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Predictive Modelling of Soaked California Bearing Ratio in Nano-Silica Stabilized Sub-grade Soil in Lesser Himalayan Region

Ishwor Thapa[1,*]

[1]*Research Scholar, Department of Civil Engineering, Sharda University, Greater Noida, India*

**Corresponding Author: 2022822566.ishwor@dr.sharda.ac.in*

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Abstract

This research employs predictive modelling techniques to comprehensively understand the soaked CBR, a key parameter indicating the soil's load-bearing capacity under wet conditions. Experimental investigations are conducted on Nano-Silica (NS) treated sub-grade soil samples collected from the Lesser Himalayan Region. These experiments encompass a range of Nano-Silica concentrations and soaking conditions to capture the diverse environmental factors prevalent in the region. Advanced statistical and machine learning tools are applied to analyze the data and develop predictive models. The objective is to establish correlations between Nano-Silica content, soaking conditions, and the resulting soaked CBR. The models are validated against independent datasets to ensure their reliability and generalizability. The findings of this study hold significant implications for sustainable infrastructure development in the Lesser Himalayan Region. A robust predictive model for soaked CBR in Nano-Silica stabilized sub-grade soil not only contributes to the understanding of soil stabilization mechanisms but also aids in optimizing construction practices for enhanced road performance in challenging terrains. This research bridges the gap between traditional geotechnical engineering and emerging nanotechnology applications in soil stabilization, paving the way for resilient and durable infrastructure in geologically complex regions.

Keywords: *California bearing ratio, lesser Himalayan region, machine learning, soil stabilization, sub-grade,*

1. Introduction

The Lesser Himalayan Region, encompassing diverse soil types and challenging geological conditions, presents a unique set of challenges for infrastructure development. The sub-grade soils in this region are subject to dynamic environmental influences, including rainfall, temperature variations, and seismic activity. Adequate stabilization of these soils is crucial to prevent excessive settlement, deformation, and failure of transportation infrastructure. However, the application of traditional stabilization methods may fall short of addressing the specific challenges posed by the Lesser Himalayan Region. Nano-silica, with its potential to alter the microstructure and mechanical properties of soils, offers an innovative approach to enhance the performance of sub-grade soils. The current lack of comprehensive research on the predictive modelling of soaked Californian Bearing

Ratio (CBR) in Nano-silica stabilized sub-grade soils in the Lesser Himalayan Region underscores the need for a detailed investigation. This research aims to fill this gap by conducting a systematic study on the influence of Nano-silica on the CBR of sub-grade soils under varying environmental conditions. Through predictive modelling, the goal is to develop a robust understanding of the relationship between Nano-silica content and the CBR of stabilized soils. This knowledge will not only contribute to the scientific understanding of soil stabilization with Nano-silica but will also provide practical insights for engineers and policymakers involved in infrastructure development in the challenging terrain of the Lesser Himalayan Region.

Researchers created a Gaussian process regression (GPR) model for forecasting California Bearing Ratio (CBR) in road pavement design using hydrated lime-activated rice husk ash (HARHA) treated soil. The GPR exhibited superior performance compared to artificial neural network (ANN) and gene expression programming (GEP) models, emphasizing HARHA's significance as a key influencing factor (Ahmad et al., 2023). Aamir et al., (2019) investigate the application of alum sludge, a byproduct of water treatment, as an affordable and environmentally conscious soil stabilizer in road construction. Notably, a substantial enhancement in soil strength was identified at an 8% incorporation, evidenced by California Bearing Ratio tests and various physical property assessments. The utilization of Artificial Neural Networks was instrumental in delineating correlations between alum sludge concentration and soil characteristics, underscoring its promise to promote eco-friendly soil stabilization and effective waste management. Coir fibre and activated carbon were employed as environmentally friendly additives, alongside lime as a conventional binder, to improve the characteristics of residual soils. The study utilized Finite Element and random forest models, effectively forecasting and enhancing California Bearing Ratio values, showcasing the efficacy of this integrated methodology (Tamassoki et al., 2023). Raja et al., (2022) explore employing artificial neural networks, regression methods, and tree-based algorithms to evaluate the California bearing ratio (CBR) in geosynthetic-reinforced soil. The artificial neural network exhibited superior performance, resulting in the development of a functional relationship for CBR estimation, followed by a sensitivity analysis. Rajakumar and Reddy Babu, (2021) aim to forecast soaked California bearing ratio (CBR) values for highway construction through Multiple Regression Analysis (MRA) and Artificial Neural Network (ANN) models. Stabilization includes industrial waste, geogrid layers, and input variables. Notably, the ANN model demonstrates superior accuracy (R=0.94317, MSE=0.49) compared to MRA.

