Exploring Machine Learning Approaches for Resilient Modulus in Rejuvenated Reclaimed Asphalt Pavement

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1 INTRODUCTION

Machine learning (ML), a dynamic subset of artificial intelligence (AI), emphasizes creating algorithms that can learn and improve autonomously from data without being explicitly programmed. These algorithms process extensive datasets to uncover patterns, trends, and correlations, enabling them to make predictions or decisions based on the insights they gain (Khuntia et al., 2014). As ML systems are exposed to new data, their predictive accuracy and performance evolve over time. The adaptability and broad applicability of ML make it valuable in numerous fields such as healthcare, finance, marketing, and beyond. It empowers automation, enhances efficiency, and extracts insights from data that might elude human analysis. Consequently, ML has the potential to transform industries and foster innovation by leveraging the untapped value embedded in vast data repositories (Goel et al., 2022).

In recent years, the adoption of ML techniques in transportation engineering has garnered significant attention and is set to revolutionize the field in various aspects (Uwanuakwa et al., 2020). For instance, in the performance of asphalt mixtures, ML offers considerable potential for delivering accurate and dependable predictions regarding material behavior, performance characteristics, and failure mechanisms.

The resilient modulus (MR) of asphalt is a critical parameter used to evaluate its elastic behavior under repeated loading, providing insight into its performance and durability in pavement structures. Conducting experimental studies to determine MR requires sophisticated and costly laboratory setups, including advanced testing equipment and precise control of variables such as temperature, load frequency, and specimen preparation (G. Shafabakhsh & Tanakizadeh, 2015). These challenges make experimental determination of MR a complex and resource-intensive process. However, to overcome such limitations, researchers increasingly opt for ML techniques as an alternative.

ML offers a cost-effective and efficient approach to predict MR by using existing experimental data, thereby bypassing extensive physical testing but maintaining a high degree of accuracy in the predictions.

Many studies on asphalt pavement utilized machine learning technique-based approaches such as Artificial neural Network (ANN) and support vector machines (SVM) methods towards performance prediction and simulation through different scenarios that have similarly been concerned with parameters, such as temperatures and loadings due to traffic conditions (Gulisano et al., 2024).

Zhang et al. (2021) used ML methods, specifically SVM and genetic programming (GP), for the prediction of Marshall parameters in flexible pavement base and wearing courses by using the data obtained from four different road sections located in Pakistan. Results show that SVM presents higher prediction accuracy than GP ($R > 0.85$) whereas GP presents a validated empirical formulation for a practical estimation of Marshall parameters (Zhang et al., 2021). Similarly, study by Shafabakhsh et al. (2021) utilized ANN for performance predicting of pavements in terms rutting (G. H. Shafabakhsh et al., 2015). Other studies have been related to the use of deep learning techniques to overcome limitations imposed by data. Bongjun et al. (2023) proposed a Bayesian deep learning framework for prediction of asphalt binder rheological properties using Atomic Force Microscopy images and Dynamic Shear Rheometer tests with improvements in prediction accuracy, reduction of testing time, operator-independent test results, and uncertainties. (Ji et al., 2023). ML has similarly been used to model the effects of rejuvenators and modifiers on asphalt, mostly in reclaimed asphalt pavement (RAP) mixtures. Study by Ayazi et al. (2024) employed ML techniques to estimate the effects of rejuvenators on the mechanical properties of RAP, targeting to optimize the mix design for enhanced performance (Ayazi et al., 2024).

The aim of this research is to investigate the possibility of ML techniques in predicting the MR of asphalt mixtures that contain different percentages of RAP, modified with rejuvenators. This study uniquely applies multiple machine learning models (RT, KNN, ANN, GP) to predict MR in rejuvenated RAP mixtures, capturing complex relationships between RAP content, rejuvenator dosage, and temperature. Unlike previous studies focused on empirical models, this research provides a comparative ML-based analysis, highlighting key factors influencing MR and optimizing RAP-based mix designs. The dataset for this study was obtained from an experimental analysis where asphalt mixes containing RAP contents ranging from 0% to 100% were tested at different temperatures (25°C, 35°C, and 45°C) to measure the MR value. This research study shall focus on applying ML models viz. RT, KNN, ANN, GP to predict the values of MR against the experimental data. This set of ML models trained on the dataset so as to identify the inter-relations between RAP content and rejuvenator usage, Temperature, and other input variables with MR values.

