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Modification in Strength Parameter (CBR) of Sub-Grade Soil with Addition of Fly Ash

Abhijit Jadhav [a,*], R D Nalawade [b], D P Gaikwad [b]

[a] Department of Civil Engineering, AISSMS College of Engineering, Kennedy Road, Pune, Maharashtra, India
[b] Department of Chemical Engineering, AISSMS College of Engineering, Kennedy Road, Pune, Maharashtra, India
[c] Department of Computer Engineering, AISSMS College of Engineering, Kennedy Road, Pune, Maharashtra, India

Corresponding author: [*]asj.chem@gmail.com

***Abstract*— The determination of the California Bearing Ratio value of soil is tiresome, uneconomical, and time-consuming in the laboratory. Therefore, there is a required automation system to determine the California Bearing Ratio value of soil. Machine learning algorithms are being used for automation systems. In this paper, Artificial Neural Network has been proposed for the prediction of the California Bearing Ratio value of soil. Ash percentage, Liquid Limit, Plastic_Limit, Plasticity index, Shrinkage Limit, MDD and OMC parameters of soil affect the value of the California Bearing Ratio. In the laboratory, the training dataset has generated using these parameters of soil. The proposed classifier has been trained and tested using the training and testing dataset. Experimental results show that the proposed Artificial Neural Network is very accurate to predict California Bearing Ratio values of soil. It is also observed that the linear regression algorithm is very easy and useful to determine the value of the California Bearing ratio depending on seven attributes of soil. The rules generated by J48 and PART can be used to determine the California Bearing ratio. These models are very useful for civil engineers and civil constructors as a California Bearing ratio prediction automation system.**

***Keywords*— CBR; UCS; artificial neural network; rule learner; soil.**

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I. Introduction

Civil engineering projects such as bridges, roadways, fly-over, and buildings are resting on the soil. The stability of civil works is dependent upon the strength of the soil. The failure of the structure is due to the poor characteristics of the soil on which the structure is resting. Expansive soil is not suitable because of its drying and swelling behavior. On changing moisture levels, expansive soils drop a large amount of volume. Expansive soil expands and contracts during the rainy and dry seasons. So, problematic soils should avoid manage when encountered as subgrade materials. This behavior of expansive soil is very harmful because it can result in cracking civil construction [1]. Due to shrinkage and swelling, the cost of civil work damage is increasing worldwide. Most Civil engineers deal with expansive soils by stabilizing them using additives, doing the alignment, or replacing them with specific materials. In the last few decades, researchers are stabilizing expansive soil using various stabilizers to construct roads and other contractions. Stabilizers such as cement fly ash, lime, Portland cement, lime, fly ash, patented chemicals, medical waste ash, and bagasse ash are being used for soil stabilization [2]. The effective solution is cement stabilization[3]. For the stabilization of expansive soil, different types of stabilizers are used to determine the effective performance of additives in terms of index, physical properties, and chemical and engineering properties of soil. Soaked CBR values are used to measure the strength of the soil. It is an actual depiction of subgrade soil under moisture fluctuation [4].

The strength of the subgrade is measured in terms of its California Bearing Ratio (CBR) value. Measuring the strength of soil in terms of CBR is complex and time-consuming in the laboratory. a process that causes a delay in construction and increases the cost of any civil project. To reduce the cost of the project and time, there is a need for automation to statically correlate the CBR of expansive soil with other independent variables.

The liquid limit (LL), plasticity index (PI), bagasse ash fraction (BAF), calcined termite clay powder fraction (CTCPF),), optimum moisture content (OMC), and maximum dry density (MDD) are free variables for the stabilized soil. For this purpose, a machine-learning model can be used [5]. Most of the research has developed machine learning models for the prediction of CBR values. Specifically, artificial neural networks and regression-based models have been proposed for the prediction of CBR values.

In literature, many studies have focused solely on the experimental approach. The researchers found that the utilized stabilizers have a significant effect on the soil's strength (CBR). it is also found that a few scientific models were developed to predict soaked CBR values in a timely. Artificial neural networks have been proposed in [6] to study the effect of lime on clayey soil. This model also is used to predict the plasticity index (PI), optimum moisture content (OMC), and maximum dry density (MDD) of lime-stabilized clayey soil. Determining the values of PI, OMC, and MDD is not time-consuming and tiresome in the laboratory. But, the prediction of CBR values of soil is very complex and time-consuming, so there is a required prediction model. To fill the above-mentioned gaps, this study is focused on the experimental, statistical, and machine learning approach to investigate the effect of bagasse ash and hydrated lime on the strength, index, and microstructural of CBR values. The main objectives of this study are given below.

