PREDICTION OF THE RESILIENT MODULUS OF SUBGRADE SOIL USING MACHINE-LEARNING TECHNIQUES

Mohammed Amin BENBOURAS
PhD, Habil, Departement of Civil Engineering, University of Sciences and Techology Houari Boumediene, Bab Ezzouar, Algiers, Algeria, mohammedamin.benbouras@usthb.edu.dz

Lyacia SADOUDI
PhD, Habil, Departement of Civil Engineering, University of Sciences and Techology Houari Boumediene, Bab Ezzouar, Algiers, Algeria, sadoudi29@yahoo.com

Abdelghani LEGHOUCHI
PhD, Civil Engineering Department, Mohammed Seddik Benyahia University, Jijel, Algeria, ghanileghouchi@hotmail.fr

Abstract. The resilient modulus (M_R) of subgrade soil is crucial in pavement design, as it significantly affects its structural performance. However, Traditional methods, aimed at estimating this parameter, are characterized by inefficiency, time consumption, and high costs. This study introduces a novel alternative model using ten advanced machine-learning techniques including Deep Neural Network (*DNN*), Extreme Learning Machine (ELM), Support Vector Regression (*SVR*), LASSO regression (*LASSO*), Random Forest (*RF*), Ridge Regression (*Ridge*), Partial Least Square Regression (*PLSR)*, Stepwise Regression (*Stepwise*), Kernel Ridge (*KRidge*), and Least Square Regression (*LSR*), to predict the resilient modulus (M_R). The model is trained on a comprehensive dataset comprising 891 repeated load triaxial tests, and it considers nine pertinent factors as input parameters based on literature suggestions. Evaluating the efficacy of the machine-learning methods reveals that the Deep Neural Network (*DNN*) model outperforms others in accuracy. Subsequently, a user-friendly graphical interface called "*ResiMod2024*" based on the *DNN* model is developed to streamline the estimation process of resilient modulus, offering significant time and cost savings for researchers and civil engineers.

Key words: resilient modulus, machine learning, deep neural network, K-fold cross-validation approach, repeated load triaxial tests.

1. Introduction

The primary objective of designing pavements is to strike a balance, between durability and cost-effectiveness ensuring it can withstand the traffic demands over a specific timeframe. Typically flexible pavement comprises four layers; the surface, base, and two unbound layers (sub-base and subgrade). These combined layers are responsible for enduring the varying loads generated by passing vehicles. The subgrade, consisting of soil compositions plays a role in providing foundational support, for all pavement components (Sadrossadat *et al.,* 2016; Thompson and Robnett, 1979). Subgrade soils serve as a flexible foundation, undergoing deformation, compaction, and distortion. The initial loading of vehicles on the pavement causes significant deformation in the subgrade soil due to deviator stress. With repeated stress, the plastic strain decreases and becomes almost fully recoverable. Uneven settlement or rutting, indicating an early reach of the serviceability limit state, is a result of this subgrade deformation, affecting the sub-base layer. It is essential to study soil deformation under dynamic and cyclic loading to comprehend these events (Guo *et al*., 2013; Sas *et al*., 2017; Sun *et al*., 2015; Zhou and Gong, 2001). The Resilient Modulus (M_R) of soil is an important parameter in defining the stress-strain properties of subgrade soil. It represents the elastic modulus that can recover from strain under cyclic loading. The fact that it is included in the Mechanical Empirical Pavement Design Guide (MEPDG) highlights its significant impact on pavement performance when subjected to repetitive traffic loads (Sadik, 2023). Resilient modulus (M_R) is mathematically defined as deviator stress (σ_d) divided by its recoverable strain (ε) as shown in Equation 1.

$$M_R = \frac{\sigma_d}{\varepsilon_r} \quad (1)$$

There are multiple ways to determine the M_R, such as in-situ and lab tests like cyclic tri-axial load testing, torsional shear testing, and resonant column testing (Andrei *et al*., 2004; Kim and Kim, 2007; Mazari *et al*., 2014). Nevertheless, these tests are frequently associated with drawbacks such as being time-consuming, expensive, and demanding a skilled workforce for accurate execution. Conversely, several codes and guidelines, including the American Association of State Highway and Transportation Officials (*AASHTO*), the Mechanistic-Empirical Pavement Design Guide (*MEPDG*), and the National Cooperative Highway Research Program (*NCHRP*), support the idea of incorporating M_R into the structural analysis and design of multi-layered pavement systems (Kim and Kim, 2007; Mazari *et al*., 2014). When designing pavements using the Mechanistic-Empirical Pavement Design Guide (*MEPDG*), it is important to accurately model how the pavement behaves under pressure. This involves analyzing different material properties in the layers of the pavement to determine the M_R value. It is also essential to understand the factors that affect M_R, as this will help make more accurate estimations, taking into account changes in traffic flow and environmental factors (Park *et al*., 2013; Xiao and Amirkhanian, 2008; Zhou *et al*., 2015). As a result, many research studies have been done to come up with different models that can help calculate M_R based on relevant factors like loads, stress, and soil properties (Malla and Joshi, 2008; Rahim, 2005; Zhou *et al*., 2015). These models are typically created through traditional regression analysis, commonly portrayed as basic correlation equations. These equations link M_R with soil physical characteristics such as moisture content, specimen dry density, maximum dry density, liquid limit, plasticity index, uniformity coefficient, coefficient of curvature, percent passing N° 200 sieve (*P200*), and more. A thorough collection of these model developments can be discovered in previously published works, along with citations (Malla and Joshi, 2008; Park *et al*., 2013; Witczak and Uzan, 1988; Zhou *et al*., 2015).

Interestingly, the proposed empirical equations are simple and efficient, which has greatly benefited their use. Despite the advantages, researchers have started to notice some limitations as they delve deeper into this approach. A major concern is the overlook of certain parameters when estimating the resilient modulus, potentially oversimplifying its complex mechanism. It's important to consider all factors that contribute to the predictability of empirical equations in predicting the resilient modulus (Benbouras *et al.*, 2019). Moreover, traditional regression techniques often rely on oversimplified assumptions, such as linear patterns or heuristic production, which may limit their effectiveness in capturing the intricate and dynamic nature of resilient modulus behavior. As a result, scientists have endeavored to create analytic models that provide more straightforward and precise solutions than the standard empirical formulas employed for forecasting M_R (Cai *et al.*, 2022).

