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California Bearing Ratio estimation using AI: a review of current practices and emerging trends

Jitendra Khatti[1#], Kamaldeep Singh Grover[1]

Review Article

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Artificial intelligence
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Abstract

This study investigates the capabilities and reliability of artificial intelligence (AI) tools in estimating the California Bearing Ratio (CBR) for pavement design purposes. The conventional procedure of determining the soaked and unsoaked CBR is time-consuming and cumbersome. Therefore, investigators and scientists developed various AI methods, categorized according to their learning procedure, i.e., machine learning, advanced machine learning, deep learning, and hybrid learning, to compute the soil CBR. This review article compares the performance of the different computational models used in predicting the CBR of soil. It is noted that the performance of these computational models varied due to the use of different databases. Still, the impact of the quality and quantity of the database on predicting the soaked and unsoaked CBR was not analyzed. Additionally, the impact of database multicollinearity on the model's performance was not analyzed. The study demonstrated that the hybrid learning models are more accurate than the deep and machine learning models in predicting the CBR. Still, configuring the hybrid models (model hyperparameters plus optimization algorithm hyperparameters) is complex and creates structural multicollinearity, which affects the models' performance and accuracy. The literature showed that the combined effect of structural and database multicollinearity was not analyzed and reported. Therefore, considering these gaps in the literature study, the investigators and scientists can extend the published research and report some interesting outcomes.

1. Introduction

The California bearing ratio is the most popular parameter among highway engineers as an empirical soil value. The CBR value of soil is experimentally determined according to IS 2720:1979 (P-16), BS 1377:1990, AASHTO T193, and ASTM D1883-16 for designing flexible pavements (Al-Refeai & Al-Suhaibani, 1997; Harini & Naagesh, 2014). Every flexible pavement comprises four layers: base course, subbase course, binder course, and surface course. The thicknesses of these layers are determined by the CBR value and design vehicle load (Datta & Chottopadhyay, 2011). CBR is a percentage strength of standard crushed stones (Harini & Naagesh, 2014). The CBR of any soil is determined for soaked and unsoaked conditions. For the soaking condition, the soil sample is placed in the curing pond for four days. Figure 1 illustrates the experimental setup for determining the CBR of soil.

To determine the soaked CBR of soil, the soil sample is oven-dried, and optimum moisture is determined by the proctor test. The required water content is added to the oven-dried soil sample (passes through a 19 mm sieve and retains on a 4.75 mm sieve), and the soil sample is filled into the mould in five layers. A 4.5 kg rammer compacts each layer. Now, the mould is mounted by a dial gauge to measure the volumetric change in the compacted soil during the curing period, as shown in Figure 2. Using this procedure, the geotechnical and highway engineers and designers require four days to determine the soaked CBR of any soil, which is a time-consuming and cumbersome task. Therefore, several studies have suggested developing different methods to assess the soaked CBR of soil.

1.1 Empirical methods

Initially, researchers employed simple and multivariable regression analysis. Regression analysis is the most powerful statistical tool for drawing a relationship between two variables and making preliminary predictions. Scala (1956) assessed the subgrade soil strength using dynamic cone penetration (DCP) results for compaction quality control.

[#]Corresponding author. E-mail address: jitendrakhatti197@gmail.com
[1]Rajasthan Technical University, Department of Civil Engineering, Kota, Rajasthan, India

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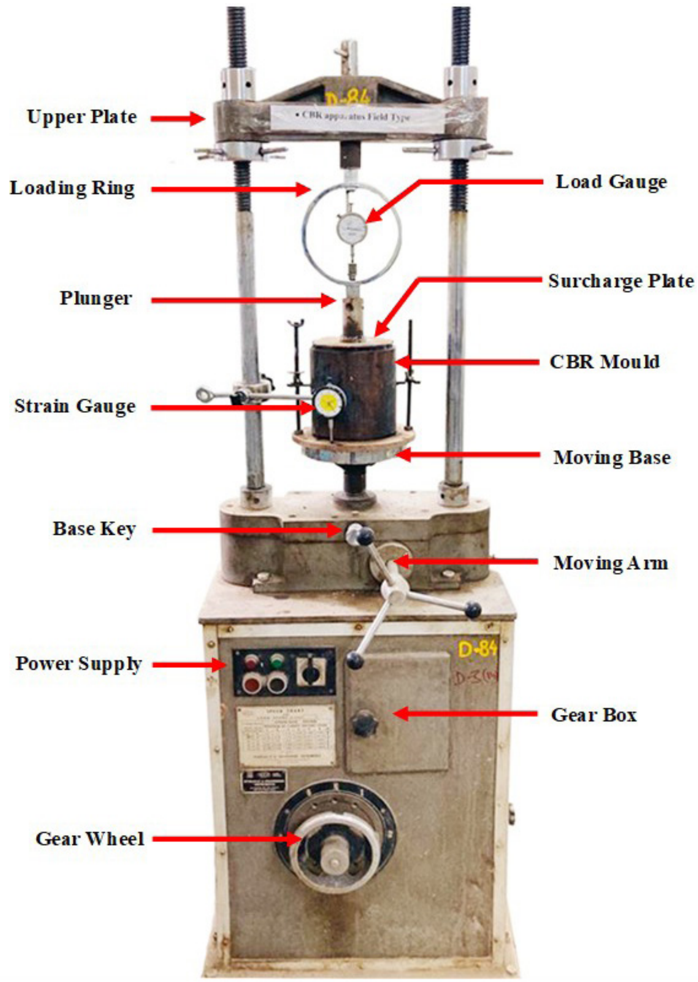

Figure 1. Experimental setup for CBR test.

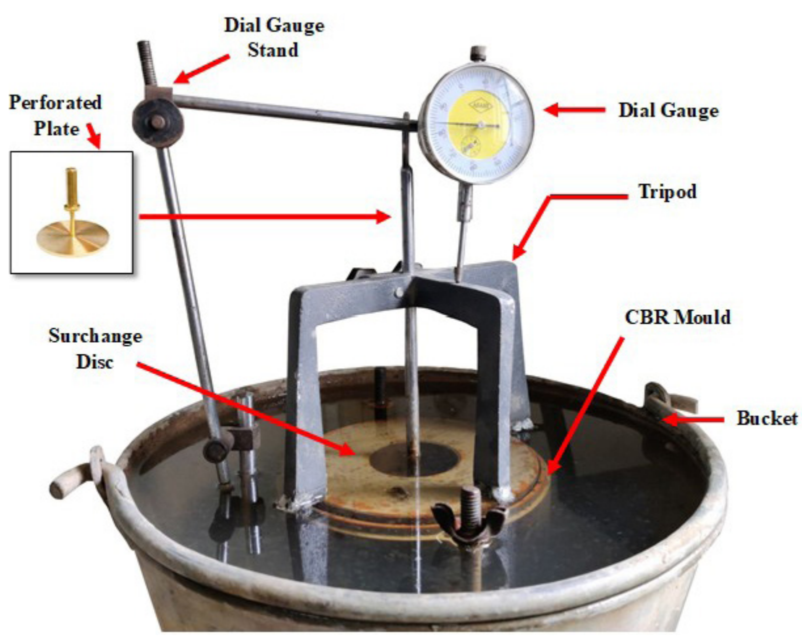

Figure 2. Adjustment of the dial gauge on a mould for soaked CBR.

