A comparative analysis of machine learning models for predicting faulting in jointed plain concrete pavements

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ABSTRACT: Faulting is defined by variations in elevation at transverse joints in Jointed Plain Concrete Pavements resulting from environmental factors, subgrade properties, and traffic loads. It is a major distress for rigid pavements, possessing crucial challenges for maintaining road safety standards. Traditional regression methods often fail to address the complexities of faulting, while machine learning approach utilizes data driven learning to enhance prediction accuracy. Datasets for this study were sourced from the LTPP database, focusing on dry climate zones. Key environmental factors affecting wheel path faulting include Yearly Precipitation, Temperature, Freeze-Thaw Cycles, along with structural properties such as Pavement Thickness, Pavement Age, Tensile Strength, and Optimum Moisture Content are utilized as model input. Five machine learning methodologies, including Support Vector Machine, Decision Tree, Linear Discriminant Analysis, Ensemble and Artificial Neural Network were implemented. Among these, ANN demonstrated highest prediction accuracy, attaining an R^2 of 0.81. The ANN model was further evaluated to assess the influence of the input variables on the model output through sensitivity analysis.

1 LITERATURE REVIEW

Faulting is a major issue in jointed concrete pavements (JCPs). Many prediction models are being developed for predicting fault failure. In the AASHTO 1993 version of the pavement design guide, faulting and cracking were accounted for by maintaining and serviceability above a defined threshold. In the 1990s, Simpson et al. attempted to separate these two concerns and forecast faults independently based on pavement design, traffic, weather conditions (Simpson *et al.*, 1994). In recent years various studies suggested that faulting in rigid pavements, particularly in Jointed Plain Concrete Pavement (JPCP), is influenced by a multitude of factors that span structural, environmental, and design considerations (Hossain, Gopisetti and Miah, 2019; Ehsani, Moghadas Nejad and Hajikarimi, 2023; Ahmed, Isied and Souliman, 2024). Traffic loads and the cumulative effect of axle load distributions are significant contributors, as they induce stress and deformation in the pavement layers, particularly affecting the base layer's plastic deformation (Chen, Saha and Lytton, 2020). Most of the prediction models used the LTPP database, which included faulting measurements at doweled and non-doweled joints and some measurements at transverse crack locations. Ehsani et al. used both artificial neural and random forest methods with 19 input variables to develop a prediction model (Ehsani, Moghadas Nejad and Hajikarimi, 2023). Ker et al. developed a prediction model for transverse joint faulting incorporating the ERESBACK 2.2 program for back calculation to get more accurate data (Ker, Lee and Lin, 2008). The mechanistic-empirical erosion-based faulting model incorporated traffic parameters with the application of erosion test showed the correlation between traffic and environmental factors with faulting (Jung and Zollinger, 2011). The current faulting model integrated into the Pavement ME design procedure considers pavement response, climatic conditions, traffic, and base erodibility. This model is uniformly applied to all types of JCPs, regardless of their structural makeup (such as conventional concrete pavement, unbonded concrete overlay, bonded concrete overlay, etc.). This suggests that the pumping mechanism is assumed to be consistent across all pavement structures. Furthermore, it assumes uniformity in the rate of faulting development and the maximum faulting regardless of pavement structure. The focus of this study is to develop a machine learning-based approach for predicting faulting JCPs. Traditional models struggle with complex interactions, whereas machine learning algorithms offers a data-driven solution thus improving prediction accuracy and supporting better pavement maintenance strategies.

2 OBJECTIVES

The main objective of this research is to explore the potential of machine-learning approaches, mainly neural network-based models, for predicting JPCP faulting. Datasets are collected from LTPP to train the model for the dry climatic zone in the US. Additionally, to confirm the internal relationship among input parameters and their corresponding output results, a sensitivity analysis on the best model was evaluated.

3 DATA COLLECTION, SELECTION, AND PROCESSING

For training the neural network model data sets are collected from The LTPP database. The LTPP program regularly collects joint and crack faulting data at each jointed concrete pavement test site using the Georgia Fault Meter (GFM). Figure 1 shows the diagram for GFM faulting measurement.

