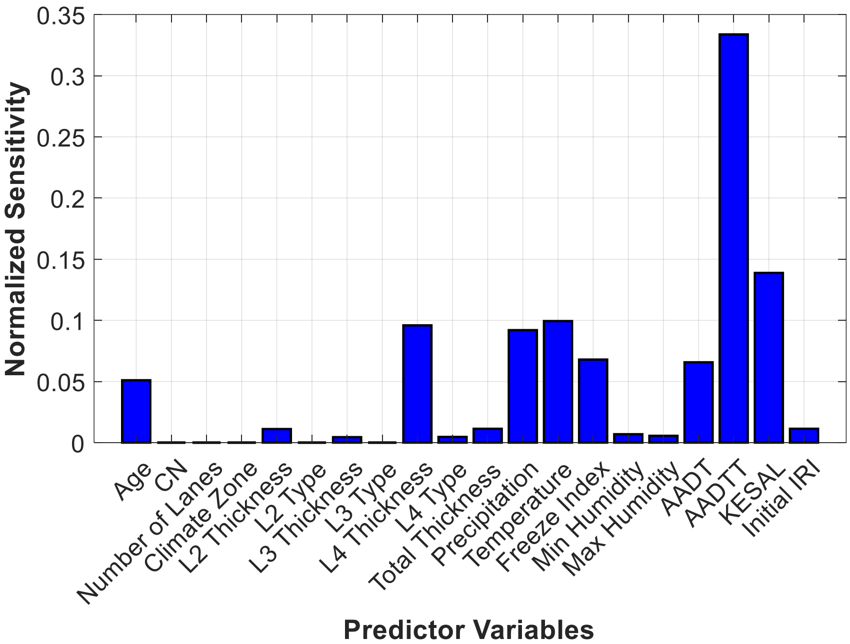

Figure (7): Normalized sensitivity analysis of GA-GBM

CONCLUSIONS

This study developed and evaluated GA-GBM, a hybrid machine learning model, to predict transverse cracking in Continuously Reinforced Concrete Pavement (CRCP). Using data from the Long-term Pavement Performance (LTPP) database, the study evaluated 33 CRCP sections and 20 independent variables, including traffic, structural, climatic, and performance-related parameters. In terms of predictive performance, the GA-GBM model outperformed baseline models such as standard GBM, Random Forest, Support Vector Regression (SVR), Linear Regression, and Artificial Neural Networks (ANNs). Annual Average Daily Truck Traffic (AADTT), Annual Average Daily Traffic (AADT), and Kilo Equivalent Single Axle Load (KESAL) were the most important factors influencing transverse cracking in CRCP. This underscores the effect of traffic loads on pavement deterioration. Because cracking is progressive, Age also had a big impact. L2 Thickness (Sub-base), L3 Thickness (Base), L4 Thickness (Portland Cement Concrete), and Total Thickness were the main structural factors that contributed to the reduction of cracking. The relevance of environmental stresses on pavement performance was reinforced by the modest impact of climate parameters, especially Temperature and Precipitation. Sensitivity analysis confirmed these findings, showing that AADTT and KESAL were the most sensitive variables, followed by structural and climatic variables. These findings demonstrate how traffic loads, structural features, and weather all work together to cause transverse cracking in CRCP. By optimizing hyperparameters, the Genetic Algorithm (GA) convergence analysis produced a highly accurate and dependable GA-GBM model.

The model's strong predictive ability and low bias in comparison to other models were further confirmed by the visualization of scatter plots and residuals. Furthermore, the sensitivity and feature importance analyses offered vital information for ranking important predictors in pavement management plans. To sum up, the GA-GBM model has shown itself to be a reliable and efficient method for forecasting transverse cracking in CRCP. In order to improve the accuracy and applicability of predictive models, this study highlights the importance of including traffic, structural, and climatic factors. The results can help inform data-driven decision-making about how best to design and maintain pavements. For even greater predictive accuracy and wider applicability to a variety of pavement conditions, future research should think about adding more variables, like material properties and construction methods, and investigate cutting-edge machine learning techniques, such as ensemble and deep learning models.

Availability of Data and Materials

The dataset used in this study was extracted from the Long-term Pavement Performance (LTPP) database, a publicly available resource maintained by the Federal Highway Administration (FHWA). The LTPP database can be accessed *via* the DataPave platform at https://infopave.fhwa.dot.gov/. Specific data processing and analysis steps are described in the manuscript to ensure reproducibility. Additional details or derived datasets used in this research are available from the corresponding author upon reasonable request.

Conflict of Interests

The authors declare that they have no competing interests.

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