Also, Kleyn (1975), Smith & Pratt (1983), Livneh (1987), Harison (1989), Livneh et al. (1992), Coonse (1999), and Gabr et al. (2000) mapped the nonlinear, i.e., log, relationship between field dynamic cone penetration index (DCPI) and lab CBR values. Wilson & Williams (1951) derived a relationship to predict the CBR using suction (S_U) and bearing capacity factor (N_q) parameters. Black (1962) plotted a relationship between unsoaked CBR (CBR_U) and soaked CBR (CBR_S) using the effective degree of saturation (ζ). The effective degree of saturation was termed as $\left(p_1 - \Delta p / p_2 - \Delta p\right) \times 100$, where p_1 is the moisture content, p_2 is saturated moisture content, $\Delta p = LL - 17 - 1.2 \times PI$, LL is the liquid limit, and PI is the plasticity index. Al-Refeai & Al-Suhaibani (1997) derived a nonlinear relationship between the' penetration depth (D) of six soils and CBR. The investigators found that (i) poorly graded sand with silt and gravel (SP-SM), (ii) silty sand with gravel (SM), and (iii) clean clay with sand (C-S) had good agreement between D and CBR. Divinsky et al. (1998) designed the pavement thickness (t_g) using CBR, wheel function (g_m), number of converges for the design life (C), assembly load (L), and parameters, i.e., a and b. Roy et al. (2010) determined the soaked CBR for highly plastic clays and silts (CH, MH), silty clays and sandy clays (ML, MI, CL, CI), and clayey sands and silty sands (SC, SM) in the range of 2-3%, 4-5%, and 6-10%, respectively. The researchers also suggested a soaked CBR value of less than 2% for the black cotton soil. Datta & Chottopadhyay (2011) applied the conventional regression models (reported by Vinod & Reena (2008); Patel & Desai (2010), Roy et al. (2009)) to assess the soaked CBR of soil published by Roy et al. (2010). The investigators reported that (i) the model presented by Vinod & Reena (2008) gives a better prediction for CI (medium plastic inorganic clays) soil than CL (low plastic inorganic clays) soil, (ii) the regression model of Patel & Desai (2010) shows good agreement between predicted and actual CBR values. Joseph & Vipulanandan (2011) determined a good correlation between unsoaked CBR and soil properties. Additionally, unsoaked CBR exhibits a strong correlation with undrained shear strength. The simple regression model developed using gravel content (G) has a good determination coefficient (i.e., 0.86) (Yildirim & Gunaydin, 2011). Alawi & Rajab (2013) predicted CBR based on Los Angeles (LA) abrasion test results using multilinear regression analysis with a correlation of 0.97. Sabat (2013) assessed the CBR of lime (L) and quarry dust (QD) stabilized soil for different curing periods (CP) using ANN and multilinear regression analysis (MRA). Bhatt et al. (2014) reported that the soil's CBR correlates more with MDD than fine content (FC) and G. Also, a combination of gravel content (G), sand content (S), fine content (FC), liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), and maximum dry density (MDD) predicts CBR with a correlation of 0.9405 using multilinear regression analysis. Harini & Naagesh (2014) used LL, PL, OMC, MDD, and FC to create ten combinations to predict the CBR using MRA models. The researchers found that the MRA model predicted CBR with a correlation coefficient of 0.86 using FC and LL. Jiang et al. (2015) reported that the CBR of graded crushed rocks increases with piston diameters. Conversely, the loading rate has the least effect on the CBR. Puri & Jain (2015) employed twelve SRA models to relate the CBR with soil properties. The authors noted that soaked (R = 0.923) and unsoaked (R = 0.74) CBR have a good relationship with S. Also, the authors found that the FC, S, and MDD-based MRA model predicts the soaked CBR with a correlation of 0.922. Moreover, the unsoaked CBR can be predicted using MDD, FC, and S with a correlation of 0.7413. The ratio between soaked and unsoaked CBR is 0.415. Ul-Rehman et al. (2015) mapped the CBR relationship with gradation and modified proctor parameters. The researchers found that particle size at 60% finer (D_{60}) and MDD can predict the CBR with a determination coefficient of 0.88. Chandrakar & Yadav (2016) estimated the CBR using OMC, MDD, D_{60}, and D_{30} parameters, achieving a testing performance of 0.9989. Janjua & Chand (2016) also assessed the soaked CBR using a regression model, achieving a performance of 0.9143. Mason & Baylot (2016) derived a relationship among CBR, rating cone index (RCI), and soil properties. Pradeep Kumar & Harish Patel (2016) compared the artificial neural network (ANN) and multiple regression analysis (MRA) models and reported that the ANN model predicts CBR more accurately than the MRA model. Roy (2016) reported that (i) specific gravity has a strong relationship, (ii) C_U and C_C have a poor relationship, (iii) LL and PL have a poor relationship, (iv) PI has a good relationship, (v) OMC and MDD have a very strong relationship with CBR of soil. Abdella et al. (2017) performed regression analysis and predicted CBR with a determination coefficient of 0.731. Egbe et al. (2017) used the LL, PL, OMC, MDD, coarse sand (CS), medium sand (MS), and fine sand (FS) content of 45 soil samples to employ the MRA model and assess the CBR of soil. Rehman et al. (2017a) assessed the CBR using soil gradational parameters with a determination coefficient of 0.85. Rehman et al. (2017b) predicted CBR using the index properties of soil. The authors reported that the LL and PI can predict the soaked CBR with a determination coefficient of 0.9. Shaban & Cosentino (2017) analyzed the relation among elastic modulus, CBR, and miniaturized pressure meter tests. The investigators concluded that a more accurate CBR prediction can be achieved using the initial elastic modulus. González Farias et al. (2018) also estimated the CBR of soil using index properties. For that purpose, the authors used ninety-six datasets. The authors suggested separately predicting the CBR for soil with 35% more and less gravel content. Narzary & Ahamad (2018) observed that the CBR decreases with an increase in OMC and a decrease in MDD. The soil starts losing its MDD due to its low penetration resistance capacity. Suthar & Aggarwal (2018) estimated the CBR of pond ash with lime and lime sludge stabilized soil using a regression model with a correlation of 0.9622. Katte et al. (2019) mapped the correlation between CBR and soil properties using 33 datasets. The investigators reported that MRA predicts the CBR better than SRA. Khatri et al. (2019) performed simple linear and multiple linear regression analyses using 36 soil samples. The researchers reported that the MRA predicts the CBR of coarse-grained soil with over 70% accuracy. Nujid et al. (2019) mapped the relationship between CBR and PI of marine stabilized soil with cockle shell powder (CSP). Ravichandra et al. (2019) noted that MDD is important in assessing CBR, followed by PI, LL, and OMC. Reddy et al. (2019) utilized 105 datasets to investigate the empirical relationship between soil properties and the CBR. Sagar et al. (2019) noted that the coefficient of uniformity and PI improve the relationship of the multilinear regression equation of CBR. Duque et al. (2020) analyzed the effect of gradational parameters on the prediction of CBR. The investigators used 77 datasets to derive the equation and predict the CBR of 20 soil samples. Ji et al. (2020) stated that the CBR of rock can be predicted by the discrete element method and computed tomography. Kumsa (2020) derived a nonlinear equation using the DCPI parameter to predict the soaked CBR of soil. Nagaraju et al. (2019) employed a particle swarm optimization algorithm with inertia weights of 0.4, 0.5, 0.6, and 0.7 to compute the CBR of soil. The authors utilized G, S, FC, LL, PL, OMC, and MDD parameters from 134 soil samples in their published work. The results analyzed demonstrate that the 0.4 inertia weight equation predicted better CBR than other equations.

Lime-stabilized soil exhibits superior geotechnical properties compared to virgin soil and can be utilized as a pavement material. The CBR estimates the dynamic resilient modulus for pavement design (Ai et al., 2021). Ambrose & Rimoy (2021) estimated soaked CBR using SG and FC of coarse-grained soil with a determination coefficient of 0.94. Also, the authors derived a regression equation using SG, PI, and grading modulus (GM) with a determination coefficient of 0.91. Gül & Çayir (2021) predicted CBR using peak particle velocity (PPV) and standard penetration test (SPT) results (N60) with correlations of 0.975 and 0.964, respectively, based on 21 soil samples. Haupt & Netterberg (2021) derived a relationship between the soaked and unsoaked CBR of the Standard Proctor test, with a correlation of 0.89. The authors also derived the relationships among modified American Association of State Highway Officials (MAASHO), specifically MAASHO MDD, MASSHO OMC, standard proctor test (OMC, MDD), moisture content (MC), soaked CBR, and unsoaked CBR. Khatti & Grover (2021) mapped the relationship among LL, PL, PI, OMC, MDD, and CBR of soil. The authors reported that CBR has a good relationship with MDD, i.e., 0.6929. Furthermore, the authors derived a multilinear regression equation and predicted CBR with a correlation coefficient of 0.7466 in the testing phase. Mohammed et al. (2021) related consistency limits, grain size, compaction parameters, and free swell index to the CBR of soil. Rashed et al. (2021) estimated the CBR using compaction and consistency parameters of fine-grained soil. The authors reported that multilinear regression analysis predicts CBR more accurately than simple regression analysis. Lakshmi et al. (2021a) correlated unsoaked CBR with unconfined compressive strength (UCS) of poorly graded sand (SP) and clayey sand (SC). The authors reported that (i) the UCS of SC soil has a correlation of 0.9891 and (ii) the UCS of SP soil has a correlation of 0.9917. Lakshmi et al. (2021b) computed the soaked CBR of SC soil using light and heavy compaction parameters. Akinwamide et al. (2022) derived the relationship between soaked CBR and soil properties using 40 soil samples. The derived multilinear regression equation achieved a determination coefficient of 0.2865. Encinares et al. (2022) predicted the CBR using DCP with a determination coefficient of 0.7647. Gökova (2022) mapped a correlation between CBR and shear strength (SS) of pavement at different water contents. Hassan et al. (2021) predicted CBR using compaction and index parameters of low-plastic fine-grained soil. The authors developed MRA models and reported that the proposed models range the determination coefficient from 0.786 to 0.957. Okonkwo et al. (2023) used the logarithmic model to estimate the CBR of lateritic soil stabilized by rice husk ash (RHA) and cement. The authors constructed a database using the results of stabilized soil with 2 to 8% cement and 4 to 28% RHA. Sani et al. (2022) performed simple and multilinear regression analyses to assess the CBR using soil consistency, compaction, and gradation parameters. The authors observed that (i) the FC predicts the CBR more accurately than LL, PL, PI, OMC, and MDD, and (ii) the combination of FC, LL, PL, MDD, and OMC predicts CBR with good agreement compared to the actual CBR. The details of the conventional regression models for CBR prediction are reported in Table 1.

Table 1. Conventional regression model for CBR prediction.

Model	Case	R^2	Reference
$CBR = S_U N_q / 10$	CBR vs S_U, N_q	NA	Wilson & Williams (1951)
$CBR_U = (\zeta)^{2.3} * (CBR_S)$	CBR_U vs ζ, CBR_S	NA	Black (1962)
$\log(CBR) = -1.270 * \log(DCPI) + 2.620$	CBR vs DCPI	NA	Kleyn (1975)

Table 1. Continued...