- To devise a model based on machine learning to predict variation in CBR values of the Sub-grade soil.
- To optimize results for reduction of construction cost and time.
- To minimize the error function by comparing available laboratory test results.

It is very difficult to design and implement a new optimal engineering model to predict the CBR value of soil. It requires a great deal of effort and experience to be completed perfectly. In stabilization we have to carry out a comparative analysis of a number of tests carried out previously using varying parameters by the conventional method is too much tedious and difficult and time-consuming, to solve such problems and get the best possible and optimized solution. In this paper, machine learning approaches have been proposed to predict the CBR values of soil. Linear regression and one Rule learner have proposed to predict CBR values of soils. The rest of the paper is organized as below. Section 2, is used to expose existing models. In section 3, the research methodology has discussed. In section 4, the proposed model has presented. Section 5 is used to discuss experimental results. Finally, In section 6, the paper have concluded.

Amir S H Alavi and Amir Gandomi [7] have developed Different sets of LGP and LGP/SA-based prediction models for the Assessment of Stabilized Soil. The contributions of the parameters offensive UCS, MDD, and OMC are evaluated through a sensitivity analysis. Analysis of consequent parametric is carried out and the results are compared with earlier studies. It is found that the LGP-based models are observed to be more accurate than the LGP/SA-based models. Jyoti S. Trivedi, Sandeep Nair, and Chakradhar Iyyunnia [8] have formulated a model based on a Genetic Algorithm to predict CBR values of the Sub-grade Soil with a specific percentage of Fly Ash. The input values are used which directly affect the CBR values. The input values were used as Liquid Limit, Plasticity Index, Optimum Moisture Content, and Fraction of Fly Ash. Evolver 5.7 an add-in software has been used for the analysis of the stabilization of soil using fly ash. This model is useful for road construction like NHAI, Construction Contracting Organizations, and Infrastructure Developers. S. Levvaseur, Y. Mal´ecot [9] the model have developed for recognition of constitutive parameters of the Mohr–Coulomb constitutive model from in situ geotechnical capacity. In this paper, authors have used two kinds of optimization algorithms to minimize the error function. Experimental result shows that when the topology of the error function is composite then a genetic algorithm to identify the soil parameters seems particularly appropriate. Anjita N A, Christy Antony George, and Sowmya.V. Krishnankutty [10] have developed a genetic algorithm to predict the dry density of soil. The dry density of soil is maximum at the optimum moisture content. It requires more time and effort for the compaction of the soil. The genetic model was developed using a large database containing about 200 case histories from various sources. Experimental results show genetic algorithms can be used with a high degree of accuracy. The equations given in the paper can be used to predict compaction parameters for new cases. M H Bagheripour, I Shooshpasha, and M Afzalirad [11] have proposed an AFOSM technique associated with a genetic algorithm for assessing the liquefaction potential of soil. The model is examined through a comparison of the results obtained by the new relation and those predicted by other researchers. The proposed model can be used for decision-making because it is related to PL and FS. The proposed model could be beneficial to geotechnical engineers who use the common methods of FS for the evaluation of liquefaction. Lijie Cui, Daichao Sheng [12] have used a genetic algorithm and incorporated it into a displacement finite element method to find the Hasofer Lind reliability index. The probabilistic finite element method has been used to analyze the dependability of classical geotechnical systems. Experimental results show that a genetic algorithm can produce the results fairly quickly and is applicable to the evaluation of the failure performance of geotechnical problems involving a large number of decision variables. Aurélie Papon, Yvon Riou, Christophe Dano, and Pierre Yves Hicher [13] in this paper two kinds of optimization algorithms are been used for identifying soil parameters. The soil data come from the results of two pressure meter tests, resonant column testing, and complement by triaxial. Initially, the inverse analysis has performed separately on each pressure meter test. Genetics provides a collection of satisfactory solutions which can be chosen for further experimental test results. Jin-Lee Kim. Integrated genetic algorithm optimization [14] algorithm have used for soil quality checking. Authors have addressed different this issues in previous investigations.

