Machine Learning-Driven Resilient Modulus Prediction for Flexible Pavements Across Mountainous and Other Regions

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Abstract. Accurate estimation of the elastic modulus (Mr) in the compacted subgrade soil is essential for the design of flexible pavement systems that are both reliable and environmentally friendly. Mr significantly affects the structural integrity of the pavement, especially in hilly areas with varying loads and climatic conditions. This study collects 2813 data points from previous research results to create an accurate prediction model. The gradient boosted (GB) machine learning (ML) approach is selected to predict the Mr of the compacted subgrade soil. The accuracy and predictive performance of the GB model were evaluated using statistical analysis that includes fundamental metrics such as root mean square error, mean absolute error, and relative squared error. The model obtained R^2 values of 0.96 and 0.94 for the training and testing datasets. The RMSE was 5 MPa for training and 7.48 MPa for testing, while the MAE was 3.18 MPa and 5.55 MPa. These results highlight the potential of GB in predicting soil Mr, thereby supporting the development of more accurate and efficient Mr prediction, ultimately reducing time and cost.

Keywords: Resilient modulus, Gradient boosting, Machine learning

1 Introduction

The soil's resilience is one of the fundamental characteristics that affect the short-term distortion of pavement designs. By examining the mechanical characteristics of multi-layer structures, the resilience effects may be used to estimate rutting, roughness, and cracking[1]. Subgrade soils are subject to displacement, compaction, and distortion, serving as a flexible foundation. Deviator stress from initial automobile loads on the road surface results in a considerable deformation of the subgrade soil, which causes plastic strain to diminish. This subgrade distortion affects the sub-base layer and results in uneven settlement or rutting, which indicates the initial approach of the serviceability limit condition

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[2]. Higher RM values show less vertical deformation under load, which is essential in hilly sites where uneven topography can exacerbate stress concentrations and cause more cracking and degradation of the pavement layer[3]. Consequently, resilient modulus (Mr) is a crucial parameter in pavement design, and it is expressed as the percentage of the cyclic deviator stress to the axial resilient strain [4]. The principal aim of pavement design is to achieve an equilibrium between longevity and economy, ensuring the pavement's capacity to endure traffic loads for a certain period of time. There are multiple ways to determine the Mr, such as in-situ and lab tests like cyclic triaxial load testing, torsional shear testing, and resonant column testing[5-7]. Still, experimental testing has many disadvantages, including needing a professional staff, high costs, and a lengthy time. On the other hand, Mr integration into designing multi-layered pavement techniques and executing structural investigations was inspired by the American Association of State Highway and Transportation Officials (AASHTO) and many other officials. [7]. Previously, there was a discernible trend away from traditional methodologies and toward using various machine-learning approaches in analyses [8-10]. This change has advanced the industry considerably by generating more effective results. Scholars are progressively using the capabilities of machine learning algorithms to investigate intricate baselines and derive influential discoveries [11-13].

A machine learning (ML) process is trained with memory simulation abilities and powerful learning abilities, and a fundamental benefit of such algorithms is that they are data-driven, which enables them to generate reliable forecasting models based on the submitted dataset [14-16]. Many researchers further support the effectiveness of these techniques in addressing a wide variety of geotechnical problems[17-19]. Das et al. [20] estimated the UCS of stabilized soil using artificial neural networks (ANN) and support vector machines (SVM); similarly, Ghorbani et al. [21] used evolutionary polynomial regression (EPR) and ANN techniques. However, these approaches are considered a "Black Box" as it is challenging to understand the underlying mechanics, and locating errors might be problematic. Large data sets are required for these models, and shifts in data distribution may cause issues. Furthermore, despite several academics' demonstrations of strong predictive ability, one of the ensemble learning algorithms, Gradient Boosting (GB), has not yet been extensively employed in geotechnical engineering.