Model	Case	R^2	Reference
$\log(CBR) = -1.145 * \log(DCPI) + 2.555$	CBR vs DCPI	0.850	Smith & Pratt (1983)
$\log(CBR) = -1.160 * \log(DCPI) + 2.560$	CBR vs DCPI	0.930	Livneh (1987)
$\log(CBR) = -1.160 * \log(DCPI) + 2.560$	CBR vs DCPI	0.970	Harison (1989)
$\log(CBR) = -1.120 * \log(DCPI) + 2.450$	CBR vs DCPI	NA	Livneh et al. (1992)
$\log(CBR) = -1.860 * \log(D) + 3.570$	CBR vs D	0.830	Al-Refeai & Al-Suhaibani (1997)
$\log(CBR) = -1.350 * \log(D) + 2.700$	CBR vs D	0.870	Al-Refeai & Al-Suhaibani (1997)
$\log(CBR) = -1.310 * \log(D) + 2.550$	CBR vs D	0.960	Al-Refeai & Al-Suhaibani (1997)
$t_g = a * \left(g_m \cdot \left[L.\log(C) / CBR\right]\right)^b$	CBR vs t_g	NA	Divinsky et al. (1998)
$\log(CBR) = -1.140 * \log(DCPI) + 2.530$	CBR vs DCPI	NA	Coonse (1999)
$\log(CBR) = -0.550 * \log(DCPI) + 1.550$	CBR vs DCPI	NA	Gabr et al. (2000)
$CBR = -0.889\left(LL\left(1 - \frac{C}{100}\right)\right) + 45.616$	CBR vs LL, C	NA	Vinod & Reena (2008)
$\log(CBR) = \log\left(\frac{dry\,density}{wet\,density}\right) - \log(OMC)$	CBR vs density	NA	Roy et al. (2009)
$CBR = -0.301 * OMC - 18.78 * MDD - 0.093 * PI + 43.907$	CBR vs OMC, MDD, PI	NA	Patel & Desai (2010)
$CBR_U = 0.61 * S_U$	CBR vs S_U	0.710	Joseph & Vipulanandan (2011)
$CBR = 3.0798 + 0.2353 * G$	CBR vs G	0.860	Yildirim & Gunaydin (2011)
$CBR = 0.112 * OMC + 4.739 * MDD + 0.045 * S + 0.22 * G$	CBR vs G, S, MDD, OMC	0.880	Yildirim & Gunaydin (2011)
$CBR = 98.4613 * MDD - 4.7280 * OMC - 0.2856 * LA - 112.4335$	CBR vs MDD, OMC, LA	0.940	Alawi & Rajab (2013)
$CBR = 0.32 * OMC - 0.508 * MDD + 0.442 * CP + 0.54 * QD - 3.12 * L + 83.7$	CBR vs L, QD, CP, MDD, OMC	0.933	Sabat (2013)
$CBR = 7.9851 - 0.0892 * FC$	CBR vs FC	0.132	Bhatt et al. (2014)

Table 1. Continued...

Model	Case	R^2	Reference
$CBR = -0.6365 + 0.1996 * G$	CBR vs G	0.184	Bhatt et al. (2014)
$CBR = -30.56 + 21.10 * MDD$	CBR vs MDD	0.624	Bhatt et al. (2014)
$CBR = 24.7518 * MDD + 0.3487 * OMC - 0.4094 * FC + 0.4528 * S - 0.3776 * G$	CBR vs MDD, OMC, FC, S, G	0.882	Bhatt et al. (2014)
$CBR = 0.01 * FC - 0.07 * LL + 4.86$	CBR vs LL, FC	0.860	Harini & Naagesh (2014)
$CBR_s = 0.826 CBR_U^{0.967}$	CBR_S vs CBR_U	0.810	Rassoul & Mojtaba (2015)
$CBR_s = 8.22 * MDD - 1.82 * OMC - 0.309 * S - 0.0003 * FC - 0.146 * PL + 0.0150 * LL - 0.101 * OC + 61.4$	CBR_s vs MDD, OMC, S, FC, PL, LL, OMC	0.341	Rassoul & Mojtaba (2015)
$CBR_U = -2.46 * MDD - 2.63 * OMC - 0.347 * S + 0.0055 * FC - 0.335 * PL + 0.059 * LL + 3.54 * OC + 98.8$	CBR_u vs MDD, OMC, S, FC, LL, PL, OC	0.266	Rassoul & Mojtaba (2015)
$CR_s = 0.0493 * S + 3.4433$	CBR_s vs S	0.852	Puri & Jain (2015)
$CBR_U = 0.0841 * S + 9.009$	CBR_U vs S	0.548	Puri & Jain (2015)
$CBR_s = -27.004 - 0.654 * MDD + 0.366 * S + 0.317 * FC$	CBR_s vs MDD, S, FC	0.850	Puri & Jain (2015)
$CBR_U = -0.1713 * S - 0.252 * FC - 6.396 * MDD + 46.591$	CBR_U vs MDD, FC, S	0.549	Puri & Jain (2015)
$CBR = -22.242 + 1.773 * MDD + 6.368 * D_{60}$	CBR vs D_{60}, MDD	0.88	Ul-Rehman et al. (2015)
$CBR = 1.64 * D_{30} + 0.34 * D_{60} - 73.37 * MDD - 3.78 * OMC + 198.63$	CBR vs OMC, MDD, D_{60}, D_{30}	0.973	Chandrakar & Yadav (2016)
$CBR_s = -17.029 + 1.043 * MDD + 0.0283 * OMC + 0.0262 * LL + 0.142 * FC$	CBR_s vs FC, LL, OMC, MDD	0.836	Janjua & Chand (2016)
$CBR = 0.6981 * FC + 0.7802 * S + 0.9193 * G + 0 * PI + 0.0483 * LL - 0.2356 * PL + 0.1579 * OMC + 7.8239 * MDD - 73.412$	CBR vs FC, S, G, PI, LL, PL, OMC, MDD	0.927	Pradeep Kumar & Harish Patel (2016)
$CBR = -0.712 * OMC + 19.81 * MDD - 10.888$	CBR vs MDD, OMC	0.980	Roy (2016)
$CBR = 0.013 * PI^2 - 0.867 * PI + 17.227$	CBR vs PI	0.682	Abdella et al. (2017)
$CBR = 0.034 * FC + 0.068 * S + 0.121 * G$	CBR vs FC, S	0.956	Abdella et al. (2017)
$CBR = -0.086 * OMC + 4.450 * MDD$	CBR vs OMC, MDD	0.957	Abdella et al. (2017)

Table 1. Continued...

Model	Case	R^2	Reference
$CBR = -0.069 * PI - 0.026 * FC + 5.34 * MDD$	CBR vs FC, PI, MDD	0.973	Abdella et al. (2017)
$CBR = -0.098 * PI + 3.707 * MDD - 0.031 * FC + 3.591$	CBR vs FC, MDD, PI	0.731	Abdella et al. (2017)
$CBR = -0.120 * FS + 0.0246 * MS - 0.0035 * CS + 0.145 * MDD - 0.120 * PL - 0.162 * LL - 0.102 * OMC + 20.8$	CBR vs FS, MS, CS, MDD, LL, PL, OMC	NA	Egbe et al. (2017)
$CBR = 3.970 + 1.48 * C_U + 6.508 * D_{50}$	CBR vs D_{50}, C_U	0.850	Rehman et al. (2017a)
$CBR = 1 - 0.10 * LL - 0.425 * PI$	CBR vs LL, PI	0.900	Rehman et al. (2017b)
$\widehat{CBR} = -6.70 * OMC + 5.23 * MDD + 10.58 * PI^2 - 6.56 * PI - 4.72$	CBR vs PI, MDD, OMC	0.860	González Farias et al. (2018)
$CBR = 18.839 * MDD - 0.214 * OMC + 0 * CP - 0.033 * QD + 2.332 * L - 262.723$	CBR vs MDD, OMC, CP, QD, L	0.870	Roy (2018)
$CBR = 13.918 * MDD - 0.366 * OMC + 0 * CP + 2.582 * RHA + 10.516 * L - 228.643$	CBR vs MDD, OMC, CP, RHA, L	0.950	Roy (2018)
$CBR = 0.528 * CP + 0.509 * LS + 2.251 * L - 3.055 * OMC + 172.404 * MDD - 131.441$	CBR vs MDD, OMC, L, LS, CP	0.930	Suthar & Aggarwal (2018)
$CBR = 99.869 * MDD - 175.006$	CBR vs MDD	0.772	Katte et al. (2019)
$CBR = 0 * \left(\frac{C}{M}\right) - 0.668 * S + 0.049 * G - 0.055 * PI - 0.0914 * PL - 2.895 * OMC + 47.130 * MDD - 20.139$	CBR vs C/M, S, G, PI, PL, OMC, MDD	0.841	Katte et al. (2019)
$CBR = 500.60 - 0.21 * S - 121.81 * MDD - 0.59 * FC - 2.59 * LL$	CBR vs S, MDD, FC, LL	0.700	Khatri et al. (2019)
$CBR = 544.58 - 138.77 * MDD - 9.97 * OMC - 1.46 * FC - 1.13 * PI - 2.63 * LL$	CBR vs MDD, OMC, FC, PI, LL	0.700	Khatri et al. (2019)
$CBR = 546.35 - 0.78 * S - 201.84 * MDD - 9.86 * OMC + 2.99 * FC + 1.97 PI - 0.05 * LL$	CBR vs S, MDD, OMC, FC, PI, LL	0.800	Khatri et al. (2019)
$CBR = 294.74 - 71.86 * MDD - 4.22 * OMC + 0.26 * FC - 1.39 PI - 1.41 * LL$	CBR vs MDD, OMC, FC, PI, LL	0.800	Khatri et al. (2019)

Table 1. Continued...