2 METHODLOGY

2.1 *Data Collection and Experimental Setup*

Experimental data for this study were collected through laboratory tests, where asphalt mixes were prepared with RAP content ranging from 0% to 100% as per ASTM D-6927 (ASTM-D6927, 2015). Rejuvenators were added to the mixtures to assess their impact on the mechanical properties of the asphalt.

Three temperature conditions were chosen for testing: 25°C, 35°C, and 45°C, representing typical environmental conditions encountered in pavement engineering. The resilient modulus of each mix was determined using a repeated load test as per ASTM D-7369, following established procedures for measuring asphalt's elastic properties under different loading conditions.

The dataset was divided into two parts: a training set (70%) and a testing set (30%) to evaluate model generalizability. The independent variables` included RAP%, rejuvenator dosage, temperature, virgin binder%, bitumen content, performance grade, loading and rest, while the target variable was MR value.

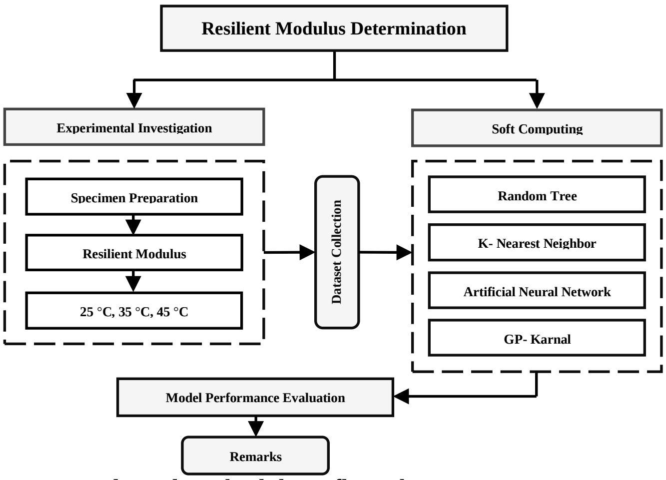

Figure 1. Adopted methodology flow chart

Once trained, the machine learning models were tested on

the unseen testing dataset. The predicted MR values were compared with the experimentally measured MR values to evaluate the accuracy and reliability of each model. The results were analyzed to determine which model provided the best predictions, and how well the models could generalize to new, unseen data.

3 MACHINE LEARNING MODELS

To predict the resilient modulus (MR) values, four machine learning models were employed: Random Tree (RT), k-Nearest Neighbor (KNN), Artificial Neural Network (ANN), and Gaussian Process (GP). These models were selected for their proven ability to handle complex and non-linear relationships inherent in the behavior of asphalt mixtures. RT is a decision-tree-based algorithm that has been known for its interpretability and efficient handling of structured data (Gul et al., 2022; Mirzahosseini et al., 2011; G. H. Shafabakhsh et al., 2015; Shah et al., 2020). KNN, a non-parametric approach, predicts outputs based on the nearest neighbors in the dataset, making it effective for capturing localized patterns. ANN, inspired by biological neural systems, models highly non-linear relationships through interconnected layers of nodes optimized iteratively. GP is a probabilistic approach that makes predictions with associated uncertainty measures, which is useful in scenarios where the dataset is very small or reliability is very important. These models were assessed using statistical performance metrics: CC, MAE, RMSE, RAE, and RRSE, thereby ensuring that the predictions made are robust and accurate.

4 RESULT AND DISCUSSION

As presented in table 1, in the training phase, KNN emerged as the best-performing model, achieving a perfect correlation coefficient (CC) of 1, the lowest mean absolute error (MAE) of 4.40 MPa, and the lowest root mean square error (RMSE) of 6.0 MPa. Additionally, it exhibited minimal relative absolute error (RAE) and root relative squared error (RRSE) at 0.24% and 0.29%, respectively. RT followed closely with an almost perfect CC of 0.99, MAE of 12.53 MPa, and RMSE of 22.52 MPa. Although the RAE and RRSE values for RT were slightly higher at 0.68% and 1.09%, its performance remained strong. ANN also demonstrated good performance with a CC of 0.99, but its error metrics, including an MAE of 89.72 MPa, RMSE of 111.13 MPa, RAE of 4.91%, and RRSE of 5.40%, were notably higher than those of KNN and RT. On the other hand, GP with the Karnal kernel showed the lowest performance during training, reflected by a CC of 0.99, the highest MAE of 276.49 MPa, RMSE of 331.76 MPa, RAE of 15.16%, and RRSE of 16.12%.