II. MATERIAL AND METHOD

The effect of the addition of Fly Ash in diverse proportions to the Soil Sample can be observed from the properties like Liquid Limit, Plastic Limit, Optimum Moisture Content, and California Bearing Ratio. For training different machine learning algorithms, the dataset is prepared in the laboratory using seven parameters of soil: ASH_per, Liquid Limit,

TABLE I
PRIMARY TRAINING DATASET

ASH %	Liquid Limit	Plastic Limit	Plasticity Index	Shrinkage Limit	OMC	MDD	CBR	MODIFIED CBR
0	69	44.87	24.13	20.83	31.05	13.4	1.57	M
0.5	65	51.32	13.68	17.34	36.54	13.02	3.21	M
1	64	51.42	12.58	17.29	36.98	12.96	3.33	M
1.5	63	51.66	11.34	17.23	37.15	12.9	3.45	M
2	63	51.78	11.22	17.2	37.94	12.86	3.51	M
2.5	62	51.84	10.16	17.12	38.1	12.82	3.68	M
3	62	51.96	10.04	17.01	38.15	12.8	3.74	M
3.5	62	51.98	10.02	17	38.54	12.79	3.89	M
4	61	51.02	9.98	16.94	38.62	12.78	4.01	MM
4.5	61	51.09	9.91	16.89	38.79	12.74	4.18	MM
5	60	52.09	7.91	16.84	38.85	12.74	4.32	MM
5.5	60	52.16	7.84	16.73	38.91	12.7	4.4	MM
6	60	52.42	7.58	16.66	38.97	12.68	4.55	MM
6.5	59	52.64	6.36	16.44	39.01	12.64	4.64	MM
7	59	52.78	6.22	16.28	39.04	12.62	4.73	MM
7.5	59	52.87	6.13	16.12	39.04	12.62	4.89	MM
8	58	52.91	5.09	16.01	40.26	12.6	4.91	MM
8.5	58	52.94	5.06	15.91	40.41	12.6	4.94	MM
9	58	52.94	5.06	15.84	40.56	12.59	5.12	H
9.5	58	52.98	5.02	15.76	40.68	12.58	5.34	H
10	58	52.98	5.02	15.65	40.47	12.58	5.42	H
10.5	58	52.98	5.02	15.62	40.56	12.57	5.48	H
11	58	52.98	5.02	15.54	40.69	12.55	5.52	H
11.5	57	53.01	3.99	12.51	40.84	12.53	5.54	H
12	57	53.1	3.9	12.45	41.12	12.51	5.59	H
12.5	57	53.12	3.88	15.41	41.54	12.51	5.61	H
13	57	53.27	3.73	15.34	41.6	12.5	5.58	H
13.5	57	53.38	3.62	15.19	41.65	12.49	5.54	H
14	57	53.46	3.54	15.1	41.72	12.49	5.48	H
14.5	57	53.58	3.42	15.21	41.79	12.48	5.41	H
15	57	53.67	3.33	15.25	41.87	12.48	5.37	H

Plastic_Limit, Plasticity_Index, Shrinkage_Limit, OMC, MDD parameters. In table 1, the prepared training dataset has presented with the values of different parameters. Finally, the CBR values in the trading dataset have been encoded in different classes according to their values. The CBR value range from 1.57 to 3.89 have encoded in the M class which represents a LOW value of CBR. The CBR value range from 4.01 to 4.94 have encoded in the MM class which represents the MEDIUM value of CBR. The CBR value range from 5.12 to 5.37 have encoded in the H class which represent HIGH value of CBR. The modified training dataset is presented in Table 1.

The training dataset is used to train Artificial Neural Networks, PART rule Learners, Decision Trees, and Linear regression. trained models will give us the predicted values of CBR for various proportions of Fly Ash added to the Soil Sample. A brief introduction to applied machine learning approaches has given below. An artificial neural network has been constructed to imitate the network of the human brain. Artificial Neural Networks are resulting from Biological neural networks that develop the structure of a human brain. Similar to the human brain, artificial neural networks also have neurons that are interconnected to one another. An Artificial Neural Network is planned and developed to make decisions in a human-like manner[15]. We can develop much simpler and more abstract neurons by leaving out much of the detail of the working principles of the human brain. Researchers have developed many types of neural networks in past for different applications. In this paper, an artificial neural network has been used to classify the CBR values of soil.