Model	Case	R^2	Reference
$CBR = 308.51 - 74.23 * MDD - 4.43 * OMC - 1.48 * PI - 1.49 * LL$	CBR vs MDD, OMC, PI, LL	0.800	Khatri et al. (2019)
$CBR = 371.35 - 108.25 * MDD - 5.89 * OMC - 1.24 * LL$	CBR vs MDD, OMC, LL	0.740	Khatri et al. (2019)
$CBR = 872.37 - 1.13 * S - 0.29 * G - 362.08 * MDD - 4.05 * OMC + 1.52 * PI + 0.28 * LL$	CBR vs S, G, MDD, OMC, PI, LL	0.800	Khatri et al. (2019)
$CBR = 0.406 * OMC + 1.574 * MDD - 0.128 * PI + 0.070 * LL + 28.812 * FC + 29.064 * S + 28.948 * G - 2914.53$	CBR vs G, S, FC, LL, PI, MDD, OMC	0.689	Kurnaz & Kaya (2019)
$CBR = -0.70 * PI + 32.638$	CBR vs PI	1.000	Nujid et al. (2019)
$CBR = 6.1596 - 0.1024 * PI$	CBR vs PI	0.943	Reddy et al. (2019)
$CBR = 24.33 - 0.72 * LL + 0.216 * D_{60} + 0.069 * FC + 0.214 * S + 0.313 * G$	CBR vs LL, D_{60}, FC, S, G	0.791	Sagar et al. (2019)
$CBR = 25.28 + 0.087 * PI - 0.76 * LL - 0.00028 * C_U + 0.238 * D_{60} + 0.116 * FC + 0.195 * S + 0.295 * G$	CBR vs PI, LL, C_U, D_{60}, FC, S, G	0.797	Sagar et al. (2019)
$CBR = 8.72 - 0.86 * PI - 0.00022 * C_U + 0.25 * D_{60} + 0.136 * FC + 0.24 * S + 0.329 * G$	CBR vs PI, C_U, D_{60}, FC, S, G	0.790	Sagar et al. (2019)
$CBR = 28.30 + 4.558 * S^{0.614}$	CBR vs S	0.922	Taha et al. (2019)
$CBR = -38.97 + 77.68 * D_{60}^{0.162}$	CBR vs D_{60}	0.926	Taha et al. (2019)
$CBR = 6.61 * D_{60} + 11.03$	CBR vs D_{60}	0.930	Duque et al. (2020)
$CBR_s = 773.3 + 252.54 * DCPI$	CBR_s vs DCPI	0.860	Kumsa (2020)
$CBR = 7219.16 + 11.5871 * MDD + 2.2575 * OMC + 0.7671 * PL - 0.4137 * LL - 72.8630 * FC - 72.5434 * S - 72.2516 * G$	CBR vs G, S, FC, LL, PL, OMC, MDD	NA	Nagaraju et al. (2019)
$CBR_s = -20 + 4 * GM - 0.3 * PI + 10 * SG$	CBR vs SG, PI, GM	0.910	Ambrose & Rimoy (2021)
$CBR_s = -200 - 0.4 * FC + 125 * SG$	CBR vs FC, SG	0.940	Ambrose & Rimoy (2021)
$CBR = -2.606 + 2.1199 * N_{60}$	CBR vs N_{60}	0.929	Gül and Çayir (2021)
$CBR = 113.97 - 13.535 * PPV_{3m}$	CBR vs PPV_{3m}	0.951	Gül and Çayir (2021)
$CBR_s = 1.2 + 1.15 * CBR_U$	CBR_s vs CBR_U	0.792	Haupt & Netterberg (2021)
$CBR_U = 56.54\left(e^{-1.42 MC/OMC}\right) CBR_s^{0.48}$	CBR_s vs CBR_U	0.884	Haupt & Netterberg (2021)
$CBR_s = 53.52\left(e^{-1.12 MC/OMC}\right) CBR_s^{0.45}$	CBR_s vs CBR_U	0.922	Haupt & Netterberg (2021)

Table 1. Continued...

Model	Case	R^2	Reference
$CBR_s = 59.13\left(e^{-1.33MC/OMC}\right) CBR_s^{0.46}$	$\mathrm{CBR_s}$ vs $\mathrm{CBR_U}$	0.903	Haupt & Netterberg (2021)
$CBR_s = -74.763 + 50.33 * MDD$	CBR vs MDD	0.480	Khatti & Grover (2021)
$CBR_s = -84.603 + 54.424 * MDD + 0.5174 * OMC - 0.441 * PI + 0.0589 * LL$	CBR vs MDD, OMC, PI, LL	0.557	Khatti & Grover (2021)
$CBR = 24.018 - 0.4829 * LL$	CBR vs LL	0.767	Rashed et al. (2021)
$CBR = 20.497 - 0.5815 * PL$	CBR vs PL	0.542	Rashed et al. (2021)
$CBR = 14.148 - 0.7331 * PI$	CBR vs PI	0.519	Rashed et al. (2021)
$CBR = 17.338 - 0.8079 * OMC$	CBR vs OMC	0.508	Rashed et al. (2021)
$CBR = -43.714 + 27.094 * MDD$	CBR vs MDD	0.649	Rashed et al. (2021)
$CBR = 8.563 * MDD - 0.13504 * OMC + 0.26614 * LL - 0.01607 * PL - 0.13662 * PI + 4.32$	CBR vs MDD, OMC, LL, PL, PI	0.820	Rashed et al. (2021)
$CBR = 0.0315 * UCS + 0.0011 * UCS^2 - 0.627$	CBR vs UCS of SC soil	0.978	Lakshmi et al. (2021a)
$CBR = 84.918 - 9.2633 * UCS + 0.304 * UCS^2 - 0.0028 * UCS^3$	CBR vs UCS of SP soil	0.984	Lakshmi et al. (2021a)
$CBR = 5826.6 * MDD - 2894.8 * MDD^2 + 479.91 * MDD^3 - 3907.6$	CBR vs MDD of light compaction	1.000	Lakshmi et al. (2021b)
$CBR = 8674.9 * MDD - 4761.1 * MDD^2 + 870.95 * MDD^3 - 5267.6$	CBR vs MDD of heavy compaction	1.000	Lakshmi et al. (2021b)
$CBR = 0.0006 * MDD - 0.0275 * OMC - 0.0037 * PL - 0.0168 * LL - 0.0565 * FC - 0.0697 * S - 0.0044 * G + 8.4583$	CBR vs G, S, FC, LL, PL, OMC, MDD	0.286	Akinwamide et al. (2022)
$CBR = -52.9\ln(FC) - 32.6\ln(S) - 15.6\ln(G) + 321 * MDD - 8.97 * PL + 6.76 * LL - 835$	CBR vs LL, PL, MDD, G, S, FC	0.9000	Bakri et al. (2022)
$CBR = -0.79 * OMC^2 + 2257 * MDD^2 + 0.0145 * S^2 + 0.211 * FC^2 - 0.0074 * G^2 + 16.6 * OMC - 9284 * MDD - 10.01 * PL + 7.86 * LL + 2.6 * S - 4.8 * FC + 5.1 * G + 9184$	CBR vs LL, PL, MDD, G, S, FC	0.942	Bakri et al. (2022)
$CBR = 105.88 / DCP^{0.928}$	CBR vs DCP	0.765	Encinares et al. (2022)
$CBR = 0.4687 + 0.0471 * SS$	CBR vs SS	0.960	Gökova (2022)
$CBR = -0.173 * FC + 19.438$	CBR vs FC	0.370	Sani et al. (2022)
$CBR = -0.539 * OMC + 1.562 * MDD - 0.412 * PL - 0.153 * LL, 0.183 * FC + 23.325$	CBR vs FC, LL, PL, MDD, OMC	0.520	Sani et al. (2022)

1.2 Advanced computational methods

Artificial intelligence (AI) methods, particularly artificial neural networks (ANN), have been extensively applied to predict the California Bearing Ratio (CBR) of soils with high accuracy. Taskiran (2010) used ANN and gene expression programming (GEP), reporting GEP's superior performance (0.9881). Venkatasubramanian & Dhinakaran (2011) found regression more accurate than ANN. Sabat (2013) achieved a correlation of 0.9905 with ANN, while Bhatt et al. (2014) reported 0.9806 and found ANN better than MLA and SRA. Harini & Naagesh (2014) and Rassoul & Mojtaba (2015) also showed ANN's superiority over MRA and OLS, respectively. Vadi et al. (2015) demonstrated ANN (5-6-1) achieving 0.9931, and Ali et al. (2016) found a 12-neuron ANN performing best (0.9926). El Amin et al. (2017) attained 0.9996 using ANN. Ghorbani & Hasanzadehshooiili (2018) and Roy (2018) used ANN and ML for stabilized soils. Suthar & Aggarwal (2018) applied ANN and regression for pond ash soils. Günaydin et al. (2019) used decision trees (0.8899 correlation). Kurnaz & Kaya (2019) reported GMDH better than MRA and BR_ANN with RMSE = 1.6911. Onyelowe et al. (2019) used Scheffe's method, and Salahudeen & Sadeeq (2019) reported ANN accuracy of 0.9976 (soaked) and 0.9806 (unsoaked). Suthar & Aggarwal (2019) found random forest superior to M5P. Taha et al. (2019) used ANN (testing accuracy 0.95). Alam et al. (2020) used krigging, ANN, and GEP on West Bengal soils. Al-Busultan et al. (2020) showed soluble salts were more influential than PI and obtained 0.9592 correlation using ANN. Bairagi et al. (2020) confirmed ANN as a fast predictive tool. Islam & Roy (2020) compared MRA, SVM, and ANN, with ANN achieving up to 0.998. Tesfaye (2020) predicted CBR of GP and ESP-stabilized soil using ANN (correlation 0.99996). Tenpe & Patel (2020) applied SVM and GEP (performances: 0.898 and 0.833) and later (2020b) found GEP outperforming ANN.