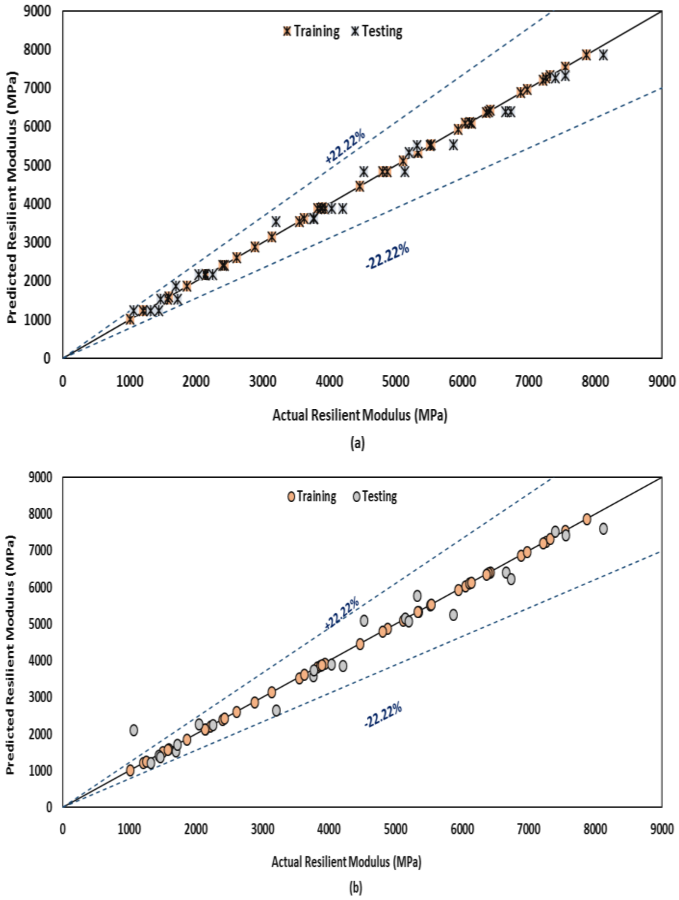

Figure 2. Concordance Plot for Actual vs. Predicted MR of (a) Random Tree (b) K- Nearest Neighbor

The testing dataset revealed some variations in the models' performance. RT maintained its high accuracy with a CC of 0.99, MAE of 205.47 MPa, and RMSE of 222.79 MPa, along with relatively low RAE and RRSE values of 10.83% and 10.08%, respectively. KNN showed a slight decline in performance compared to training, with a CC of 0.98, MAE of 268.12 MPa, RMSE of 371.84 MPa, RAE of 14.13%, and RRSE of 16.83%. ANN exhibited strong performance during testing, achieving a CC of 0.99, the lowest MAE of 180.74 MPa, and RMSE of 236.92 MPa, coupled with moderate RAE and RRSE values of 9.52% and 1.72%, respectively. Conversely, GP's performance remained relatively low, with a CC of 0.99 and the highest error metrics: MAE of 315.85 MPa, RMSE of 350.43 MPa, RAE of 16.64%, and RRSE of 15.86%.