Tseganeh and Quezon(2022) examine how bagasse ash (BA) and calcined termite clay powder (CTCP) affect highly expansive soil. Various laboratory tests, including CBR, were performed on soil mixtures with different BA and CTCP proportions. Effective stabilization, particularly with 9% BA and 20% CTCP, led to notable reductions in plasticity, improvements in strength, and alterations in soil microstructure, as validated by SEM analysis. The superiority of artificial neural networks (ANNs) over multiple linear regression (MLR) was evident in predictive modelling. Alisha et al., (2023) studied the utilization of glass powder, NaCl, and pond ash as additives for strengthening expansive clays, taking into account environmental and economic considerations. Findings reveal enhanced unconfined CBR (UCS) and California bearing ratio (CBR). The effective prediction of UCS and CBR values is achieved through artificial neural networks (ANN), showcasing correlation coefficients of 0.986 and 0.980, respectively. This underscores the significance of ANN as a valuable tool in civil engineering for the efficient prediction of time-consuming variables. Examining twelve machine learning models, this study aims to predict the California Bearing Ratio (CBR) of stabilized soil, taking into account variables such as cement and Atterberg's limits (Ho and Tran, 2022). Notably, models employing gradient boosting, random forest, and hybrid methods demonstrate notable accuracy.

Key factors affecting CBR prediction include plasticity index and cement content. Ghorbani and Hasanzadehshooiili, (2018) explore the challenges posed by Iranian desert sands for construction and suggest mitigating these issues through stabilization using lime and micro-silica. A series of 90 tests provide data for developing predictive models, including Back Propagation Artificial Neural Network (BP-ANN) and Evolutionary Polynomial Regression (EPR), to estimate Unconfined CBR (UCS) and California Bearing Ratio (CBR). The optimal models identified are a 5-5-8-1-layer BP-ANN and an EPR model employing a hyperbolic tangent function. Kumar and Singh, (2023) assess the suitability of municipal solid waste incinerator bottom ash for geotechnical applications, emphasizing fibre-reinforced cement stabilization. The study identifies that the most effective combination involves 1% fibre and 9% cement, resulting in improved CBR and California bearing ratio. Successful predictions of outcomes are achieved using machine learning models such as Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference systems, while multilinear regression proves less impactful.

Back Propagation Artificial Neural Networks, or BP-ANNs, are used in civil engineering research because of their ability to manage the complex and non-linear interactions present in soil stabilization procedures. BP-ANN was chosen due to its proficiency in handling intricate datasets with a wide variety of variable types and ranges. This allows it to extract pertinent features from input data without requiring a lot of manual feature engineering. As more data is added to the system, the model's robust learning power through backpropagation and flexibility to different data kinds and scales allow it to continuously improve its predictions. The ability of BP-ANN to generalize well to new data is very important in civil engineering applications, as it guarantees correct predictions even for situations or soil compositions that aren't explicitly included in the training dataset. Essentially, BP-ANN proves to be a potent instrument for predicting the California Bearing Ratio, utilizing its ability to perform sophisticated research and learn from mistakes to improve the building of infrastructure and optimize soil stabilization plans.

2. Materials and Methods

The study involved conducting analyses for grain size, Standard Proctor compaction and soaked California Bearing Ratio (CBR) experiments of (NS) stabilized problematic soil. Furthermore, these tests were replicated on blends of the problematic soil with (NS) at different percentages ranging from 0% to 2.5%. The specific details of these examinations are elaborated upon in the subsequent sections.

2.1 Soil Database

On-site soil samples from the Mid-Hill Road project segment in Gandaki Province (GP), Nepal, formed the basis for a comprehensive database. To ensure quality, a total of 123 soil samples underwent laboratory examination. A 70:30 ratio is used to split the data into training and testing datasets, with 86 samples (or 70%) of the 123 soil samples going toward training and 37 samples toward testing. This method guarantees that a sizeable fraction of the data is used for training while keeping a different sample for assessing model performance. The division makes impartial evaluation easier, which is important when determining how well the model applies to new data. Key geotechnical parameters such as %Clay, %Silt, MDD (g/cc), %OMC, and CBR at 2.5mm were determined and assessed under controlled conditions using the Bureau of Indian Standards (BIS). Descriptive statistics for the training and testing datasets are presented in Tables 1 and 2. These tables detail statistical information, including maximum, minimum, mean, mode, median, standard deviation (SD), and variance for each factor. Analysis of these descriptive statistics provides valuable insights into dataset distribution and variability, facilitating informed decision-making and conclusions.