Several recent studies have employed artificial intelligence (AI), machine learning (ML), and hybrid optimization techniques to predict the California Bearing Ratio (CBR) of various stabilized soils. Attah et al. (2021) predicted the CBR of expansive soil treated with cement kiln dust and metakaolin using the Scheffé optimization algorithm. Ikeagwuani (2021) used gradient boosting (GBoost), random forest (RF), and multivariate adaptive regression splines (MARS), reporting determination coefficients of 0.7147, 0.7528, and 0.7309, respectively. Inputs included LL, PL, PI, MDD, OMC, sawdust ash (SDA), QD, and OPC. Iqbal et al. (2021) compared ensemble random forest (ERF) with adaptive neuro-fuzzy inference systems using 121 datasets. Khatti & Grover (2021) tested SVM, GPR, RF, DT, and ANN on 266 datasets and found ANN best for soaked CBR (0.9736). Li et al. (2021) used a biogeography-based ANN (BBO_ANN) for pond ash with lime and lime sludge, achieving over 99% accuracy. Onyelowe et al. (2021) applied gene expression programming (GEP) on HARHA-treated soil, attaining a correlation of 0.996. Raja et al. (2022) compared several models (RF, M5, ANN, lazy k-star, etc.) for geosynthetic-reinforced soil, with lazy k-star performing best. Rajakumar et al. (2021) used ANN (93% accuracy) for soil reinforced with geotextile and bagasse ash. Timani and Jain (2021) reported 93% accuracy for a clay-gravel mixture using ANN. Tran & Do (2021) predicted the CBR of soil with industrial/agricultural waste using light gradient boosting (R^2 = 0.9385). Trong et al. (2021) used RSS_ET, RSS_REPTS, and REPTs models on 214 samples; RSS_ET performed best (R^2 = 0.968). Vu et al. (2021) also used RF on the same data and achieved R^2 = 0.9592. Nagaraju et al. (2021) used ANN on 480 datasets, obtaining a correlation of 0.94656. Bardhan et al. (2021a) evaluated MARS_L, MARS_C, GPR, and GP, finding MARS_L superior. Bardhan et al. (2021b) tested advanced models like ELM_MPSO, ELM_TPSO, ELM_IPSO, ELM_GWO, SMA_ELM, ELM_HHO, ANN, GP, SVM, and GMDH. ELM_MPSO showed the best performance with over 92% accuracy and 0.0435% residuals. Alzabeebee et al. (2022) employed evolutionary polynomial regression (EPR) with inputs like gradation, compaction, and consistency limits. Amin et al. (2022) predicted CBR of chemically stabilized coal gangue using ANN and RF; ANN achieved soaked/unsoaked CBR correlations of 0.995 and 0.997. Bakri et al. (2022) compared GEP and multivariate regression for granular soil. Erzin et al. (2022) used ANN for lime and tyre buffing stabilized soil, attaining 98.61% accuracy.

Hao & Pabst (2022) tested MRA, DT, RF, kNN, ANN, and NEAT for resilient modulus-based CBR prediction; RF performed best (R^2 = 0.9). Ho & Tran (2022) optimized ANN, GBoost, XGB, RF, SVM, and kNN using random restart hill-climbing, with RF outperforming others. Khasawneh et al. (2022) tested ANN, M5P, kNN, and nonlinear regression on 110 samples and found ANN had the least residuals (7.89%). Li (2022) used BBO and PSO-optimized radial basis function models to achieve 99% accuracy. Li et al. (2022) used the same data and BBO-optimized ANN with R^2 = 0.9977. Mohamed (2022) reported that ANN showed good agreement with actual CBR values. Verma & Kumar (2022) found multi-expression programming (MEP) yielded better predictions. Baghbani et al. (2023) studied alum sludge-stabilized soil and found ANN (R^2 = 0.980) better than SVM and GP. Kumar & Singh (2023) assessed fiber-reinforced waste incinerator bottom ash using ANN, ANFIS, and MRA. Nagaraju et al. (2023) implemented a cooperation search-optimized ELM (CSO_ELM) model, achieving an RMSE of 0.84 for lateritic soil. Onyelowe et al. (2023) found ANN superior to GP and EPR. Othman & Abdelwahab (2023) developed ANN models (linear, logistic, Tanh activations) using 240 samples with various configurations. The best model used four hidden layers, 15 neurons, and a sigmoid function, achieving R^2 = 0.945. Salehi et al. (2023) used ANN to predict the CBR of cement/lime-pozzolan stabilized soil with crushed stone waste. Verma et al. (2023) compared GPR, kNN, and kernel ridge regression and found GPR best for soaked CBR. Khatti & Grover (2023a) applied hybrid relevance vector machine (RVM) models, concluding that the GA-optimized Laplacian kernel RVM outperformed others. Khatti & Grover (2023b) also tested ANN, LSTM, and LSSVM for unsoaked CBR, with LSTM showing 96% accuracy (Table 2).

Table 2. Summary of the advanced computational models.

Approach	Input Variables	Datasets	R Test	Reference
GEP	LL, PI, OMC, MDD, C+Si, S, G	151	0.9881	Taskiran (2010)
RA	MDD, OMC, UCS, G, S, C, Si, LL, PL, PI, SG, CBR_U	15	0.9432	Venkatasubramanian & Dhinakaran (2011)
ANN	G, S, OMC, MDD	124	0.9747	Yildirim & Gunaydin (2011)
ANN	L, QD, CP, OMC, MDD	90	0.9905	Sabat (2013)
ANN	LL, OMC	40	0.9400	Harini & Naagesh (2014)
ANN (Soaked)	OC, LL, PL, FC, S, OMC, MDD	386	0.8200	Rassoul & Mojtaba (2015)
ANN (Unsoaked)	OC, LL, PL, FC, S, OMC, MDD	386	0.7200	Rassoul & Mojtaba (2015)
ANN	FC, LL, PI, MDD, OMC	50	0.9931	Vadi et al. (2015)
ANN	L, RHA, CP, MDD, OMC	48	0.9926	Ali et al. (2016)
ANN	FC, S, G, PI, LL, PL, OMC, MDD	12	0.9998	Pradeep Kumar & Harish Patel (2016)
ANN	FC, S, LL, OMC, MDD	220	0.9996	El Amin et al. (2017)
ANN (CBR_{10})	L, MCS, CP, CD	90	0.9900	Ghorbani & Hasanzadehshooiili (2018)
ANN ($CBR3_0$)	L, MCS, CP, CD	90	0.9900	Ghorbani & Hasanzadehshooiili (2018)
ANN (CBR_{65})	L, MCS, CP, CD	90	0.9900	Ghorbani & Hasanzadehshooiili (2018)
LM_ANN	QD, L, CP, OMC, MDD	54	0.9935	Roy (2018)
BR_ANN	QD, OMC, MDD	54	0.9935	Roy (2018)
SCG_ANN	QD, OMC, MDD	54	0.9975	Roy (2018)
LM_ANN	L, OMC, MDD	54	0.9975	Roy (2018)
BR_ANN	RHA, L, OMC	54	0.9985	Roy (2018)
SCG_ANN	RHA, L	54	0.9960	Roy (2018)
ANN	MDD, OMC, L, LS, CP	51	0.9788	Suthar & Aggarwal (2018)
DT	G, S, FC, LL, PL, OMC, MDD	124	0.8899	Günaydin et al. (2019)
GMDH	G, S, FC, LL, PI, OMC, MDD	158	0.9783	Kurnaz & Kaya (2019)
BR_ANN	G, S, FC, LL, PI, OMC, MDD	158	0.9703	Kurnaz & Kaya (2019)
ANN	SG, Ls, C_U, C_C, LL, PL, OMC, MDD	72	0.9976	Salahudeen & Sadeeq (2019)
ANN	SG, Ls, C_U, C_C, LL, PL, OMC, MDD	72	0.9806	Salahudeen & Sadeeq (2019)
RF	MDD, OMC, L, Ls, CP	51	0.9701	Suthar & Aggarwal (2019)
ANN	G, S, FC, LL, MDD, OMC	218	0.9500	Taha et al. (2019)
GEP	G, C_U, C_C, LL, PL, PI, OMC, MDD	20	0.9900	Alam et al. (2020)
ANN	G, S, M, C, MDD, OMC, LL, PI, SO_3,	35	0.8816	Al-Busultan et al. (2020)
ANN	QD, L, OMC	54	0.9975	Islam & Roy (2020)
ANN	RHA, L, CP, OMC, MDD	54	0.9989	Islam & Roy (2020)
ANN	LL, PL, PI, OMC, MDD	30	0.9999	Tesfaye (2020)
GEP	G, S, FC, LL, PI, OMC, MDD	389	0.833	Tenpe & Patel (2020)
SVM	G, S, PI, OMC	389	0.898	Tenpe & Patel (2020)
RF	LL, PL, PI, MDD, OMC, SDA. QD. OPC	109	0.8676	Ikeagwuani (2021)
ANFIS	HARHA, LL, PL, PI, OMC, AC, MDD	121	0.9946	Iqbal et al. (2021)
ERF	HARHA, LL, PL, PI, OMC, AC, MDD	121	1.000	Iqbal et al. (2021)
ANN	LL, PI, OMC, MDD	266	0.9736	Khatti & Grover (2021)