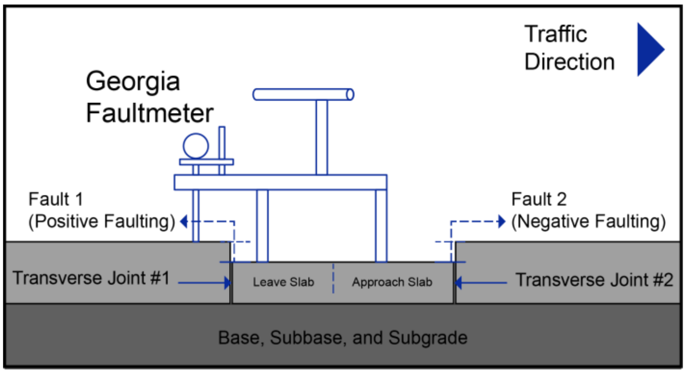

Figure 1. Diagram of manual Faulting measurement using the GFM. (Source: FHWA).

Figure 2 shows the faulting measurements over 30 years of lifespan at the wheel path for the Dry-Freeze and Dry No-Freeze climate regions subjected to this study.

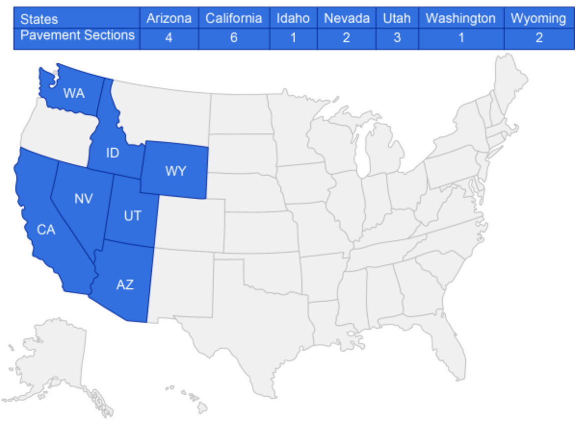

Figure 2. Study Area Containing States with observations numbers in Dry Climatic region.

The prediction models require the normalization of datasets before the training phase. Figure 3 presents the input parameters of the prediction models and their corresponding abbreviations, which are used throughout the article.

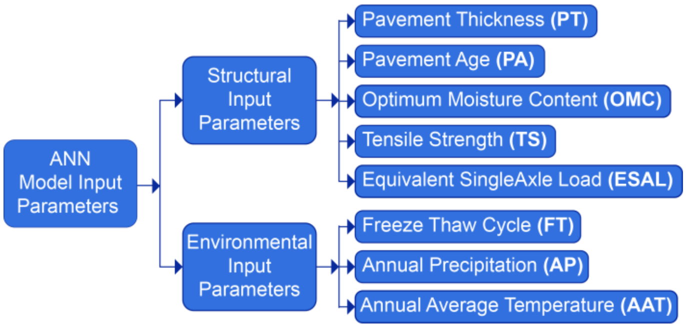

Figure 3. Input Variables for ANN model training.

Table 1 outlines the maximum, minimum, average, and standard deviation of the training dataset. These statistical measures provide essential insights into data distribution, variability, and model generalization, ensuring the robustness and reliability of the prediction model. Subsequently, these statistical values are employed in the equation formulation process. ESAL ranges significantly, with a high standard deviation (501,379), indicating a wide range of traffic loads.

Table 1. Descriptive Statistics of the Training Data.

Inputs	Min	Max	Avg	Std Dev
ESAL	1995922	1887	698061	501379
AP (mm)	785.70	70.20	269.72	132.02
AAT (°C)	19	5.3	10.59	2.15
FT (days)	195	12	116.18	41.25
TS (psi)	846	471	691.78	127.11
PT (mm)	11.70	8.10	9.34	0.88
PA (yr)	39	1	21.60	9.13
OMC (%)	14	2	7.87	3.71

4 FAULTING PREDICTION MACHINE LEARNING MODEL DEVELOPMENT

Significant progress has been made in forecasting models with the introduction of Machine learning as a computational model. These networks are inspired by the workings of neurons in the human brain, and they leverage learning algorithms that can adapt and improve as new data is collected. As a result, they are particularly effective at modeling non-linear statistical data. After developing the datasets from LTPP database, correlation heatmap was generated. This linear regression analysis demonstrates the correlation between the input and output parameters, which was subsequently assessed through the correlation heatmap illustrated in Figure 4. The variable ESAL and the thickness of the pavement exhibit the highest positive correlation, attaining a value of 0.5. In contrast, the annual mean temperature displays a considerable negative correlation (-0.74) with the occurrence of faulting, thereby signifying a strong inverse relationship between the two variables.