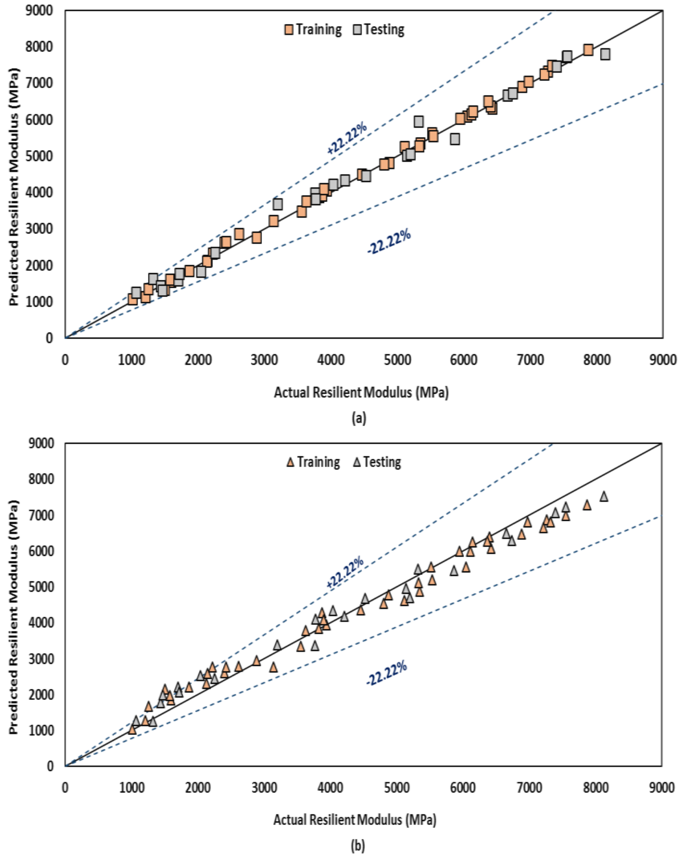

Figure 3. Concordance Plot for Actual vs. Predicted MR of (a) Artificial Neural Network (b) Gaussian Process

Figure 1 (a, b) depict scatter plots of actual versus predicted resilient modulus values for RT and KNN models, respectively, illustrating a strong alignment between actual and predicted values for both models, with KNN demonstrating near-perfect accuracy during training. Figure 2 (a, b) presents similar plots for ANN and GP models, where ANN shows robust performance, particularly in the testing phase, while GP exhibits greater deviation, indicating comparatively lower accuracy. Overall, KNN demonstrated the best performance in the training dataset, achieving perfect accuracy with minimal error metrics, whereas ANN emerged as the most accurate model during testing with the lowest MAE and RMSE values. RT consistently performed well across both datasets, and GP with the kernel lagged behind the other models in terms of prediction accuracy and error metrics. Performance Assessment parameters of all applied models in both training and testing stages are tabulated in table 1. And relative error among actual data and predicted data is presented in figure 5.

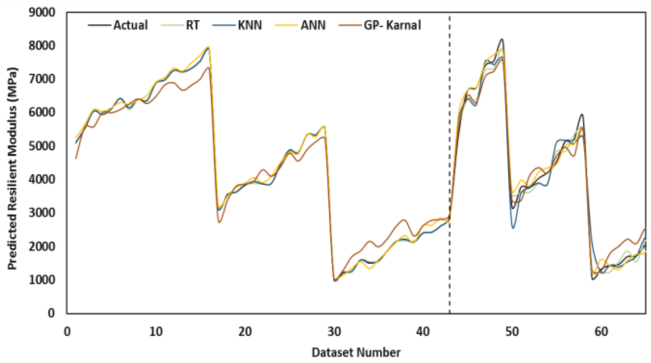

Figure 5. Relative error in both training and testing stages

Table 1. Performance parameters metrics of used models

Models	CC	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
Training					
RT	0.99	12.53	22.52	0.68	1.09
KNN	1	4.40	6.06	0.24	0.29
ANN	0.99	89.72	111.13	4.91	5.40
GP	0.993	276.4	331.76	15.1	16.12
Testing					
RT	0.995	205.4	222.79	10.8	10.08
KNN	0.986	268.1	371.84	14.1	16.83
ANN	0.994	180.7	236.92	9.52	1.72
GP	0.993	315.8	350.43	16.6	15.86

5 CONLUSION

This study demonstrates the effectiveness of machine learning models RT, KNN, ANN, and GP—in predicting the MR value of asphalt mixtures. Among these models, KNN emerged as the most reliable during the training phase, achieving perfect accuracy with minimal error rates. ANN performed exceptionally well during the testing phase, offering the lowest error metrics and maintaining high accuracy. RT consistently delivered strong predictive performance across both datasets, proving its robustness. In contrast, the GP model showed relatively lower accuracy, reflecting room for improvement in its predictive capabilities. Sensitivity analysis indicates RAP% and temperature are the most influential factors affecting MR predictions across all ML models.

These findings highlight the applicability of machine learning techniques in pavement engineering, where accurate predictions of material properties are crucial for design and maintenance. The results underline that selecting an appropriate model depends on the desired balance between accuracy and error tolerance for specific applications.

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