RA is regression analysis, LL is liquid limit, PI is plasticity index, OMC is optimum moisture content, MDD is maximum dry density, C+Si is clay + silt content, S is sand content, G is gravel content, UCS is unconfined compressive strength, SG is specific gravity, CBR_U is unsoaked CBR, GEP is gene expression programming, ANN is artificial neural network, L is lime content, QD is quarry dust, CP is curing period, OC is organic content, L is lime content, RHA is rice husk ash content, CBR_{10} is CBR at 10 hammer blows, CBR_{30} is CBR at 30 hammer blows, CBR_{65} is CBR at 65 hammer blows, MCS is microsilica, CD is curing condition, LM_ANN is Levenberg-Marquardt artificial neural network model, BR_ANN is Bayesian regularization artificial neural network model, SCG_ANN is scaled conjugate gradient artificial neural network model, LS is lime sludge, DT is decision tree, GMDH is group method of data handling model, Ls is linear shrinkage, SG is specific gravity, SO_3 is Sulfur trioxide, SS is soluble salt, GPM is gypsum, O is organic, SDA is sawdust ash, OPC is ordinary Portland cement, RF is random forest, HARHA is hydrated lime activated rice husk ash, AC is clay activity, BBO_ANN is Biogeography-based artificial neural network, DUW is dry unit weight, TSG is tensile strength of geosynthetic, NL is number of layers, P1 is position of 1st layer, PS is position of subsequent layers, BA is share of pulp ash additional, GL is range of geotextile layers, AT is ash type, ACC is ash content, LGBoost is light gradient boosting model, RSS_ET is random subsurface-based extra tree model, S&C is sand and clay content, MS is medium sand, CS is coarse sand, FS is fine sand, GD is gypsum dosages, MRA is multilinear regression analysis, MNA is multi-nonlinear regression analysis, TRT is triaxial test, MR is modulus resilient, DST is dust, and AH is ashes, PCA is principal component analysis, NMC is natural moisture content, Sld is sludge, CN is number of blows, OMCx is OMC of mixture, MDDx is MDD of mixture, SCL is soil classification, SWL is swell, AN is AASHTO number, GA_RVM is genetic algorithm optimized relevance vector machine model.

Table 2. Continued...

Approach	Input Variables	Datasets	R Test	Reference
BBO_ANN	L, LS, MDD, OMC, CP	51	0.9988	Li et al. (2021)
GEP	HARHA, LL, PL, OMC, AC, MDD	121	0.9960	Onyelowe et al. (2021)
Lazy k-star	LL, PL, PI, DUW, OMC, FC, S, TSG, NL, P1, PS	97	0.9772	Raja et al. (2022)
ANN	OMC, MDD, PI, BA, GL	15	0.9654	Rajakumar et al. (2021)
LGBoost	MDD, OMC PL, LL, AT, ACC	207	0.9385	Tran & Do (2021)
RSS_ET	OMC, MDD, PI, PL, LL, O, SC, FS, CS, G	214	0.9680	Trong et al. (2021)
RF	OMC, MDD, PI, PL, LL, O, SC, FS, CS, G	214	0.9592	Vu et al. (2021)
ANN	G, S, FC, LL, PL, OMC, MDD	480	0.9465	Nagaraju et al. (2021)
MARS_L	G, CS, MS, FS, S&C, PI, MDD, OMC	362	0.9842	Bardhan et al. (2021a)
ELM_MPSO	G, CS, MS, FS, S&C, PI, MDD, OMC	362	0.9617	Bardhan et al. (2021b)
ANN	L, CP, GD	384	0.9970	Amin et al. (2022)
ANN	L, CP, GD	384	0.9950	Amin et al. (2022)
GEP	G, S, PI, FC, OMC	43	0.8877	Bakri et al. (2022)
ANN	L, TB, MDD, OMC	-	0.9930	Erzin et al. (2022)
RF	TRT, MR	>2300	0.9487	Hao & Pabst (2022)
RF	C, LL, PL, PI, OMC, MDD, DST, AH	-	0.9908	Ho & Tran (2022)
GEP	LL, PL, PI, G, S, FC, OMC, MDD	168	0.9700	Khan et al. (2022)
ANN	G, S, FC, LL, PL, PI, OMC, MDD	110	0.9511	Khasawneh et al. (2022)
ANN	L, Ls, MDD, OMC	51	0.9988	Li et al. (2022)
PCA (soaked)	NMC, G, S, FC, SG	480	0.1 to 0.94	Tunbosun et al. (2022)
PCA (unsoaked)	NMC, G, S, FC, SG	480	0.01 to 0.92	Tunbosun et al. (2022)
MEP	PI, FC, PL, S, PI, OMC, MDD	1011	-	Verma & Kumar, 2022
ANN	LL, PI, Sld, CN, OMC, MDD, OMCx, MDDx, SG	27	0.9899	Baghbani et al. (2023)
IPSO_ANN	G, CS, MS, FS, S&C, PI, MDD, OMC	362	0.9669	Bardhan et al. (2023)
RF	SCL, LL, PL, PI, OMC, MDD, SWL	252	0.9165	Kassa & Wubineh (2023)
CSO_ELM	G, S, FC, LL, PL, OMC, MDD	149	0.9757	Nagaraju et al. (2023)
ANN	MDD, OMC, LL, PL, FC, AN	-	0.936	Onyelowe et al. (2023)
ANN	G, S, FC, LL, PL, PI, OMC, MDD	240	0.9721	Othman & Abdelwahab (2023)
GPR	G, S, FC, LL, PL, PI, OMC, MDD	1011	0.8800	Verma et al. (2023)
GA_RVM	G, S, FC, LL, PL, PI, OMC, MDD	220	0.8631	Khatti & Grover, 2023a
LSTM	G, S, FC, LL, PL, PI, OMC, MDD	283	0.9863	Khatti & Grover, 2023b

RA is regression analysis, LL is liquid limit, PI is plasticity index, OMC is optimum moisture content, MDD is maximum dry density, C+Si is clay + silt content, S is sand content, G is gravel content, UCS is unconfined compressive strength, SG is specific gravity, CBR_U is unsoaked CBR, GEP is gene expression programming, ANN is artificial neural network, L is lime content, QD is quarry dust, CP is curing period, OC is organic content, L is lime content, RHA is rice husk ash content, CBR_{10} is CBR at 10 hammer blows, CBR_{30} is CBR at 30 hammer blows, CBR_{65} is CBR at 65 hammer blows, MCS is microsilica, CD is curing condition, LM_ANN is Levenberg-Marquardt artificial neural network model, BR_ANN is Bayesian regularization artificial neural network model, SCG_ANN is scaled conjugate gradient artificial neural network model, LS is lime sludge, DT is decision tree, GMDH is group method of data handling model, Ls is linear shrinkage, SG is specific gravity, SO_3 is Sulfur trioxide, SS is soluble salt, GPM is gypsum, O is organic, SDA is sawdust ash, OPC is ordinary Portland cement, RF is random forest, HARHA is hydrated lime activated rice husk ash, AC is clay activity, BBO_ANN is Biogeography-based artificial neural network, DUW is dry unit weight, TSG is tensile strength of geosynthetic, NL is number of layers, P1 is position of 1st layer, PS is position of subsequent layers, BA is share of pulp ash additional, GL is range of geotextile layers, AT is ash type, ACC is ash content, LGBoost is light gradient boosting model, RSS_ET is random subsurface-based extra tree model, S&C is sand and clay content, MS is medium sand, CS is coarse sand, FS is fine sand, GD is gypsum dosages, MRA is multilinear regression analysis, MNA is multi-nonlinear regression analysis, TRT is triaxial test, MR is modulus resilient, DST is dust, and AH is ashes, PCA is principal component analysis, NMC is natural moisture content, Sld is sludge, CN is number of blows, OMCx is OMC of mixture, MDDx is MDD of mixture, SCL is soil classification, SWL is swell, AN is AASHTO number, GA_RVM is genetic algorithm optimized relevance vector machine model.

2. Computational approaches

The literature study reveals that researchers and investigators have used different computational tools to compute the soil's soaked and unsoaked CBR. These computational tools are associated with different domains, i.e., conventional learning (CL), machine learning (ML), advanced machine learning (AML), hybrid learning (HL), deep learning (DL), and blended learning (BL). The learning categories of these domains are supervised, unsupervised, reinforced, and semi-reinforced. In the literature, most published models fall into the supervised learning category. In the supervised learning category, a well-prepared database is fed for training purposes. After the training procedure, the testing is conducted to determine the capabilities of trained models. The regression analysis is a tool from conventional learning, which learns linearly (Lin) or nonlinearly (NL). The polynomial (Poly), Laplacian (Lapl), exponential (EXP), Gaussian (GAU), and sigmoid (Sigm) are nonlinear methods of learning used in simple regression analysis (SRA). Multiple regression analysis (MRA) is another tool that uses more than one variable in the training phase and is more precise than SRA. Machine learning is a higher domain than the conventional domain, consisting of support vector machine (SVM), gradient boosting (GB), random forest (RF), decision tree (DT), k-nearest neighbor (kNN), and Gaussian process regression (GPR) tools. The SVM and GPR tools are based on kernel functions, called mathematical equations, and nothing else. The decision tree is a tree structure based on the hierarchical model. The random forest is an advanced type of decision tree because it consists of many decision trees. Many scientists have developed advanced computational tools using various theories and concepts, and have integrated them into a new domain known as advanced machine learning. The multivariate adaptive regression splines (MARS), gene expression programming (GEP), multi-expression programming (MEP), least square support vector machine (LSSVM), least-square boosting random forest (LSBoostRF), genetic programming (GP), minimax probability machine regression (MPMR), adaptive neuro-fuzzy inference system (ANFIS), ensemble tree (ET), neuro-symbolic system (NSS), and group method data handling (GMDH) are advanced machine learning tools. The researchers noted that the advanced machine learning tools performed better than the machine learning tools, followed by conventional tools, in predicting the California bearing ratio. Table 3 presents the limitations and advantages of the soft computing approaches utilized in the CBR prediction.

Table 3. Limitations and advantages of the soft computing approaches.