In order to estimate the Mr of subgrade soil, a considerable amount of time, labour, and resources can invested in the laboratory setup. Nevertheless, ML approaches must used to obtain accurate forecasts of subgrade Mr of soil. Applying ML techniques may decrease the cost and time associated with conducting trials. This work developed innovative GB models that can precisely indicate the Mr of subgrade soil by thoroughly investigating several statistical data.

2 Methodology

2.1 Data Collection

The present investigation made a data pool of 2813 points of more than ten subgrade soils, which are categorized by A-4, A-6 and A-7-6 in AASHTO classification or CL, CH and CL: ML in USCS classification.[22-25]. The moisture content (MC), plasticity index (PI), freeze-thaw (FT) cycles, confining stress (δc), and dry density (γd) were the critical variables for evaluating the Mr. Importantly, all variables were chosen with significant consideration based on suggestions from reputable experts and a comprehensive literature review [26-28].

2.2 Statistics summary

This analysis explores the links between Mr and the input data, which indicates the following correlation coefficients: $\gamma d = -0.37$, $\delta d = -0.079$, $\delta c = -0.049$, and $wPI = -0.025$ are the relative values. However, the MC has the most robust correlation coefficient of -0.357, as shown in Fig. 1. Table 1 presents a numerical summary of the input parameters utilized in this investigation.

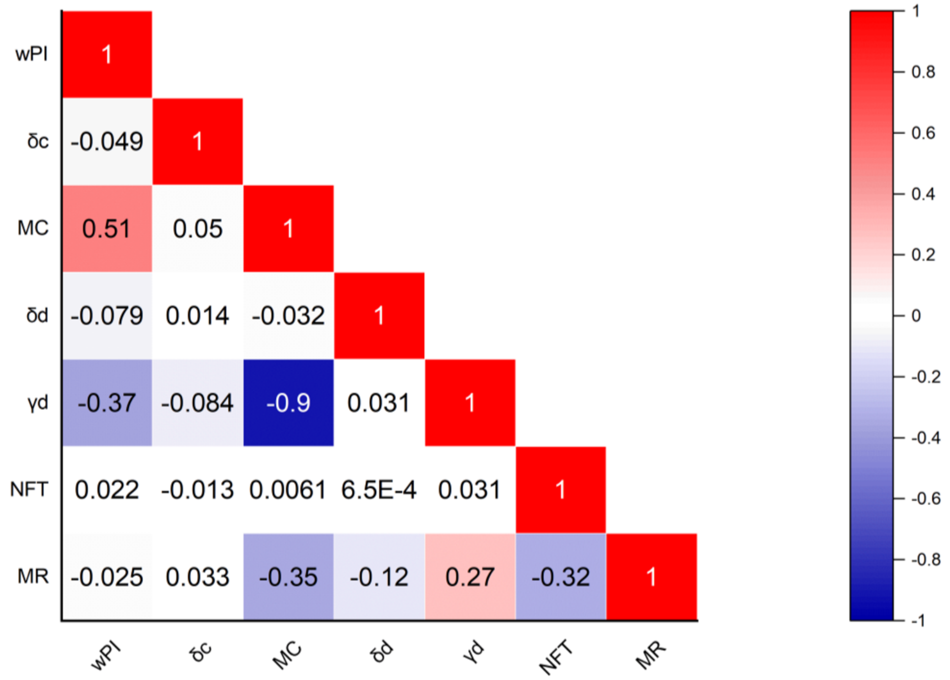

Fig.1. Correlation coefficients.

Table 1. Statistical metrics of data.

Statistical descriptive	wPI	N_{FT}	δ_c(kPa)	MC (%)	γ_d(kN/m^3)	δ_d(kPa)	M_R(Mpa)
Mean	13.90	4.13	27.17	18.36	17.73	45.64	33.81
Max	31.08	20.00	41.40	41.54	20.40	68.90	217.00
Skewness	0.72	1.23	-0.14	0.35	0.08	-0.13	2.92
SD	6.44	3.93	11.67	4.52	1.56	17.34	26.62
Kurtosis	0.00	1.90	-1.20	-0.99	-1.51	-1.11	12.05
Min	5.82	0.00	0.00	12.30	15.50	13.80	3.00

The standard deviation (SD) shows the data distribution; whereas a smaller SD implies that most outcomes are close to the mean, a larger SD denotes a more scattered distribution. Skewness and Kurtosis indicate how symmetrical, upward, or downward the data trend is concerning a normal distribution. As per Brown et al. [29], Kurtosis must be within the permissible range of -10 to $+10$. Furthermore, Fig. 2 shows a diagram to improve the graphical indication of the input variables in the form of contour plots. The input variables clearly show that the data points are dispersed randomly throughout the range.