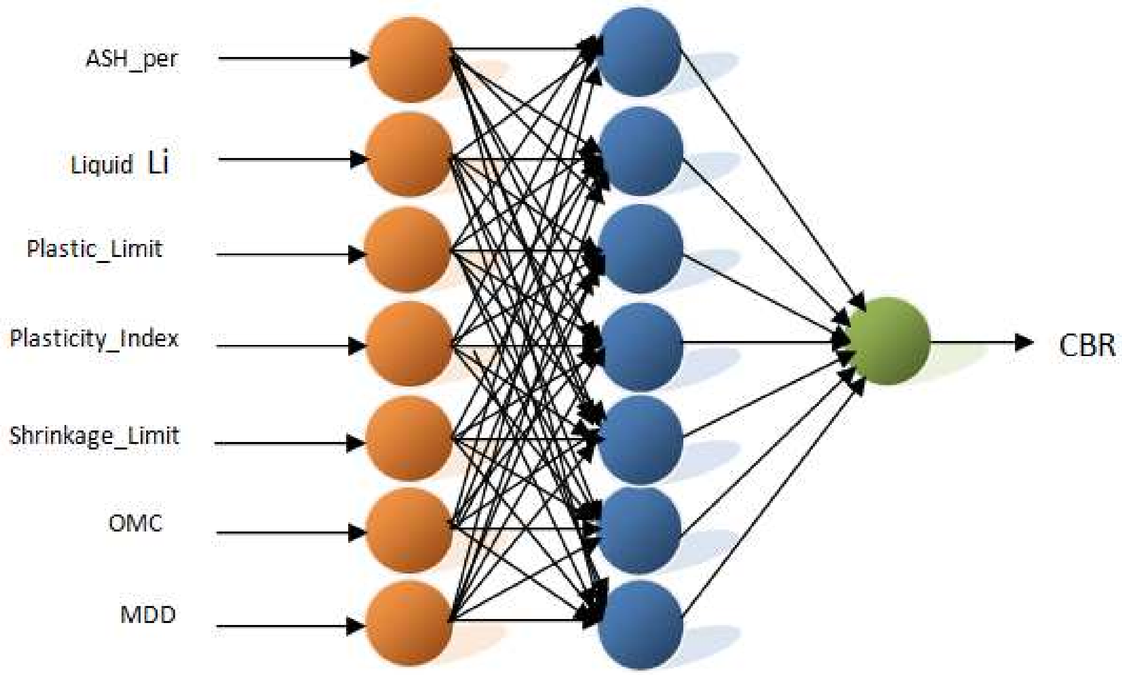

Fig. 1 Architecture of Neural Network for CBR prediction

In machine learning, decision trees are very admired and widely used for several applications. Decision trees are predictive models which are used in statistics and data mining. Decision trees are logic based and easily interpretable and consist of mathematical and computational techniques. In a decision tree, samples are represented in branches and target values are present in the leaves of the tree. In decision trees, if the target variable takes continuous value then such trees are called regression tree which is used to make decisions[16]. In a decision tree, a knowledge base is captured in a well-organized manner. In this paper, the J48 decision tree has been used to classify the CBR values of soil. There exist many rule learner algorithms to generate rules from decision trees. A partial Decision Tree is a combination of the C4.5 and RIPPER rule learners. This combined tree does not require any complex optimization stage [17]. The algorithm which is used to combine C4.5 and RIPPER is very simple, effective, and straightforward. The PART algorithm produces rule sets that are more accurate than RIPPER's rule set[18][19].

A. Proposed Work

In this section, the system architecture of the proposed CBR prediction system has presented. The selection of a classifier is important to work in the prediction system. In this paper, different machine learning algorithms have been used to predict the CBR values of soil.

Artificial Neural Networks, PART, J48, and Linear regression have been selected as classifiers for training. Initially, an Artificial Neural network has implemented on the synthesized training datasets. Following Figure 1 depicts the proposed architecture of the proposed neural network for CBR prediction.

Neural networks have been trained using a backpropagation algorithm. The backpropagation learning algorithm is a supervised learning algorithm that is used to update weights between layers. the training process is divided into two passes named; Forward pass and Backward pass.

In the forward pass, the expected output is calculated using input values, weights, and bias values using a linear function. For a complete algorithm, we can work step-by-step through the mechanics of a neural network with one input layer, and a hidden layer with bias. For the sake of simplicity, let's assume that the number of neurons in each layer is more than one. Initially, we calculate the sum of weighted input Z by using the following formulae (equations 1-6).

$$Z_m = \sum_{i=1}^{n} x_i * w_m^1 + b1_i \tag{1}$$

Where, n is number of inputs and w_i^1 is matrix of weights between input and hidden layer.
After calculation, apply activation function f to obtain output of hidden layer.

$$h_m = a_m = \sigma(Z_m) \tag{2}$$

The output of hidden layer is intermediate result. This result is input to the output layer and out of output layer is calculated as below.

$$O_i = h_i * w_i^2 + b2_i \tag{3}$$

Where n is number of inputs and w_i^2 is matrix of weights between hidden layer and output layer.

$$\hat{y}_i = \sigma(O_i) \tag{4}$$

Where n is number of inputs and w_i^2 is matrix of weights between hidden layer and output layer.