Approach	Limitations	Advantages
SVM	· High computational cost for large datasets	· Effective in high-dimensional spaces
	· Difficult to choose optimal kernel	· Robust to overfitting (with proper kernel)
GB	· Computationally expensive	· High prediction accuracy
	· Prone to overfitting without tunning	· Handles various data types well
RF	· Less interpretable	· Robust to overfitting
	· Can be slow with many trees	· Handles missing data and high
DT	· Prone to overfitting	· East to understand and interpret
	· Unstable (small changes in data different trees)	· Requires little data preprocessing
kNN	· Sensitive to noise and irrelevant features	· Simple and intuitive
	· Computationally expensive at prediction	· No training phase required
GPR	· Poor scalability with large data	· Provides uncertainty estimates
	· Choice of kernel is critical	· Flexible with non-parametric modeling
MARS	· May not perform well on highly noisy data	· Captures non-linearity well
	· Needs careful tuning of parameters	· Interpretable model
GEP	· Computationally intensive	· Model's complex relationships
	· Can result in overfitting	· Captures nonlinearities efficiently
MEP	· May produce large solutions	· Simpler expression structure
	· Less flexible than GEP	· Faster than GEP and GP
LSSVM	· Less robust to outliers	· Faster than standard SVM
	· Needs kernel selection and tuning	· Solves linear equations instead of quadratic
LSBoostRF	· High complexity	· Combine strengths of RF and boosting
	· Longer training time	· Enhanced predictive power
GP	· Expensive to compute	· Flexible model structure
	· Requires evolutionary tuning	· Handles symbolic regression well
MPMR	· Limited popularity/support	· Robust to data noise
	· Complex optimization	· Provides confidence intervals
ANFIS	· Scalability issues	· Combine ANN and fuzzy logic strengths
	· Requires domain knowledge for the rule design	· Interpretable fuzzy rules
ET	· Complex interpretation	· Reduces variance and bias
	· Requires more resources	· Improves generalization
GMDH	· Not ideal for very large or noisy data	· Self-organizing and interpretable
	· Sensitive to initial conditions	· Good for small datasets
ANN	· Black-box nature	· Captures complex nonlinear relationships
	· Requires large data and tuning	· Highly flexible
ELM	· May lead to inconsistent accuracy	· Extremely fast training
	· No iterative tuning of weights	· Simpler than traditional ANNs

To enhance the capabilities of machine learning tools and achieve better CBR prediction, the investigators implemented various metaheuristic algorithms. A metaheuristic corresponds to an advanced procedure or heuristic that is intended to locate, produce, adjust, or choose a heuristic (partial search algorithm) that could offer a decent enough solution to an optimization or machine learning problem, particularly when there is limited computation power or incomplete or imperfect information available (Balamurugan et al., 2015; Bianchi et al., 2009). The categories of the metaheuristic algorithms are swarm-based, nature-inspired, biogeographic-stimulated, evolutionary, and physics-based. Ant colony optimization (ACO), artificial bee colony (ABC), fish swarm algorithm (FSA), and particle swarm optimization (PSO) are categorized under swarm-based metaheuristic algorithms. The nature-inspired algorithms are the bat algorithm (BA), cuckoo search algorithm (CSA), invasive weed optimization (IWO), firefly algorithm (FA), and flower pollination algorithm (FPA). The spotted hyena optimizer (SHO), grey wolf optimizer (GWO), artificial immune system (AIS), dendritic cell algorithm (DCA), and krill herd algorithm (KHA) are biogeographic stimulated algorithms. On the other side, differential evolution (DE), genetic algorithm (GA), evolutionary strategy (ES), evolutionary programming (EP), and genetic programming (GP) are evolutionary metaheuristic algorithms. The physics-based metaheuristic algorithms are harmony search (HS), simulated annealing (SA), gravitational search algorithm (GSA), black hole algorithm (BHA), and central force optimization (CFO) (Kumar & Bawa, 2020). The improved squirrel search algorithm (ISSA), modified particle swarm optimization (MPSO), improved particle swarm optimization (IPSO), sandpiper optimization algorithm (SOA), sailfish optimizer (SAO), Runge Kutta Optimizer (RUN), and squirrel search algorithm (SSA) are some more metaheuristic algorithm implemented in the literature to predict the California bearing ratio. Table 4 shows the advantages and limitations of each optimization algorithm in predicting the CBR of soils.

Table 4. Limitations and advantages of the optimization algorithms.

Approach	Limitations	Advantages
SVM	· High computational cost for large datasets · Difficult to choose optimal kernel	· Effective in high-dimensional spaces · Robust to overfitting (with proper kernel)
GB	· Computationally expensive · Prone to overfitting without tunning	· High prediction accuracy · Handles various data types well
RF	· Less interpretable · Can be slow with many trees	· Robust to overfitting · Handles missing data and high
DT	· Prone to overfitting · Unstable (small changes in data different trees)	· East to understand and interpret · Requires little data preprocessing
kNN	· Sensitive to noise and irrelevant features · Computationally expensive at prediction	· Simple and intuitive · No training phase required
GPR	· Poor scalability with large data · Choice of kernel is critical	· Provides uncertainty estimates · Flexible with non-parametric modeling
MARS	· May not perform well on highly noisy data · Needs careful tuning of parameters	· Captures non-linearity well · Interpretable model
GEP	· Computationally intensive · Can result in overfitting	· Model's complex relationships · Captures nonlinearities efficiently
MEP	· May produce large solutions · Less flexible than GEP	· Simpler expression structure · Faster than GEP and GP
LSSVM	· Less robust to outliers · Needs kernel selection and tuning	· Faster than standard SVM · Solves linear equations instead of quadratic
LSBoostRF	· High complexity · Longer training time	· Combine strengths of RF and boosting · Enhanced predictive power
GP	· Expensive to compute · Requires evolutionary tuning	· Flexible model structure · Handles symbolic regression well
MPMR	· Limited popularity/support · Complex optimization	· Robust to data noise · Provides confidence intervals
ANFIS	· Scalability issues · Requires domain knowledge for the rule design	· Combine ANN and fuzzy logic strengths · Interpretable fuzzy rules
ET	· Complex interpretation · Requires more resources	· Reduces variance and bias · Improves generalization
GMDH	· Not ideal for very large or noisy data · Sensitive to initial conditions	· Self-organizing and interpretable · Good for small datasets
ANN	· Black-box nature · Requires large data and tuning	· Captures complex nonlinear relationships · Highly flexible
ELM	· May lead to inconsistent accuracy · No iterative tuning of weights	· Extremely fast training · Simpler than traditional ANNs

Machine learning tools can predict the CBR with a performance of more than 0.90 with a limited database. Conversely, advanced machine learning tools predict better CBR than machine learning tools if the database has less multicollinearity. Multicollinearity is a phenomenon that occurs during regression analysis. The investigators employed various deep learning tools, including recurrent neural networks (RNN), extreme learning machines (ELM), convolutional neural networks (CNN), evolutionary neural networks (ENN), and artificial neural networks (ANN), to predict the CBR using an extensive database. Furthermore, many researchers implemented metaheuristic algorithms to optimize deep learning tools. The Adam, Stochastic Gradient Descent with momentum (SGDM), and Root Mean Square Prop (RMSProp) algorithms optimized the RNN model and achieved high performance in predicting the CBR. However, the blended learning tools, namely station rotation (SR) and lab rotation (LR), have not been employed to predict the CBR in the literature study.

3. Database-based limitations for computational approaches

Artificial intelligence techniques have several limitations in solving regression and classification problems. Each artificial intelligence technique, i.e., machine learning, advanced machine learning, deep learning, and hybrid learning, is based on a database. The quality and quantity of the database play a crucial role in achieving more accurate predictions. Khatti & Grover (2023c, d, e) reported that the quality and quantity of the training database play a significant role in predicting compaction parameters and unconfined compressive strength of fine-grained soil. Additionally, the strong relationship between the dependent and independent variables in the database is crucial for the computation. A poor relationship leads to poor prediction. On the other hand, multicollinearity in the database can't be ignored when predicting the CBR of soil. Multicollinearity is a phenomenon that occurs during the regression analysis. The performance of the machine and advanced machine learning models is affected if a database consists of many variables, and a few variables have the same correlation. However, hybrid computational models can handle the effect of database multicollinearity; however, sometimes, hybrid models achieve unexpected results due to structural multicollinearity. Still, many researchers have questions about the quality and quantity of the database. A good database always provides a better solution if it covers the required range of parameters. Conversely, the large database may improve the computational model's performance. Additionally, the large database increases the likelihood of complexity and can lead to overfitting. Considering all these factors, it can be stated that excellent results can be achieved if a suitable approach is selected and configured well.

4. Practical use of computational tools

The structural, geotechnical, transportation, water resource, environmental, coastal, materials, and urban engineering are substreams of Civil Engineering. In recent years, Cao & You (2024), Kazemi et al. (2023a, b, c), Yahiaoui et al. (2023), and Tang et al. (2022) have employed different computational approaches to solve complex problems related to structural engineering. In addition, Daniel et al. (2024), Kamath et al. (2024), Alavi et al. (2024), Kellouche et al. (2024), and Bansal et al. (2024) evaluated the strength parameters of various types of concrete. Conversely, Bahmed et al. (2024), Khatti & Grover (2023f, g, 2024a, b), Mahabub et al. (2024), and Khatti et al. (2024) estimated the rock and soil parameters, including the bearing capacity of the foundation, using the models based on machine, deep, and hybrid learning approaches. Also, many researchers used different artificial intelligence techniques to solve environmental issues, i.e., environmental monitoring, predictive modelling, resource management, natural disaster management, environmental remediation, climate change mitigation, and biodiversity conservation (Lima et al., 2024; Gerges et al., 2024; Mishra & Gupta, 2024; Sajib et al., 2024; Morshed et al., 2024; Aram et al., 2024). It is fascinating that many researchers have solved the problems associated with tunnelling and mining engineering using computational approaches. Hosseini et al. (2023), Fissha et al. (2023a, b), and Taiwo et al. (2023a, b, c) employed deep and hybrid learning approaches to evaluate ground vibrations and toe volume in mining projects. Samadi et al. (2021, 2023a, b) and Mahmoodzadeh et al. (2022) stated that soft computing techniques are reliable for solving tunnel problems.