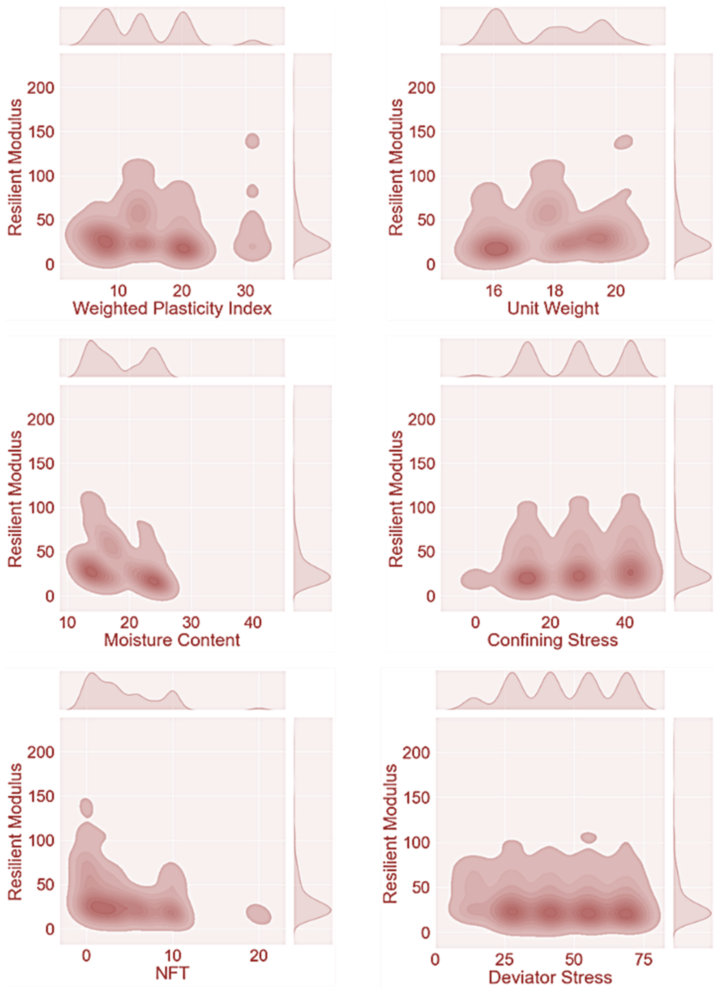

Fig. 1. Contour plots for data records.

2.3 Models development and assessment

Gradient Boosting (GB) is a machine learning technique that builds an ensemble of decision trees to improve predictive accuracy. Each tree is trained sequentially to fix the errors of the previous ones by minimizing a loss function. This iterative process continues until the model converges or a set number of iterations is reached, resulting in a final model that combines the predictions of all the trees to form a strong predictor.

In this study, GB was employed to predict the Mr of compacted subgrade soils using a ratio of 70 and 30% for training and testing purposes. The GB model was selected for its ability to capture complex patterns and interactions in the data, which is crucial for modeling the nonlinear relationships inherent in soil properties. The implementation of the GB model was evaluated utilizing statistical metrics such as R^2, MSE, RMSE, MAE, and others. A grid search method was utilized to optimize the hyperparameters of the GB model, ensuring optimal predictive performance. This method systematically explored different combinations of hyperparameters to enhance the model's accuracy and efficiency.