Since the early nineties, the advancement of machine learning methods in civil engineering has progressed significantly (Benbouras *et al.*, 2021; Çılgın and Gökçen, 2023; Alioua *et al.*, 2024). In recent years, there has been significant progress in civil engineering, particularly in the development of machine learning methods. These advancements have led to studies demonstrating improved precision in estimating M_R compared to traditional approaches. Among the fundamental research addressing M_R, Sadik (2023) employed genetic programming to model M_R. This study utilized a database containing 891 tests, with selected input parameters including percent passing sieve *N° 200*, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress. The *GP* model exhibited efficient predictions of M_R, outperforming traditional methods. Furthermore, Pal and Deswal (2014) utilized Radial Basis Function Kernel-based Support Vector Machine (*RBF-SVM*), Simple Extreme Learning Machine (*SELM*), and Polynomial Kernel-based Extreme Learning Machine (*PKBELM*) to predict M_R. The study concluded that *PKBELM* yielded the most effective model, achieving a high correlation coefficient of 0.98. Additionally, Sadrossadat *et al*. (2016) constructed a robust model employing Adaptive Neuro-Fuzzy Inference Systems Artificial Neural Network (*ANFIS*). The model was trained on extensive datasets, comprising a substantial 891 samples. Remarkably, the ANFIS model demonstrated superior stability compared to other methods. Ikeagwuani *et al*. (2022) utilized various methods, including Gradient Boosting Regression (*GBR*), Adaptive Neuro-Fuzzy Inference System (*ANFIS*), and Artificial Neural Network (*ANN*), to predict soil resilient modulus. Their input layer incorporated factors such as liquid limit, plastic limit, plasticity index, gravel fraction, sand fraction, silt fraction, clay fraction, fines fraction, compaction density, compaction moisture content, confining stress, and nominal maximum axial stress. The proposed *GBR* model demonstrated high efficiency, with a notable correlation coefficient of 0.952. Gabr *et al*. (2022) employed Artificial Neural Network (*ANN*), Support Vector Regression (*SVR*), and Random Forest Regression (*RFR*) methods to model a database consisting of 779 tests. Among these methods, the *RFR* model exhibited efficient predictions for M_R, outperforming other techniques. Table 1 summarizes some relevant studies proposing Machine Learning models in the literature to predict M_R.

Table 1. Proposed machine-learning models in the literature to estimate the M_R.

Authors	Inputs	Methods	Database
Sadik (2023)	Percent of passing sieve *N° 200*, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress.	Genetic programming.	891
Pal and Deswal (2014)	Percent of passing sieve *No. 200*, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress.	Radial Bases Function Kernel-Support Vector Machine (*RBF-SVM*), Simple Extreme Learning Machine (*SELM*), and Polynomial Kernel- Extreme Learning Machine (PK-ELM).	891
Sadrossadat *et al.* (2016)	Percent of passing sieve *N° 200*, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress.	Adaptive Neuro-Fuzzy Inference Systems Artificial Neural Network (*ANFIS-ANN*).	891
Azam *et al.* (2022)	Percent of passing sieve *N°* 200, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress.	Least Square Support Vector Machine (*LSSVM*) hybridized with Particle Swarm Optimization (*PSO*), Grey Wolf Optimizer (*GWO*), Symbiotic Organisms Search (*SOS*), Salp Swarm Algorithm (*SSA*), Slime Mold Algorithm (*SMA*), and Harris Hawks Optimization (*HHO*).	891
Indraratna *et al.* (2023)	Cyclic loading frequency (*Fr*), number of cycles (*N*), magnitude of cyclic load (*qmax, cyc*), and confining pressure (σ').	Artificial neural network (*ANN*), and the adaptive neuro-fuzzy inference system (*ANFIS*).	196
Ikeagwuani *et al.* (2022)	Liquid Limit, plastic limit, plasticity index, gravel fFraction, sand fraction, silt fraction, clay fraction, fines fraction, compaction density, compaction moisture content, confining stress, and nominal maximum axial stress.	Gradient boosting regression (GBR), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural network (ANN).	779
Kardani *et al.* (2022)	Dry unit weight, weighted plasticity index, deviator stress, confining stress, number of freeze-thaw cycles, and moisture content.	Gradient boosting regression (*GBR*), decision tree regression (*DTR*), K nearest neighbor regression (*KNR*), and random forest regression (*RFR*).	2813
Ghorbani *et al.* (2024)	Liquid Limit, plastic limit, plasticity index, gravel fFraction, sand fraction, silt fraction, clay fraction, fines fraction, compaction density, compaction moisture content, confining stress, and nominal maximum axial stress.	Artificial neural network (*ANN*); Support Vector Regression (*SVR*); and Random Forest Regression (*RFR*).	779
Gabr *et al.* (2022)	CBR, maximum dry density, optimum moisture content, and shear strength parameters (apparent cohesion, and internal angle of friction).	Extreme learning machine (*ELM*) hybridized *ELM-BBO*, *ELM-EO*, and *ELM*-GA.	224

To the best of the authors' knowledge, previous studies aimed at predicting M_R have primarily employed machine learning methods, although recent research in civil engineering field suggests that deep learning could yield more effective and accurate results (Narendra *et al*., 2006; Othman and Abdelwahab, 2023; Rezania and Javadi, 2007; Zhang *et al*., 2021; Nakata *et al*., 2018). The assessment of predictive capability in these models often relied on a single data split, raising concerns about over-fitting and under-fitting issues. Additionally, many published papers have presented machine-learning models as mathematical equations, which can be challenging to replicate in future studies, limiting their practical value for other researchers and civil engineers. To address these limitations, investigators are encouraged to present their optimal models in the form of a programmed interface or a simple script using widely used programming languages like Python or Matlab. This approach enhances accessibility and usability for researchers at various levels interested in modeling similar problems.

The current study contributes by introducing an accessible and user-friendly interface, named "*ResiMod2024*," for predicting M_R. This contribution is twofold: firstly, the study employs advanced machine learning methods not previously utilized for this purpose, aiming to enhance prediction accuracy. Secondly, the optimal model's ability to address over-fitting and under-fitting issues is tested using the K-cross-validation approach. Ultimately, the proposed optimal model is used to develop a graphical user interface (*GUI*) accessible to civil engineers and researchers. "*ResiMod2024*" is designed to be practical, reliable, and cost-effective, providing an efficient means of predicting M_R based on readily available parameters without the need for expensive laboratory and in-situ tests.