Final step in forward pass is to calculate error E using loss function or cost function. Following function is used to calculate cost function in which T is expected output and ŷ is actual output of neuron at each output neuron.

$$E = \frac{1}{2}(\hat{y} - T)^2 \tag{5}$$

The total error at output neurons is calculated as below.

$$E_{Total} = \sum \frac{1}{2}(\hat{y}_i - T_i)^2$$

In the backward pass, weights between layer are updated using partial derivatives of the cost function or total error is calculated with respects to the different parameters are propagated back through the network. The process continues until the error is at the lowest value. Following equations of derivative is used to calculate derivative of total with respective weight.

$$\frac{\delta E_{Total}}{\delta w_j} = \frac{\delta E_{Total}}{\delta O_i} * \frac{\delta O_i}{\delta h_i} * \frac{\delta h_i}{\delta w_j}$$

where w_i is weight to be updated

For calculating new weight value of w_j, firstly, we have to calculate Δw using following equation.

$$\Delta w_j = \eta \frac{\delta E_{Total}}{\delta w_j}$$

where η is a training rate and $\frac{\delta E_{Total}}{\delta w_j}$ is error gradient with repective w_j

Then , we can calculate new weight value of w_j is calculated as.

$$w_{j_{new}} = w_{j_{old}} + \Delta w_j \tag{6}$$

In similar way we can calculate new weight values of all old weights w.

Once we calculate new weight values of all weights between layers, we can again go to the forward pass to calculate total error δE_{Total}. If δE_{Total} is not minimum or acceptable, we can go to backward pass to recalculate new weight values. These two passes are repeated until we get minimum error at output neurons.

Similarly other classifiers have implemented and trained on synthesis dataset. Decision tree J48 have trained on training dataset. Following three rules have generated by J48 for CBR values classification. The size of J48 is shown five in number.

1. MDD <= 12.59: H
2. MDD > 12.59 and Liquid_Limit <= 61: MM
3. MDD > 12.59 and Liquid_Limit > 61: M

PART Rule learner have trained on training dataset. Following three rules have generated by PART rule learner for CBR values classification.

1. MDD <= 12.59: H
2. Liquid_Limit <= 61: MM (10.0)
3. Liquid_Limit >61: MM: m (8.0/1.0)

Finally, linear Regression have applied to calculate the real value of CBR based on other six attributes. Linear regression can be used to calculate CBR value using given six attribute which can be used directly by engineers and other civil bodies. The model performance for training set is given as below.

RMSE is 0.14115323445070782
R2 score is 0.9780544741428223
Accuracy: 97.80%

The linear regression model have tested on six attributes standardized values as given below.

Test Sample= [-1.67705098, 3.24312809, -4.81582285, 3.91393315, 3.2374972 , -3.89282999,13.40]

Which indicates values of ASH_per, Liquid Limit, Plastic_Limit, Plasticity_Index, Shrinkage_Limit, OMC, MDD attributes respectively.

Target value of CBR : 1.57
Output Value of CBR : 1.58872642

The result shows that proposed linear regression algorithm predict approximately equal to target value of CBR of soil.

III. Results and Discussion

In this section, the experimental results have presented in detail. The experimental results are used to assess the performance of all classifiers. All experiments have performed on laptop with 64-bit Core microprocessor i5 4300U, 9GHz and RAM: 4.0GB. Several experiments have conducted using synthesized training dataset. The classification accuracy of classifiers have evaluated in term of precision, accuracy and recall using followings equations [7-9].

$$Accuracy = \frac{TPc + TNc}{TPc + TNc + FPc + FNc} \tag{7}$$

$$Pc = \frac{TPc}{TPc + FPc} \tag{8}$$

$$Rc = \frac{TPc}{TPc + FNc} \tag{9}$$

Where, TP_c presents True positives) and TN_c is True Negative. FP_c is False positives and FN_c present False negative. The performances of classifiers have measured in terms on accuracy, false positive rate, precision, recall and F-score. The accuracies, precisions, recall and F-measure values are listed in Table 2.