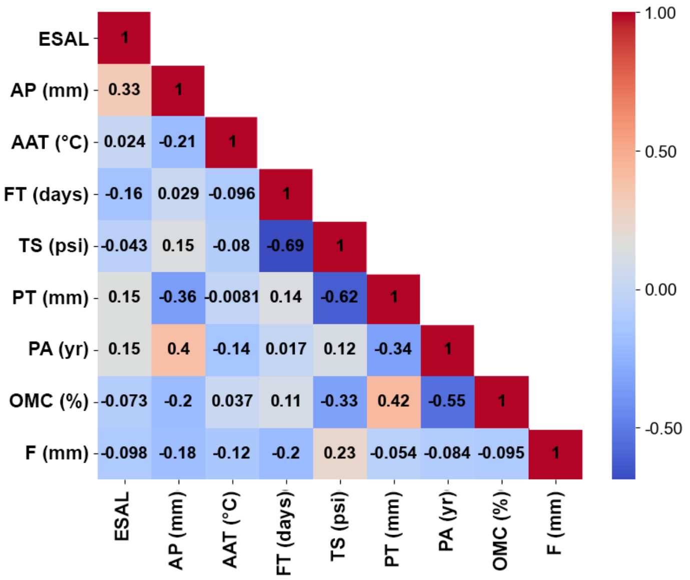

Figure 4. Correlation heatmap between input parameters and output parameters.

To enhance model performance and ensure balanced learning, min-max normalization was applied to scale all input features between 0 and 1, preventing dominance by variables with larger magnitudes. Additionally, the dataset was split into 70% training, 15% testing, and 15% validation to optimize model generalization. The training set allows the model to learn patterns, the validation set fine-tunes hyperparameters and prevent overfitting, and the testing set provides an unbiased evaluation of predictive accuracy. This approach ensures a well-validated and reliable model for faulting prediction in JPCPs.

Five machine learning models, Artificial Neural Network (ANN), Decision Tree (DT), Linear Discriminant Analysis (LDA), Ensemble (E), and Support Vector Machine (SVM), were developed to forecast faulting. The coefficient of determination (R^2) of all the developed models is depicted in Table 2.

Table 2: Coefficient of determination (R^2) of all the prediction models.

Prediction Model	Coefficient of Determination (R^2)
Artificial Neural Network (ANN)	0.81
Decision Tree (DT)	0.58
Linear Discriminant Analysis (LDA)	0.41
Ensemble (E)	0.62
Support Vector Machine (SVM)	0.43

The ANN model achieved the highest R^2 value (0.81), signifying its competence in capturing the intricate and nonlinear relationship of input parameters associated with faulting, attributable to its adaptability in modeling. The Ensemble model exhibits moderate performance with an R^2 of 0.62, gaining advantages from the clustering capabilities of multiple predictive outputs, although it lacks the depth of ANN's feature extraction. The Decision Tree and SVM models showed relatively lower R^2 values of 0.58 and 0.43, respectively, likely due to their limitations in handling nonlinear or noisy data. LDA underperforms with the lowest R^2 of 0.41, reflecting the inadequacy of a linear approach for this problem. Overall, these findings underscore the premise that nonlinear models, especially ANN, are more suitable for faulting prediction, as they can capture the underlying complexity of pavement faulting behavior in JPCP. Figure 5 represents the regression plots of all the forecast models.

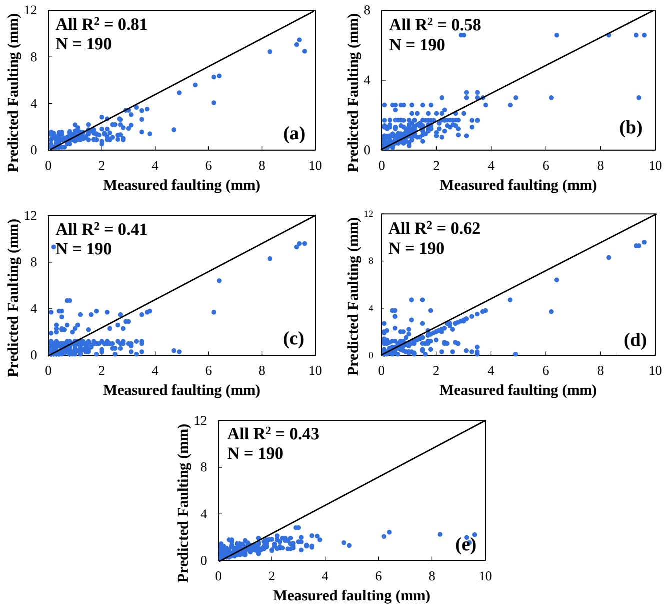

Figure 5. Regression plots of the prediction model's output – (a) ANN, (b) DT, (c) LDA, (d) E, and (e) SVM.