2. Materials and methods

2.1. Overview of the methodology

The study utilizes advanced machine learning methods, including Deep Neural Network (*DNN*), Extreme Learning Machine (*ELM*), Support Vector Regression (*SVR*), LASSO Regression (*LASSO*), Random Forest (*RF*), Ridge Regression (*Ridge*), Partial Least Square Regression (*PLSR*), Stepwise Regression (Stepwise), Kernel Ridge (*Kridge*), and Least Square Regression (*LSR*), to analyze 891 samples collected from previous studies (Hanittinan, 2007). Various input parameters such as percent passing sieve *N° 200*, optimum moisture content, water content, liquid limit, plasticity index, degree of soil saturation, unconfined compressive strength, confining stress, and deviator stress are considered. The effectiveness of these machine learning methods in modeling the input parameters is evaluated using various statistical indicators. To assess the predictive ability of the optimal model, a k-fold cross-validation approach with 5 splits is employed. Finally, a reliable, user-friendly graphical interface is designed based on the optimal model, intended to assist civil engineers and researchers in predicting M_R in future studies.

2.2. Database

The selection of relevant inputs is crucial for achieving accurate predictions, and this study incorporates relevant factors that cover various aspects of the M_R estimation. The database consists of 891 datasets derived from three distinct types of soils classified as A-4, A-6, and A-7-6 based on the *AASHTO* soil classification code. This dataset is obtained from

(Hanittinan, 2007), which consolidates data from previous studies conducted on three types of cohesive Ohio soils at the soil mechanics research laboratories of Ohio State University, Purdue University, and the University of Mississippi (Pal and Deswal, 2014). Specifically, 418 datasets were collected from nine *A-4* soil locations, approximately 283 from seven *A-6* soil locations, and 190 from four *A-7-6* soil locations (Hanittinan, 2007). Within this database, All M_R tests in the database followed *AASHTO* designation T294-94 standards (Hanittinan, 2007). Testing equipment included load application tools, a tri-axial pressure chamber, and a computer with data acquisition capabilities. Table 2 summarizes the input and output parameters used in the study.

2.3. Machine Learning Methods

This paper utilizes various Machine Learning (*ML*) techniques to perform a thorough investigation and develop an efficient model. *ML* approaches have proven successful in a wide range of applications. Consequently, only the specific methods employed and corresponding references are provided for readers seeking a deeper understanding of each technique. The methods used in this study are Deep Neural Network (*DNN*) (Benbouras 2022), Extreme Learning Machine (*ELM*) (Huang *et al*., 2006), Random Forest (*RF*) (Biau and Scornet, 2016), Support Vector Regression (*SVR*) (Tikhamarine *et al*., 2020), Partial Least Square Regression (*PLSR*) (Geladi and Kowalski, 1986), LASSO regression (*LASSO*) (Hebiri and Lederer, 2013), Kernel Ridge Regression (*KRidge*) (Douak *et al*., 2013), Ridge Regression (*Ridge*) (Hoerl and Kennard, 1981), and Stepwise Regression (*Stepwise*) (Jennrich and Sampson, 1968). Matlab is utilized for modeling the algorithms corresponding to each technique, and the controlling parameters for *ELM, DNN, SVR, RF, LASSO, PLSR, Ridge, KRidge,* and *Stepwise* algorithms utilized in this study are presented in Table 3.

2.4. Statistical Performance Indicators

The performance of the proposed models is assessed using several statistical metrics and visualized with graphical representations. These metrics include Mean Absolute Error (*MAE*), Index of Scattering (*IOS*), Root Mean Squared Error (*RMSE*), Pearson correlation coefficient (*R*), Coefficient of Determination (R^2), and Index of Agreement (*IOA*). The mathematical formulas for calculating these metrics are presented in Table 4 (Amin and Petrisor, 2021; Tikhamarine *et al*., 2020).

Table 2. Input and output parameters of the proposed model.

Parameter Code	Parameter Type	Type of variable	Variable	Code	Unit
X1	Input	Quantitative	Percent of passing sieve N° 200	*p200*	*%*
X2	Input	Quantitative	Optimum moisture content	*OMC*	*%*
X3	Input	Quantitative	Water content	*WC*	*%*
X4	Input	Quantitative	Liquid limit	*LL*	
X5	Input	Quantitative	Plasticity index	*PI*	
X6	Input	Quantitative	Degree of soil saturation	*Sr*	*%*
X7	Input	Quantitative	Unconfined compressive strength	*Qu*	*kPa*
X8	Input	Quantitative	Confining stress	$\sigma 3$	*kPa*
X9	Input	Quantitative	Deviator stress	σd	*kPa*
Y	Output	Quantitative	Soil resilient modulus	*Mr*	*Mpa*

Table 3. Input and output parameters of the proposed model.

Algorithms	Algorithm parameters	Value
ELM	Hidden layers	H=1
	Hidden neurons	N=12
	Activation function	'linear'
	Regulation parameter	C = 1
DNN	Hidden layers	H=2
	Hidden neurons in the first layer	N1=[1-20]
	Hidden neurons in the second layer	N2=[1-20]
	Activation function in the first layer	'Tansg'
	Activation function in the second layer	'Tansg'
SVR	Regulation parameter C	Series of C
	Regulation parameter lambda	Series of lambda
	Kernel function	Radial basis function "RBF"
RF	nTrees	nTrees=100
	mTrees	mTrees= 26
LASSO	Lambda	series of lambda
PLS	PLS components	NumComp = 3 for PSO NumComp = 4 for GT and FS
Ridge	Regularization parameter lambda	lambda = 1
KRidge	Regularization parameter lambda	lambda = 1
	Kernel function	'linear'
	Parameter for kernel	sigma = 2x10-7

Where, Y_{tar}, Y_{out}, $\overline{Y_{tar}}$ and $\overline{Y_{out}}$ represent the target, output, mean of the target, and mean of output resilient modulus values for *N* data samples, respectively. Additionally, error indicators such as Mean Absolute Error (*MAE*), Index Of Scattering (*IOS*), and Root Mean Square Error (*RMSE*) offer quantitative measures of the disparities between the target and output values. They help gauge the accuracy and precision of the model's predictions, enabling assessment of its ability to capture underlying data patterns. Conversely, correlation indicators like Pearson Correlation Coefficient (*R*), Index Of Agreement (*IOA*), and Coefficient Of Determination (R^2) assess the strength and direction of the relationship between target and output values, providing insights into the model's consistency and reliability. These indicators indicate how well the model captures overall trends or patterns in the data and reflect the degree to which output variations mirror those in the target values. Moreover, the suggested machine learning model, characterized by the minimum *RMSE, IOS, and MAE* values and the maximum *IOA*, R^2, *and R* values, represents the optimal one, closest to experimental values (Amin and Petrisor, 2021; Tikhamarine *et al*., 2020).