3 Results and Discussion

The GB model revealed predictive solid interpretation, as illustrated in Fig. 3 (a) and Table 2, with R^2 outcomes of 0.96 and 0.94 for the training and testing sets. A low average error in predictions is presented by the RMSE and MSE values, which were 5 and 25.38 MPa for the training set and 7.48 and 56 MPa for the testing set. Additionally, the error distribution in Fig. 3 (b) supports the model's effectiveness, which shows that most errors are below 5 MPa.

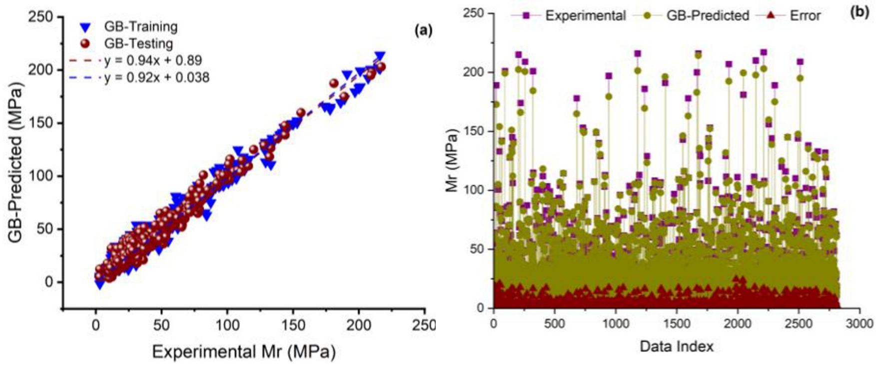

Fig. 2. Model evaluation plots (a) regression and (b) error plots.

Table 1. Statistical assessment.

Stage	MAE	MSE	RMSE	R^2
GB-Training	3.185	25.388	5.039	0.965
GB-Testing	5.557	55.999	7.483	0.945

These findings demonstrate the accuracy of GB for predicting the Mr of subgraded soil. The strong R^2 values suggest that the model can account for a significant portion of the variability in Mr, and the low RMSE and MAE values show that the predictions are accurate. The GB model's success can be ascribed to its capacity to represent intricate connections between the Mr and input variables. Furthermore, the application of GB here is consistent with the overall trend in geotechnical engineering to improve material design and performance prediction by utilizing sophisticated machine-learning approaches. Overall, the results bolster the viability of reliable, user-friendly, and cost-effective MR prediction solutions.

4 Conclusion

This research shows a breakthrough in predicting soil resilient modulus (Mr), a critical parameter in civil engineering. It demonstrates the GB model's effectiveness as a predictor of Mr. It is essential to properly evaluate and integrate Mr into design processes to construct durable infrastructure that can withstand the specific challenges encountered in hilly terrains. The traditional laboratory test procedures for measuring Mr have several difficulties, such as high complexity, expenditure, time-consuming, and expert staff. Thus, this analysis focuses on utilizing an innovative machine learning technique, namely GB, to accurately forecast the MR of subgrade soil. The model executed high accuracy, as noted by R^2 values of 0.96 and 0.94 and low RMSE and MAE values (5 MPa and 3.18 MPa). In order to boost prediction accuracy and generalizability, future research may investigate the use of other ML approaches and broaden the dataset.