5 SENSITIVITY ANALYSIS OF THE DEVELOPED ANN MODEL

To investigate how an individual input variable is related to the output, the change of predicted faulting vs the change of a single input variable is plotted for the ANN model. The sensitivity analysis presented in Figure 6 illustrates the principal factors influencing the faulting model in rigid pavement structures. The variables of traffic load (ESAL), temperature, and precipitation exhibit a positive correlation with faulting, thereby indicating that traffic volumes, elevated temperatures, and increased rainfall intensify pavement faulting. The structural attributes of the JPCP, including tensile strength and thickness, serve to mitigate faulting, thereby implying that pavements exhibiting greater strength and thickness demonstrate enhanced resilience. Freeze-thaw cycles and pavement age also contribute to higher faulting, reflecting the impact of environmental stresses and aging on pavement degradation. Moreover, an elevated optimum moisture content amplifies the occurrence of faulting, highlighting the critical need for moisture regulation. These results suggest that faulting prediction models should prioritize traffic, environmental conditions, and structural factors to improve predictive accuracy.

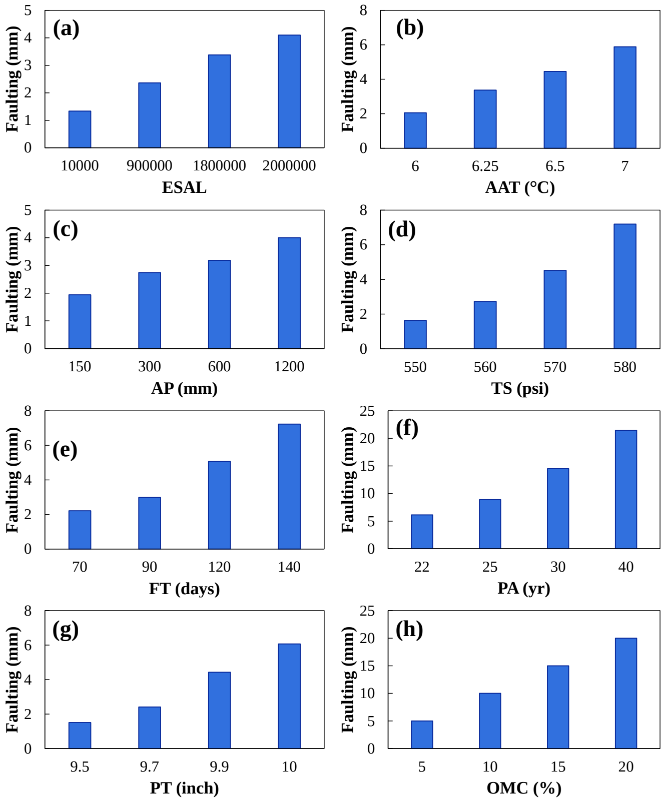

Figure 6. Sensitivity Analysis of predicted faulting (mm) with the change of each input variable – (a) ESAL, (b) AAT, (c) AP, (d) TS, (e) FT, (f) PA, (g) PT, (h) OMC.

6 CONCLUSIONS

With the help of machine learning approaches, a prediction model for faulting in Rigid Pavements for Dry-Freeze and Dry No-Freeze Climatic Zone was developed. For training the ANN model, 190 observations over 30 years of lifespan were evaluated. By incorporating environmental, structural, and traffic elements as input parameters the model aims to anticipate faulting in rigid pavements in dry regions. The conclusions and suggestions in the following bullets are based on the analysis and study findings:

1. In the present study, five Machine learning-based faulting models are created. The models' performance in making predictions was comparable in training and testing.
2. Among all the developed models, ANN achieved the highest prediction accuracy with an R^2 of 0.81, followed by Ensemble and Decision Tree with an R^2 of 0.62 and .58 respectively.
3. Based on the Sensitivity analysis among all the input variables, thickness and tensile strength have a major effect on the faulting mitigation of rigid pavements. On the other hand, temperature, precipitation, and Freeze-thaw cycles intensify JPCP faulting.
4. As all the model input parameters are presented. Future users will be able to reproduce the models and utilize them for different regions.

While the study demonstrates the potential of machine learning models in predicting faulting in JCPs, certain limitations should be acknowledged. As the accuracy of faulting predictions relies heavily on the quality and completeness of the data surveyed. The dataset used in this study consists of 190 observations from Dry-Freeze and Dry No-Freeze climate regions. As limited dataset size may lead to overfitting, particularly in complex models such as ANN, where the model may capture noise rather than true underlying patterns. Future investigations should concentrate on broadening the dataset by integrating a more extensive variety of pavement sections across distinct climatic regions. Furthermore, to alleviate overfitting, alternative regularization methods can also be investigated.

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