After selecting the best model based on statistical performance indicators, its predictive capability is assessed using the K-fold cross-validation technique. This approach is crucial for evaluating the model as it offers a more consistent and dependable estimate of performance, aids in optimizing model parameters, promotes better generalization, and maximizes the use of available data. Moreover, this advanced technique enhances the accuracy and robustness of assessing the model's ability to address issues of over-fitting and under-fitting during the learning process (Breiman and Spector, 1992; Oommen and Baise, 2010). When working with a limited dataset, randomly dividing it into training and validation sets can result in significant variability in performance estimation. Additionally, overfitting and underfitting can occur when a model memorizes the training data instead of generalizing well to new unseen data. K-fold cross-validation helps identify overfitting and underfitting by training the model multiple times on different data subsets and assessing its performance on distinct validation sets. For instance, if the model performs well on the training data but poorly on the validation data across multiple folds, it indicates overfitting. In this approach, the dataset is divided into k equal portions, with each k-1 folds used for training and the remaining fold utilized for validation. This procedure is reiterated K times until all splits have been utilized for validation (Amin, 2021; Goetz *et al*., 2015). The benefit of this method is that it models all data during both the training and validation steps. By averaging the results across these iterations, a more reliable estimation of the model's performance is achieved (Oommen and Baise, 2010). Breiman and Spector (1992) have demonstrated that *K*=10 or *K*=5-fold cross-validation is the best choice for assessing the predictive ability of the suggested models. In the current study, K-fold cross-validation with *K*=5 was selected to evaluate the predictive capability of the optimal model.

2.5. Methodology

This study outlines a multi-phased approach to develop a machine-learning model for predicting M_R. The methodology, visually represented in Fig. 1, is summarized below:

- Database Construction: A comprehensive database was established by compiling data from published studies. This database included 891 repeated load triaxial tests.
- Machine Learning Exploration: Various machine learning algorithms, including ELM, DNN, SVR, RF, LASSO, PLS, Ridge, K Ridge, and Stepwise, were applied to the chosen input parameters. This exploration resulted in the identification of 10 potential models for predicting M_R.
- Optimal Model Selection: The most suitable model for M_R estimation was chosen based on key statistical performance metrics. These metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Index of Agreement (IOA), Coefficient of Determination (R^2), Pearson Correlation Coefficient (R), and Impact on Agreement (IOA).

Table 4. Statistical indicators of model fit quality used in the current study.

Statistical indicators	Equations
Mean Absolute Error (MAE)	$MEA = \frac{1}{N}\sum_{i=1}^{N}\left\|Y_{tar,i} - Y_{out,i}\right\| \quad (0 < \text{MAE} < \infty)$ (2)
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{tar,i} - Y_{out,i}\right)^2} \; (0 < \text{RMSE} < \infty)$ (3)
Index Of Scattering (IOS)	$IOS = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{tar,i}-Y_{out,i})^2}}{\overline{Y_{tar}}} \quad (0 < \text{IOS} < \infty)$ (4)
Coefficient of determination (R2)	$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{tar,i}-Y_{out,i})^2}{\sum_{i=1}^{N}(Y_{tar,i}-\overline{Y_{tar}})^2} \quad (0 < R^2 < 1)$ (5)
Pearson correlation coefficient (R):	$R = \frac{\sum_{i=1}^{N}\left(\left(Y_{tar,i} - \overline{Y_{tar}}\right)\left(Y_{out,i} - \overline{Y_{out}}\right)\right)}{\sqrt{\sum_{i=1}^{N}\left(\left(Y_{tar,i} - \overline{Y_{tar}}\right)^2\left(Y_{out,i} - \overline{Y_{out}}\right)^2\right)}} (-1 < \text{R} < 1)$ (6)
Index Of Agreement (IOA)	$IOA = 1 - \frac{\sum_{i=1}^{N}(Y_{tar,i}-Y_{out,i})^2}{\sum_{i=1}^{N}\left(\sum_{i=1}^{N}\left\|Y_{out,i}-\overline{Y_{tar}}\right\|+\sum_{i=1}^{N}\left\|Y_{tar,i}-\overline{Y_{tar}}\right\|\right)^2} \quad (0 < \text{IOA} < 1)$ (7)

- Predictive Capability Evaluation: The K-fold cross-validation technique (K=5) was employed to assess the optimal model's ability to predict M_R accurately. This evaluation ensured that the model could avoid both underfitting and overfitting issues.
- AI Interface Design: Finally, a user-friendly graphical interface was developed based on the chosen optimal model. This interface allows for convenient interaction with the model for M_R prediction.

3. Results

3.1. Database Compilation

This study leverages a dataset compiled from prior research, encompassing 891 samples. This diverse data provides a sufficient foundation for robust analysis. To ensure precise modeling, the dataset was balanced for training and validation purposes. Samples within each phase were randomly selected and entirely independent. Table 5 summarizes the descriptive statistics of the user database, calculated using *SPSS* software. These statistics include range, minimum, maximum, mean, standard deviation, variance, skewness, and kurtosis. The skewness values indicate a relatively even distribution across all parameters. Additionally, the data encompasses a broad range of values. This comprehensive dataset proves valuable for developing new empirical equations and models, as well as evaluating the predictive accuracy of existing formulas.

3.2. Correlation Between Resilient Modulus and Input Parameters

SPSS software was used to explore the statistical relationship between M_R and the input parameters. Figure 2 presents a correlation matrix summarizing the data distribution. This matrix reveals an irregular distribution between M_R (Y) and most input variables. However, X6 and *X7* exhibit a negative correlation, suggesting that increasing these parameters leads to a proportional decrease in M_R. Table 6 details the Pearson correlation coefficient (R) and its significance level between M_R and each input parameter. All correlations between target and inputs values show a significance level below 0.05, indicating statistically significant relationships. Based on Smith's classification (1986), M_R exhibits moderate correlations with most input parameters, except for *X4, X5, and X9*, which have weak correlations. This suggests a potentially complex, non-linear relationship between M_R and these specific parameters. Consequently, sophisticated machine-learning techniques might be necessary for accurate modelling in these cases.

3.3. Resilient Modulus Prediction Through AI Models

To determine the optimal machine learning model, the study followed a two-step process. This two-step process identified the most suitable machine-learning model for predicting M_R. First, influential input parameters were chosen based on literature recommendations. Subsequently, various machine learning methods were evaluated and compared based on their performance during the training and validation phases. Six statistical measures were used to assess model performance: Mean Absolute Error (*MAE*), Root Mean Squared Error (*RMSE*), Index Of Scattering (*IOS*), Coefficient Of Determination (R^2), Pearson Correlation Coefficient (R), and Index Of Agreement (*IOA*). The data was randomly split into 80% for training and 20% for validation (Table 7).