References

1. P. Thanh-Tung *et al.*, "RESILIENT MODULUS OF SOIL USING FOR SUBGRADE OF PAVEMENT: A CASE STUDY IN VIETNAM," *Acta Geodynamica et Geomaterialia,* vol. 20, no. 3, 2023.
2. M. A. Benbouras, L. Sadoudi, and A. Leghouchi, "Prediction of the Resilient Modulus of Subgrade Soil Using Machine-Learning Techniques," *Urbanism. Arhitectura. Constr,* vol. 16, pp. 1-14, 2025.
3. M. Bouatia, "Analysis of Flexible Pavement Structural Behavior Considering Decreased Subgrade Resilient Modulus," in *MATEC Web of Conferences*, 2024, vol. 394: EDP Sciences, p. 01004.
4. Z. Han and S. K. Vanapalli, "Relationship between resilient modulus and suction for compacted subgrade soils," *Engineering geology,* vol. 211, pp. 85-97, 2016.
5. D. Andrei, M. W. Witczak, C. W. Schwartz, and J. Uzan, "Harmonized resilient modulus test method for unbound pavement materials," *Transportation Research Record,* vol. 1874, no. 1, pp. 29-37, 2004, doi: https://doi.org/10.3141/1874-04.
6. D. Kim and J. R. Kim, "Resilient behavior of compacted subgrade soils under the repeated triaxial test," *Construction and Building Materials,* vol. 21, no. 7, pp. 1470-1479, 2007, doi: https://doi.org/10.1016/j.conbuildmat.2006.07.006.
7. M. Mazari, E. Navarro, I. Abdallah, and S. Nazarian, "Comparison of numerical and experimental responses of pavement systems using various resilient modulus models," *Soils and Foundations,* vol. 54, no. 1, pp. 36-44, 2014, doi: https://doi.org/10.1016/j.sandf.2013.12.004.
8. U. Asif, M. F. Javed, M. Abuhussain, M. Ali, W. A. Khan, and A. Mohamed, "Predicting the mechanical properties of plastic concrete: An optimization method by using genetic programming and ensemble learners," *Case Studies in Construction Materials,* vol. 20, p. e03135, 2024, doi: https://doi.org/10.1016/j.cscm.2024.e03135.
9. Y. Luo, X. Liu, F. Chen, H. Zhang, and X. Xiao, "Numerical simulation on crack–inclusion interaction for rib-to-deck welded joints in orthotropic steel deck," *Metals,* vol. 13, no. 8, p. 1402, 2023, doi: https://doi.org/10.3390/met13081402.
10. R. Alyousef, M. Khan, K. Arif, M. Fawad, A. M. Hassan, and N. A. Ghamry, "Forecasting the strength characteristics of concrete incorporating waste foundry sand using advance machine algorithms including deep learning," *Case Studies in Construction Materials,* vol. 19, p. e02459, 2023, doi: https://doi.org/10.1016/j.cscm.2023.e02459.
11. U. Asif, S. A. Memon, M. F. Javed, and J. Kim, "Predictive Modeling and Experimental Validation for Assessing the Mechanical Properties of Cementitious Composites Made with Silica Fume and Ground Granulated Blast Furnace Slag," *Buildings,* vol. 14, no. 4, p. 1091, 2024, doi: https://doi.org/10.3390/buildings14041091.
12. Y. Hu, A. A. Alaskar, F. Althoey, M. A. Abuhussain, G. Alfalah, and F. Farooq, "Strength evaluation sustainable concrete with waste ingredients at elevated temperature by employing interpretable algorithms: Optimization and hyper tuning," *Materials Today Communications,* vol. 36, p. 106467, 2023, doi: https://doi.org/10.1016/j.mtcomm.2023.106467.
13. X. Zhang, S. Wang, H. Liu, J. Cui, C. Liu, and X. Meng, "Assessing the impact of inertial load on the buckling behavior of piles with large slenderness ratios in liquefiable deposits," *Soil Dynamics and Earthquake Engineering,* vol. 176, p. 108322, 2024, doi: https://doi.org/10.1016/j.soildyn.2023.108322.
14. D. Han *et al.*, "LMCA: a lightweight anomaly network traffic detection model integrating adjusted mobilenet and coordinate attention mechanism for IoT," *Telecommunication Systems,* vol. 84, no. 4, pp. 549-564, 2023, doi:

https://doi.org/10.1016/j.enggeo.2016.06.020.
15. Y. Zheng, Y. Wang, and J. Liu, "Research on structure optimization and motion characteristics of wearable medical robotics based on improved particle swarm optimization algorithm," *Future Generation Computer Systems,* vol. 129, pp. 187-198, 2022, doi: https://doi.org/10.1016/j.future.2021.11.021.
16. L. Wang, W. Zhang, and F. Chen, "Bayesian approach for predicting soil-water characteristic curve from particle-size distribution data," *Energies,* vol. 12, no. 15, p. 2992, 2019, doi: https://doi.org/10.3390/en12152992.
17. N. Kardani, A. Zhou, S.-L. Shen, and M. Nazem, "Estimating unconfined compressive strength of unsaturated cemented soils using alternative evolutionary approaches," *Transportation Geotechnics,* vol. 29, p. 100591, 2021, doi: https://doi.org/10.1016/j.trgeo.2021.100591.
18. S. K. Sinha and M. C. Wang, "Artificial neural network prediction models for soil compaction and permeability," *Geotechnical and Geological Engineering,* vol. 26, pp. 47-64, 2008.
19. R. Morgan, D. Morgan, and H. Finney, "A predictive model for the assessment of soil erosion risk," *Journal of agricultural engineering research,* vol. 30, pp. 245-253, 1984, doi: https://doi.org/10.1016/S0021-8634(84)80025-6.
20. S. K. Das, P. Samui, and A. K. Sabat, "Application of artificial intelligence to maximum dry density and unconfined compressive strength of cement stabilized soil," *Geotechnical and Geological Engineering,* vol. 29, pp. 329-342, 2011, doi: https://doi.org/10.1007/s10706-010-9379-4
21. A. Ghorbani and H. Hasanzadehshooiili, "Prediction of UCS and CBR of microsilica-lime stabilized sulfate silty sand using ANN and EPR models; application to the deep soil mixing," *Soils and foundations,* vol. 58, no. 1, pp. 34-49, 2018, doi: https://doi.org/10.1016/j.sandf.2017.11.002.
22. W.-l. Zou, Z. Han, L.-q. Ding, and X.-q. Wang, "Predicting resilient modulus of compacted subgrade soils under influences of freeze–thaw cycles and moisture using gene expression programming and artificial neural network approaches," *Transportation Geotechnics,* vol. 28, p. 100520, 2021, doi: https://doi.org/10.1016/j.trgeo.2021.100520.
23. Y. Ren, L. Zhang, and P. N. Suganthan, "Ensemble classification and regression-recent developments, applications and future directions," *IEEE Computational intelligence magazine,* vol. 11, no. 1, pp. 41-53, 2016, doi: https://doi.org/10.1109/MCI.2015.2471235.
24. L.-q. Ding, Z. Han, W.-l. Zou, and X.-q. Wang, "Characterizing hydro-mechanical behaviours of compacted subgrade soils considering effects of freeze-thaw cycles," *Transportation Geotechnics,* vol. 24, p. 100392, 2020, doi: https://doi.org/10.1016/j.trgeo.2020.100392.
25. M. T. Rahman, "Evaluation of moisture, suction effects and durability performance of lime stabilized clayey subgrade soils," 2014.
26. B. Ghorbani, A. Arulrajah, G. Narsilio, S. Horpibulsuk, and M. W. Bo, "Development of genetic-based models for predicting the resilient modulus of cohesive pavement subgrade soils," *Soils and Foundations,* vol. 60, no. 2, pp. 398-412, 2020, doi: https://doi.org/10.1016/j.sandf.2020.02.010.
27. P. R. Oskooei, A. Mohammadinia, A. Arulrajah, and S. Horpibulsuk, "Application of artificial neural network models for predicting the resilient modulus of recycled aggregates," *International Journal of Pavement Engineering,* vol. 23, no. 4, pp. 1121-1133, 2022.
28. N. Kardani, M. Aminpour, M. N. A. Raja, G. Kumar, A. Bardhan, and M. Nazem, "Prediction of the resilient modulus of compacted subgrade soils using ensemble machine learning methods," *Transportation Geotechnics,* vol. 36, p. 100827, 2022, doi:

https://doi.org/10.1016/j.trgeo.2022.100827.
29. A. Alaskar *et al.*, "Comparative study of genetic programming-based algorithms for predicting the compressive strength of concrete at elevated temperature," *Case Studies in Construction Materials,* vol. 18, p. e02199, 2023.