5. Summary and conclusions

In pavement design, the strength of the base and subbase course materials is determined in terms of the California Bearing Ratio (CBR). The determination of the CBR using the laboratory procedure is time-consuming and lengthy. Therefore, many investigators have implemented various soft computing models based on conventional, machine, advanced machine, deep, and hybrid learning approaches. A thorough analysis of the published research maps the following conclusions:

- The conventional simple linear and non-linear regression methods map the relationship between consistency limits, gradational, compaction, and strength parameters. Conversely, the conventional multiple regression analysis is a non-iterative method and can achieve the primary prediction of soil CBR. Moreover, the machine and advanced machine learning models compute a better CBR value for the limited database. Still, the deep and hybrid learning models precisely compute the CBR for the high-quality large database.

- The gradational parameters can predict the CBR of soil; however, the combination of consistency limits, compaction, and gradational parameters provides the most reliable prediction of CBR. The literature study also revealed that plastic limit, plasticity index, and maximum dry density of the soil significantly improved the estimation of the CBR using machine learning.
- The moderate and problematic multicollinearity significantly affects the performance and accuracy of conventional regression models due to the non-iterative process. On the other hand, a slight impact of multicollinearity has been observed on the performance of machine, advanced machine, and deep learning models in predicting the CBR of fine-grained soil. Still, the multicollinearity of the fine-grained soil database can be mitigated by incorporating the coarse-grained soil database within certain limits.
- The performance of hybrid learning-based models in estimating the CBR of soil is less affected by the database multicollinearity. Additionally, the hybrid model predicts CBR more accurately than deep learning models.

In summary, this review article presents the positive aspects of artificial intelligence tools in assessing the CBR of soil for pavement design. This review article helps geotechnical engineers and pavement designers understand the quality of the database and select the most suitable computational tool to evaluate the soil's soaked and unsoaked CBR values.

6. Suggestions for further research

The literature study demonstrates a significant use of computational tools for predicting the CBR of the base and subbase course material. Therefore, the following suggestions may be drawn for further research:

- The researchers may compare conventional, machine, advanced machine, deep, and hybrid learning-based models in predicting the bearing capacity and settlement of piles.
- To find the most accurate optimization algorithm, investigators may compare metaheuristic algorithms (evolutionary, swarm-based, biologically inspired, nature-inspired, and physics-based), optimized machine and deep learning models in predicting the CBR of soils, both soaked and unsoaked.
- The researchers may analyze the effect of structural multicollinearity on the performance of the hybrid models in estimating the CBR of each fine and coarse-grained soil.
- The impact of large databases may be analyzed on the performance of machine, advanced machine, deep, and hybrid learning models in assessing the soaked CBR.

These suggestions will be helpful to the researchers working on applying artificial intelligence in geotechnical engineering.

Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest to report.

Authors' contributions

Jitendra Khatti: conceptualization, data curation, visualization, methodology, supervision, validation, writing – original draft, revision. Kamaldeep Singh Grover: writing – review & editing.

Data availability

No dataset was generated or evaluated in the course of the current study; therefore, data sharing is not applicable.

Declaration of use of generative artificial intelligence

No GenAI tool was utilized to prepare this manuscript.

List of symbols and abbreviations

a	regression parameter
ABC	artificial bee colony
AC	clay activity
ACO	ant colony optimization
ACC	ash content
AH	ashes
AI	Artificial intelligence
AIS	artificial immune system
AML	advanced machine learning
AN	AASHTO number
ANN	artificial neural networks
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
AT	ash type
b	regression parameter
BA	share of pulp ash additional
BA	bat algorithm
BBO	biogeography-based
BBO_ANN	biogeography-based ANN
BHA	black hole algorithm
BL	blended learning
BR_ANN	Bayesian regularization artificial neural network
C	design life
CH	highly plastic clays
CBR	California Bearing Ratio
CBR_S	soaked CBR

CBR_U	unsoaked CBR	GEP	gene expression programming
C_c	coefficient of curvature	GL	range of geotextile layers
CFO	central force optimization	GM	grading modulus
CH	Clay with high plasticity	GMDH	group method of data handling model
CL	conventional learning	GP	genetic programming
CN	number of blows	GPM	gypsum
CNN	convolutional neural networks	GPR	Gaussian process regression
CP	curing periods	GSA	gravitational search algorithm
CS	coarse sand	GWO	grey wolf optimizer
CSA	cuckoo search algorithm	HARHA	hydrated lime activated rice husk ash
CSO	cooperation search-optimized	HL	hybrid learning
C_u	coefficient of uniformity	HS	harmony search
C-S	clean clay with sand	IPSO	improved particle swarm optimization
D	penetration depth	ISSA	improved squirrel search algorithm
DCA	dendritic cell algorithm	IWO	invasive weed optimization
DCP	dynamic cone penetration	kNN	k-nearest neighbor
DCPI	dynamic cone penetration index	KHA	krill herd algorithm
DE	differential evolution	L	assembly load
DL	deep learning	L	Lime content
DST	dust	LA	Los Angeles
DT	decision tree	LGBoost	light gradient boosting model
DUW	dry unit weight	LL	liquid limit
D_{30}	particle size at 30% finer	LM_ANN	Levenberg-Marquardt artificial neural network model
D_{60}	particle size at 60% finer		
ELM	extreme learning machines	LR	lab rotation
ELM_GWO	grey wolf optimization-based extreme learning machine	LS	lime sludge
		LSSVM	least square support vector machine
ELM_HHO	harris hawks optimization-based extreme learning machine	LSBoostRF	least-square boosting random forest
		LSTM	long short-term memory
ELM_IPSO	improved particle swarm optimization-based extreme learning machine	MAASHO	modified American Association of State Highway Officials
ELM_MPSO	modified particle swarm optimization-based extreme learning machine	MARS	multivariate adaptive regression splines
		MARS_C	cubic multivariate adaptive regression splines
ELM_TPSO	time-varying acceleration coefficients coupled particle swarm optimization-based extreme learning machine	MARS_L	linear multivariate adaptive regression splines
		MDD	maximum dry density
		MEP	multi-expression programming
ENN	evolutionary neural networks	MH	highly plastic silts
ERF	ensemble random forest	ML	machine learning
EPR	evolutionary polynomial regression	ML	Silt of low plasticity
ES	evolutionary strategy	MNA	multi-nonlinear regression analysis
ESP	eggshell powder	MPMR	minimax probability machine regression
EP	evolutionary programming	MPSO	modified particle swarm optimization
ET	ensemble tree	MR	modulus resilient
FA	firefly algorithm	MRA	multilinear regression analysis
FC	fine content	MS	medium sand
FS	fine sand	M5P M5	algorithm-based regression tree
FSA	fish swarm algorithm	NEAT	neuroevolution of augmenting topologies
FPA	flower pollination algorithm	NL	number of layers
g_m	wheel function	NMC	natural moisture content
G	gravel	Nq	bearing capacity factor
GA	genetic algorithm	NSS	neuro-symbolic system
GA_RVM	genetic algorithm optimized relevance vector machine model	N60 SPT	blowcount for an energy ratio of 60%
		O	organic
Gboost	gradient boosting	OLS	ordinary least squares
GD	gypsum dosages	PCA	principal component analysis

PI	plasticity index
PL	plastic limit
PPV	peak particle velocity
PS	position of subsequent layers
PSO	particle swarm optimization
p_1	moisture content
P1	position of 1st layer
p_2	saturated moisture content
OMC	optimum moisture content
OPC	ordinary Portland cement
QD	quarry dust
RA	regression analysis
RCI	rating cone index
REPTS	reduced error pruning trees
RF	random forest
RHA	rice husk ash
RMSE	root mean square error
RMSProp	root Mean Square Prop
RNN	recurrent neural networks
RSS_ET	random subsurface-based extra tree model
RSS_REPTS	random subsurface-based reduced error pruning trees
RUN	Runge Kutta Optimizer
RVM	relevance vector machine
S	Sand
SA	simulated annealing
SAO	sailfish optimizer
SC	clayey sands
SCL	soil classification
SCG_ANN	scaled conjugate gradient artificial neural network model
SDA	sawdust ash
SG	specific gravity
SGDM	Stochastic Gradient Descent with momentum
SHA	spotted hyena optimizer
Sld	sludge
SM	silty sand
SMA_ELM	slime mould algorithm-based extreme learning machine
SOA	sandpiper optimization algorithm
SP	poorly graded sand
SP-SM	poorly graded sand with silt and gravel
SPT	standard penetration test
SR	station rotation
SRA	simple regression analysis
SS	shear strength
SS	soluble salt
SSA	squirrel search algorithm
S_U	suction
SVM	support vector machine
SWL	swell
t_g	pavement thickness
TRT	triaxial test
TSG	tensile strength of geosynthetic
UCS	unconfined compressive strength
XGB	extreme gradient boosting
ζ	effective degree of saturation
ρ	Elastic rebound measured at the pile head

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