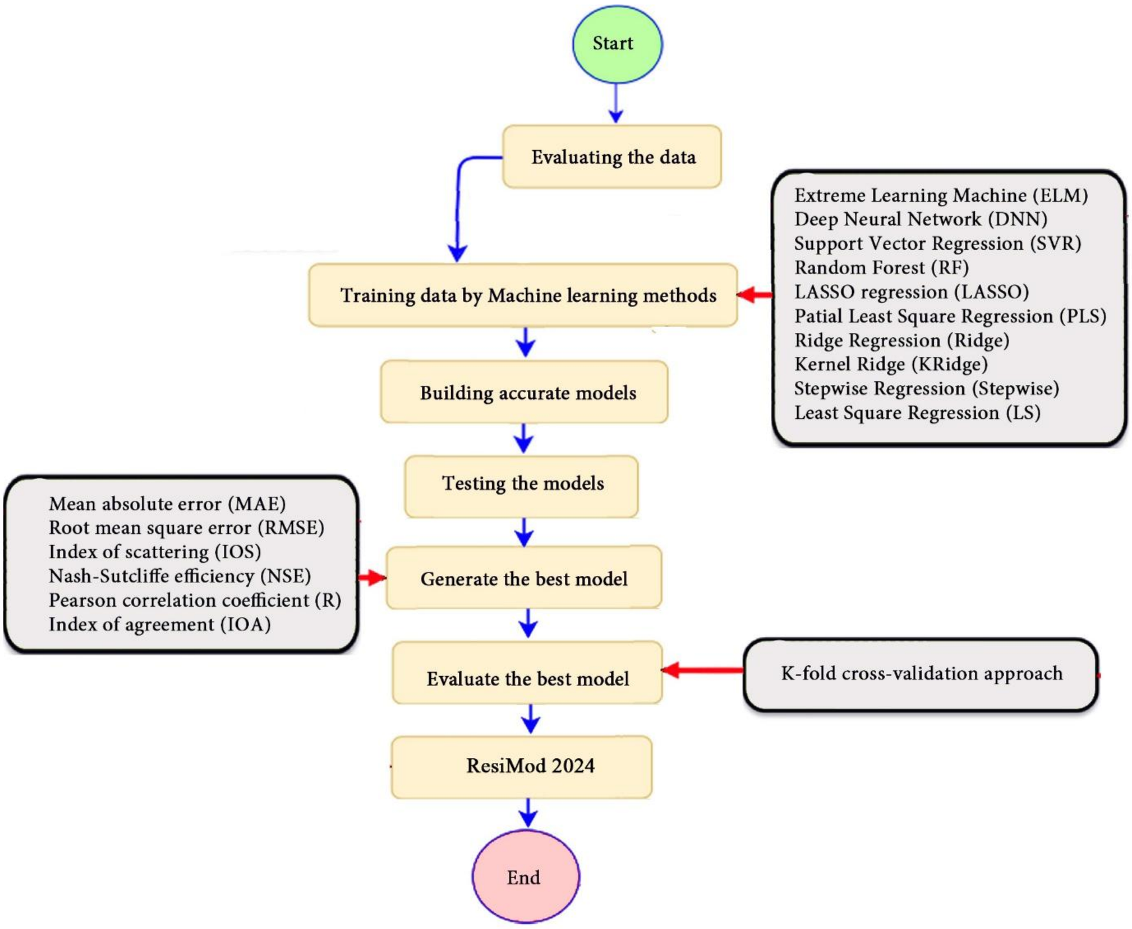

Fig. 1. Flowchart describing the key steps for the methodology of research to estimate M_R.

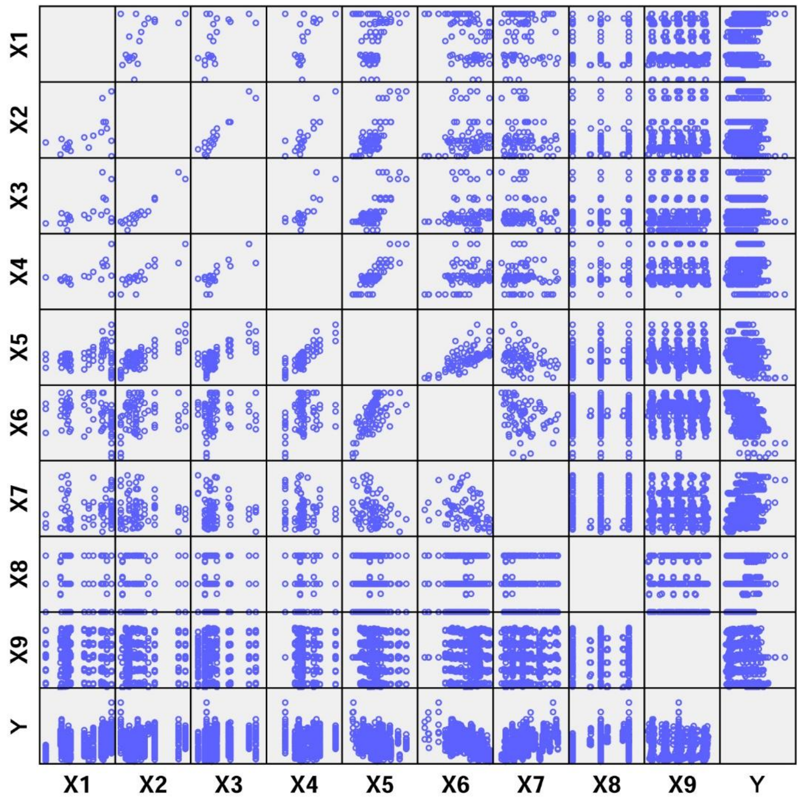

Fig. 2. The Correlation matrix between the *MR* and soil parameters.

Table 5. Descriptive statistics of the collected samples.