TABLE II
PERFORMANCES OF CLASSIFIERS

Name of Classifier	Accuracy in %	Precision	Recall	F-Measure
ANN	100	1.00	1.00	1.00
PART	96.77	0.87	0.85	0.88
Linear Regression	97.80	0.88	0.88	0.90
J48	96.77	0.88	0.88	0.88

The accuracies of different classifiers have shown in Figure 2.

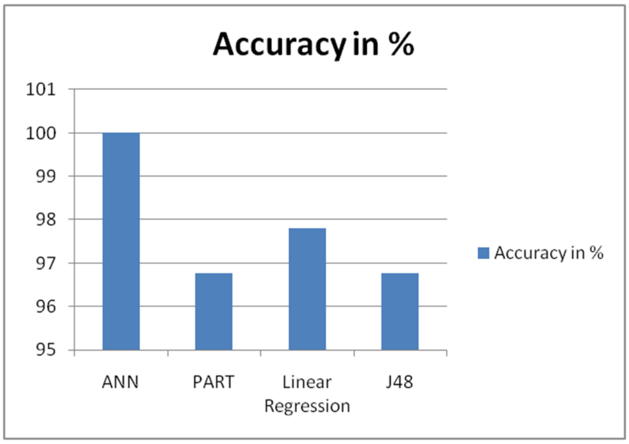

Fig. 2 Accuracies of classifiers.

The precision , recall and f-measure values of classifiers have shown in Figure 3.

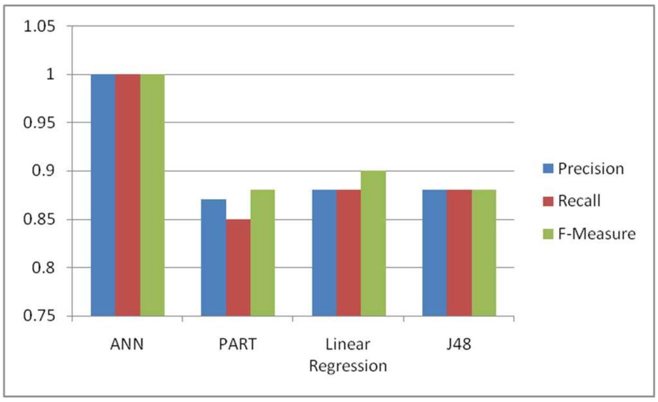

Fig. 1 Precision, Recall and F-Measure values of classifiers.

According to Table 2 and Figure 2, it can be concluded that the proposed Artificial Neural network offers 100% accuracy in the training dataset. According to table 2 and Figure 3, it is also concluded that the Artificial Neural network offers the best precision, recall, and F-measure values on the training dataset of soil. Linear regression also offers good performance on the soil dataset. The linear regression algorithm can be used importantly to calculate prediction values of CBR. The predicted value of CBR and target values are approximately equal when linear regression is used for prediction. Decision tree and PART rule learners offer similar accuracies, precisions, recall, and F-measure values. These classifiers can be used to predict CBR values using different rules which are very easy to understand and implement for the classification of soil CBR values..

IV. Conclusion

Expansive soil drops a large amount of volume when moisture levels fluctuate. This type of soil expands and contracts in the rainy season. Such soils should be avoided or suitably managed when encountered as subgrade materials. To measure the degree of compaction of soil CBR values is very important. The input values of Liquid Limit (LL), and Plasticity Index (PI) directly affect the CBR values. The potency of the subgrade is calculated in terms of its California Bearing Ratio (CBR) value which is tiresome, uneconomical, and time-consuming to determine in the laboratory. To overcome these problems, different machine learning algorithms have been implemented for the prediction of CBR values of soil. In this paper, different machine learning algorithms have been implemented to predict the CBR values of soil. ASH_per, Liquid Limit, Plastic_Limit, Plasticity_Index, Shrinkage_Limit, OMC and MDD parameters of soil have been used for training classifiers. Experimental results show that the proposed Artificial Neural Network is very accurate to predict the CBR values of soils. It is also observed that the linear regression algorithm is very easy and useful for the calculation of CBR value depending on seven attributes of soil. The decision tree and rule learner are also useful for the prediction of CBR value using rules generated by J48 and PART. These all models can be used as an automation model for CBR prediction which can be useful to civil engineers and contractors. In the future, the effective meta-heuristic search algorithm will be used to find near-optimal solutions. A large number of soil types, stabilizers, and considerable variations in their characteristic will be considered in the soil training dataset which can improve the performance of the automation system.

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