	N	Range	Minimum	Maximum	Mean	Standard Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
X1	891	58.00	42.00	100.00	75.2200	17.64484	311.340	-0.016	0.082	-1.356	0.164
X2	891	38.00	21.00	59.00	32.6004	9.92089	98.424	1.444	0.082	1.273	0.164
X3	891	34.00	2.00	36.00	12.6852	8.68857	75.491	1.499	0.082	1.462	0.164
X4	891	14.80	9.40	24.20	15.1848	3.03000	9.181	1.192	0.082	2.038	0.164
X5	891	19.67	7.53	27.20	15.3323	3.52980	12.460	0.852	0.082	1.443	0.164
X6	891	57.08	42.92	100.00	81.4342	11.17048	124.780	-0.636	0.082	0.111	0.164
X7	891	661.44	54.30	715.74	311.1139	162.79612	26502.58	0.742	0.082	-0.113	0.164
X8	891	41.40	0.00	41.40	20.9702	16.35724	267.559	-0.031	0.082	-1.416	0.164
X9	891	61.69	10.00	71.69	40.3090	18.22340	332.092	0.019	0.082	-1.120	0.164
Y	891	173.04	6.40	179.44	54.8213	29.68016	880.912	0.369	0.082	-0.397	0.164

Table 6. Matrix of the correlation between the parameters (**: Correlation is significant at the 0.01 level, *: Correlation is significant at the 0.05 level).

inputs		*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*Y*
X1	R	1.000	0.530**	0.584**	0.470**	0.380**	-0.193**	0.086*	0.030	0.010	0.340**
	Significance		0.000	0.000	0.000	0.000	0.000	0.011	0.363	0.756	0.000
X2	R	0.530**	1.000	0.885**	0.739**	0.633**	0.005	0.117**	-0.032	0.039	0.291**
	Significance	0.000		0.000	0.000	0.000	0.879	0.000	0.347	0.249	0.000
X3	R	0.584**	0.885**	1.000	0.599**	0.549**	0.001	0.073*	-0.027	0.054	0.399**
	Significance	0.000	0.000		0.000	0.000	0.968	0.029	0.427	0.105	0.000
X4	R	0.470**	0.739**	0.599**	1.000	0.746**	0.047	0.058	-0.028	-0.013	0.131**
	Significance	0.000	0.000	0.000		0.000	0.163	0.084	0.402	0.692	0.000
X5	R	0.380**	0.633**	0.549**	0.746**	1.000	0.532**	-0.202**	-0.025	-0.047	-0.206**
	Significance	0.000	0.000	0.000	0.000		0.000	0.000	0.450	0.163	0.000
X6	R	-0.193**	0.005	0.001	0.047	0.532**	1.000	-0.400**	-0.034	-0.023	-0.620**
	Significance	0.000	0.879	0.968	0.163	0.000		0.000	0.307	0.485	0.000
X7	R	0.086*	0.117**	0.073*	0.058	-0.202**	-0.400**	1.000	-0.017	-0.014	0.406**
	Significance	0.011	0.000	0.029	0.084	0.000	0.000		0.618	0.670	0.000
X8	R	0.030	-0.032	-0.027	-0.028	-0.025	-0.034	-0.017	1.000	0.008	0.345**
	Significance	0.363	0.347	0.427	0.402	0.450	0.307	0.618		0.807	0.000
X9	R	0.010	0.039	0.054	-0.013	-0.047	-0.023	-0.014	0.008	1.000	-0.095**
	Significance	0.756	0.249	0.105	0.692	0.163	0.485	0.670	0.807		0.005
Y	R	0.340**	0.291**	0.399**	0.131**	-0.206**	-0.620**	0.406**	0.345**	-0.095**	1.000
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	

The models exhibited varying performance across all metrics in both phases (training and validation). The obtained values ranged from *MAE* (0.6378 to 13.668), *RMSE* (0.9179 to 17.4615), *IOS* (0.0167 to 0.3224), R^2 (0.6568 to 0.999), and *IOA* (0.8751 to 0.9998) during training. Similarly, in the validation phase, we obtain *MAE* (2.0678 to 13.5122), *RMSE* (3.0138 to 17.3763), *IOS* (0.0553 to 0.3122), *R* (0.812 to 0.9951), R^2 (0.6594 to 0.9903), and *IOA* (0.8811 to 0.9975).

The Deep Neural Network (DNN) model with the Tan-Sigmoid activation function emerged as the most effective, achieving the highest accuracy in both training and validation phases across all performance measures. The Support Vector Regression (*SVR*) model also demonstrated good performance, ranking second. Conversely, the Ridge model exhibited the weakest performance in predicting M_R.

Based on the training phase performance, the overall ranking of the machine learning models was *DNN, SVR*, Random Forest (*RF*), Stepwise, Lasso, Extreme Learning Machine (*ELM*), Kernel Ridge Regression (*Kridge*), Partial Least Squares (*PLS*), Linear Regression (*LS*), *Ridge*.

3.4. Evaluating the Best-Fitted Model Using K-fold Cross-Validation Approach

To assess the *DNN* model's ability to predict unseen data and avoid overfitting/underfitting, a 5-fold cross-validation approach was employed. Unlike prior M_R prediction studies that relied on a single data split, this method provides a more robust evaluation. Figure 3 depicts the performance metrics of the *DNN* model using 5-fold cross-validation.

Each fold involved a validation set for performance evaluation. The results showcase the effectiveness of the *DNN* model. The correlation coefficients between predicted and actual M_R values across the validation sets in all 5 folds ranged from 0.9874 to 0.9971. This demonstrates the model's ability to learn from the training data and generalize well to new data, successfully mitigating overfitting and underfitting issues.

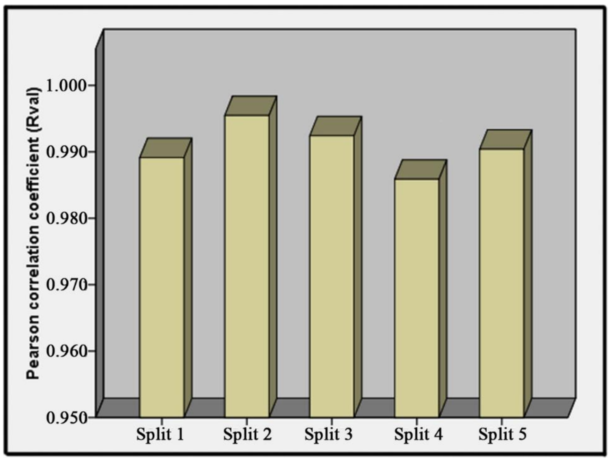

Fig. 3. Performance measures of the DNN model using the K-fold cross-validation with K=5.

Table 7. Performance indicators values of the *AI* models for predicting the M_R.

	MAE	*RMSE*	*IOS*	*R*	R^2	*IOA*
			Training			
DNN	0.6378	0.9179	0.0167	0.9995	0.9990	0.9998
ELM	12.8146	16.8975	0.3114	0.8214	0.6747	0.8956
Lasso	12.8197	16.8217	0.3102	0.8228	0.6771	0.8966
PLS	12.8594	16.8559	0.3112	0.8203	0.6729	0.8949
RF	3.0801	4.2846	0.0783	0.9908	0.9816	0.9946
Kridge	13.0258	16.9260	0.3054	0.8209	0.6739	0.8935
Ridge	13.6680	17.4615	0.3224	0.8104	0.6568	0.8751
LS	12.8931	16.9375	0.3097	0.8167	0.6671	0.8927
Step	12.7594	16.6332	0.3014	0.8304	0.6895	0.9017
SVR	1.5117	4.0431	0.0730	0.9912	0.9825	0.9952
			Validation			
DNN	2.0678	3.0138	0.0553	0.9951	0.9903	0.9975
ELM	12.0631	15.8948	0.2846	0.8457	0.7153	0.9111
Lasso	12.2361	16.1797	0.2907	0.8414	0.7079	0.9095
PLS	12.0811	15.9485	0.2818	0.8506	0.7236	0.9133
RF	4.2977	5.6539	0.1013	0.9824	0.9651	0.9886
Kridge	12.2067	16.0460	0.3013	0.8429	0.7104	0.9050
Ridge	13.5122	17.3763	0.2976	0.8239	0.6788	0.8811
LS	11.9245	15.5800	0.2877	0.8646	0.7475	0.9203
Step	12.5222	16.8967	0.3122	0.8120	0.6594	0.8934
SVR	3.9049	6.3487	0.1210	0.9758	0.9522	0.9866

Table 8. A Comparison between our *DNN* model and some of the proposed empirical models in the literature.

Authors	Database	Best Methods	Correlation coefficient
Sadik (2023)	891	*GP*	0.93
Pal and Deswal (2014)	891	*KBELMA*	0.98
Sadrossadat *et al*. (2016)	891	*ANFIS*	0.96
Azam *et al*. (2022)	891	*SOS-LSSVM*	0.942
Indraratna *et al*. (2023)	196	*ANFIS*	0.970
Ikeagwuani *et al*., (2022)	779	*GBR*	0.952
Kardani *et al*. (2022)	2813	*BG-ENSM*	0.9967
Ghorbani *et al*. (2024)	779	*RFR*	0.997
Gabr *et al*. (2022)	224	*ELM-EO*	0.924
Our study	891	Deep neural network (*DNN*)	0.9986

3.5. Comparison Between the Proposed Models and Empirical Formulae

To evaluate the effectiveness of our proposed Deep Neural Network (*DNN*) model, we compared its performance with established empirical models from the literature (Table 8). The comparison focused on the correlation coefficient (*R*), a key indicator of prediction accuracy, with values closer to 1 signifying better performance. The results demonstrate that our *DNN* model surpassed all existing models, achieving the highest accuracy with a correlation coefficient of 0.9986. The *RFR* model proposed by Ghorbani *et al.* (2021) ranked second, exhibiting good accuracy. The following summarizes the performance ranking of the compared models in our study : Proposed *DNN* Model (This Study), Ghorbani *et al.* (2021), Kardani *et al.* (2022), Pal and Deswal (2014), Indraratna *et al.* (2023), Sadrossadat *et al.* (2016), Ikeagwuani *et al.* (2022), Azam *et al.* (2022), Sadik (2023), and Gabra *et al.* (2022).

The superior performance of our *DNN* model can be attributed to its deep learning architecture. The inclusion of multiple hidden layers provides the model with the flexibility to capture complex relationships within the data, leading to more accurate predictions in various scenarios.

3.6. Graphical User Interface (GUI) Design "ResiMod2024"

Unlike traditional presentations of machine learning models in complex equations, which can be challenging to apply in future studies (Benbouras and Lefilef, 2021), this study prioritizes accessibility. Recognizing the limitations for practical use, we designed a user-friendly graphical interface (*GUI*) named "*ResiMod2024*" (Fig. 4). *ResiMod2024*, programmed using Matlab software, allows civil engineers and researchers to conveniently predict M_R, a notoriously complex parameter. The interface name signifies its purpose: "*Resi*" for resilient, "*Mod*" for modulus, and "*2024*" for the year of development. *ResiMod2024* simplifies M_R prediction by requiring users to input readily available parameters such as sieve analysis results, moisture content, soil properties (liquid limit, plasticity index, degree of saturation), and stress values. After entering these values, users simply click "Run" to obtain the predicted M_R value. This user-friendly interface is expected to be a valuable tool for civil engineers and researchers, saving them time and effort in M_R prediction tasks.

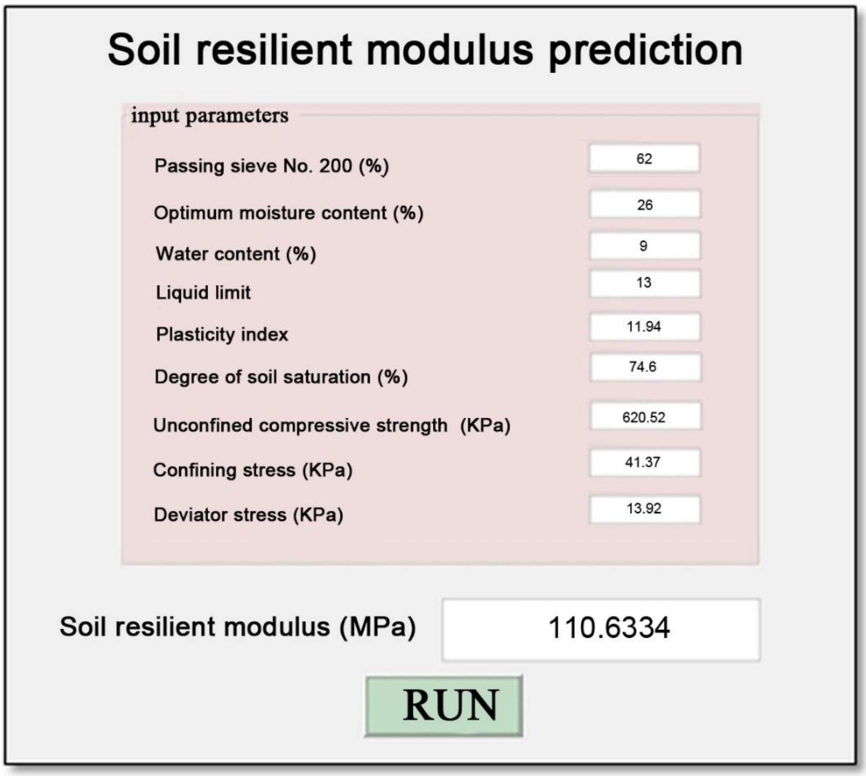

Fig. 4. *ResiMod2024* interface.

4. Discussion

This study presents a significant advancement in M_R prediction for the civil engineering community. Recognizing the impact of methodology on model performance, we explored the application of ten advanced machine-learning methods for M_R prediction. To the best of our knowledge, this is the first study to utilize such a comprehensive set of methods, including Deep Neural Network (*DNN*), Extreme Learning Machine (*ELM*), Support Vector Regression (*SVR*), LASSO Regression (*LASSO*), Random Forest (*RF*), Ridge Regression (*Ridge*), Partial Least Square Regression (*PLSR*), Stepwise Regression (Stepwise), Kernel Ridge (*Kridge*). The research began with compiling a substantial dataset of 891 repeated load triaxial tests from various sources. We then identified nine key factors influencing M_R based on literature recommendations, such as sieve analysis results, moisture content, soil properties (liquid limit, plasticity index, degree of saturation), and stress values. Subsequently, these factors underwent a statistical analysis to ascertain their influence on M_R. The results revealed that M_R demonstrates moderate correlations with the majority of input parameters, with the exceptions of *X4, X5*, and *X9*, which exhibit weak correlations. Finally, we implemented all ten machine learning methods on this optimized input set, paving the way for future research in this area.

Our analysis revealed that the Deep Neural Network (*DNN*) emerged as the most effective model for predicting M_R. Compared to other methods, the *DNN* achieved the lowest error metrics (*MAE*, *RMSE*, and *IOS*) and the highest values for accuracy metrics (R^2, *R*, and *IOA*). Additionally, the K-fold cross-validation method confirmed the *DNN*'s ability to generalize well to unseen data, avoiding overfitting and underfitting issues. Furthermore, the *DNN*'s superiority was evident when compared to existing empirical models from the literature. To enhance the practical application of the *DNN* model, a user-friendly graphical user interface (*GUI*) named "*ResiMod2024*" was developed using Matlab software. This interface simplifies M_R prediction for civil engineers and researchers by allowing them to easily input relevant parameters and obtain predicted M_R values.

ResiMod2024 simplifies M_R prediction for civil engineers and researchers by providing a user-friendly graphical interface. Unlike traditional methods that require programming expertise, ResiMod24 is accessible to anyone. This interface is built upon a powerful Deep Neural Network (*DNN*) model, rigorously optimized using K-fold cross-validation. This optimization ensures accurate predictions by avoiding overfitting and underfitting issues. *ResiMod2024* streamlines the M_R prediction process. Users simply enter the required input parameters, readily available from standard soil tests, and click "Run." The interface then generates the predicted M_R value, saving time and effort.

ResiMod2024 allows users to input a few parameters with a few clicks, saving time and effort. This intuitive interface makes it accessible to a wider range of users, even those without machine learning expertise. Furthermore, *ResiMod2024* focuses on a specific civil engineering concern - predicting resilient modulus - with the goal of reducing costs by utilizing readily obtainable parameters instead of expensive in-situ and laboratory tests. Overall, *ResiMod2024* provides a reliable, user-friendly, and cost-effective solution for M_R prediction.

The outcomes of our research prove a significant enhancement in the performance of the M_R prediction by using new machine learning methods, especially the deep neural network (*DNN*). Compared to existing approaches like *ELM-EO* (Gabra *et al.,* 2022), *GP* (Sadik, 2023), and *ANFIS* (Indraratna *et al.,* 2023), *DNN* demonstrated substantial accuracy gains: 7.47%, 6.9%, and 2.86% respectively. Deep learning's inherent ability to reduce bias and variance is believed to be the key factor behind DNN's superior performance. This helps avoid overfitting and underfitting issues, common challenges in traditional machine learning methods.

This study paves the way for further exploration of advanced optimization techniques. The promising performance of meta-heuristic algorithms, such as Bee Colony Algorithm (*BCA*), Bio-geography-Based Optimization (*BBO*), Whale Optimization Algorithm (*WOA*), Gravitational Search Algorithm (GSA), Grey Wolf Optimizer (*GWO*), Ant Colony Optimization (*ACO*), Particle Swarm Optimization (*PSO*), and others in conjunction with machine learning is well-documented (Benbouras, 2022; Sadik, 2023). Integrating these algorithms with machine learning methods conducting to improve learning and faster convergence to optimal solutions. Meta-heuristic algorithms can guide machine learning models toward a better understanding of the underlying relationships within the data. Furthermore, these algorithms may help machine learning models reach optimal solutions more efficiently, reducing training time.

4. Conclusion

This study introduces a significant advancement in predicting soil resilient modulus (M_R) - a crucial parameter in civil engineering. It presents "*ResiMod2024*," a user-friendly graphical interface, alongside a powerful machine-learning model for M_R estimation.

The foundation of this work lies in a comprehensive analysis. A large dataset incorporating various locations was compiled, and nine key factors influencing M_R were identified based on literature suggestion. Subsequently, ten advanced machine learning methods, including Deep Neural Network (*DNN*), Extreme Learning Machine (*ELM*), Support Vector Regression (*SVR*), LASSO regression (*LASSO*), Random Forest (*RF*), Ridge Regression (*Ridge*), Partial Least Square Regression (*PLSR*), Stepwise Regression (*Stepwise*), Kernel Ridge (*KRidge*), and Least Square Regression (*LSR)*, were employed to model M_R.

Rigorous evaluation using six performance metrics (*MEA, RMSE, IOS, R^2, R, and IOA*) revealed the *DNN* model as the most effective approach. It achieved superior accuracy in terms of *MAE*: (0.6378 / 2.0678), *RMSE*: (0.9179 / 3.0138), *IOS*: (0.0167 / 0.0553), R: (0.9995 / 0.9951), R^2: (0.999 / 0.9903), *IOA*: (0.9998 / 0.9975) during both the training / validation phases, demonstrating its ability to generalize well to unseen data. The consistently high correlation coefficient (0.9874 to 0.9971) across validation folds using 5-fold cross-validation confirms this advantage and avoids overfitting / underfitting issues. Additionally, comparisons with existing models from the literature solidify the *DNN* model's dominance.

To bridge the gap between complex models and practical applications, "*ResiMod2024*" was developed. This user-friendly interface, built using Matlab software, empowers civil engineers and researchers to effortlessly estimate M_R. Users simply input readily available soil parameters and obtain predicted M_R values with a few clicks, saving time and resources.

This study opens doors for further exploration. The potential benefits of integrating meta-heuristic algorithms with deep learning methods for even higher M_R prediction accuracy warrant future investigation.

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