Table 1: Descriptive statistics values for various training dataset factors

Statistical Values	% Clay	% Silt	OMC (%)	MDD (g/cc)	CBR at 2.5mm
Max	79.57	79.47	53.45	1.93	35.45
Min	5.77	7.42	1.78	1.19	2.60
Mean	48.99	38.98	30.43	1.49	12.75
Mode	19.49	77.96	29.70	1.84	4.40
Median	55.87	19.41	29.70	1.46	10.14
SD	25.44	29.01	8.82	0.17	8.11
Variance	647.07	841.76	77.81	0.03	65.84

Table 2: Descriptive statistics values for various testing dataset factors

Statistical Values	% Clay	% Silt	OMC (%)	MDD (g/cc)	CBR at 2.5mm
Max	79.70	79.47	39.96	1.89	24.27
Min	18.12	7.42	15.10	1.33	2.80
Mean	56.99	30.01	27.14	1.55	10.85
Mode	76.92	19.23	18.80	1.41	2.80
Median	68.83	19.23	27.06	1.48	8.43
SD	22.88	25.32	6.09	0.16	7.12
Variance	523.47	641.02	37.13	0.02	50.63

The Pearson correlation coefficient (PCC) serves to compute and evaluate relationships between various pairs of variables (Benesty et al., 2009). Figure 1 visually depicts the PCC of both dependent and independent variables. High positive or negative values in the matrix can complicate the interpretation of the explanatory impacts of factors on the network response. The intricate and non-linear relationship between input variables and the output CBR is evident, posing challenges in the modelling process. Specifically, Figure 1 illustrates the inverse correlation between %silt and CBR, indicating lower CBR values with higher silt content. The relationship between OMC (%) and CBR, as presented in Figure 1, yields intriguing results for moderate correlation. Notably, in the entire dataset, MDD (g/cc) exhibits a strong positive correlation with CBR, as highlighted in Figure 1. The correlation matrix of the training and testing datasets is shown in Figure 1 below.

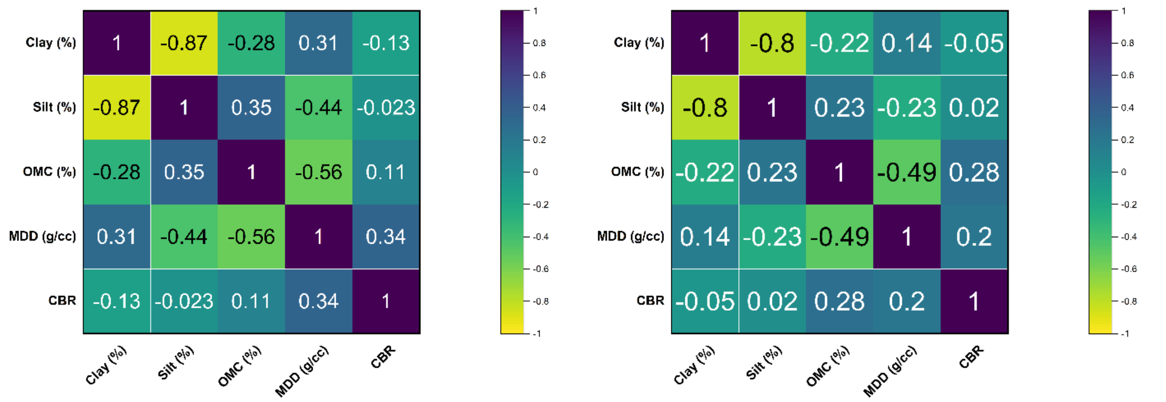


Figure 1: Pearson's correlation matrix of (a) training and (b) testing datasets

Understanding the relationships between these input parameters and the CBR in this context requires displaying the correlation matrix with various soil properties. Researchers can learn more about how variables like silt content and MDD affect soil stability and bearing capacity by observing the correlations. The properties with the strongest correlations with CBR are determined by the matrix, which helps in feature selection for model construction. Furthermore, it facilitates the identification of multicollinearity between variables, which helps prediction models be improved. All things considered, the correlation matrix improves the analysis by offering a succinct summary of the relationships between CBR values and soil properties, which helps with well-informed soil engineering decision-making.

2.2 Machine Learning Approach

Artificial Neural Network (ANN)

The inaugural journal article exploring the use of neural networks in civil and structural engineering dates back to 1989. Subsequently, a plethora of articles on neural networks have surfaced in esteemed research journals, with a notable concentration in structural engineering, construction engineering, and management. Neural networks find applications across diverse domains within civil engineering, spanning environmental and water resources engineering, traffic engineering, highway engineering, and geotechnical engineering (Adeli, 2001).

The 21st century witnessed the swift growth of AI as a prominent sector, primarily attributed to its remarkable ability to handle fuzzy, incomplete, distorted, and erroneous data. Its outstanding capacity to navigate uncertainties in input data has established AI as an optimal solution for tackling geotechnical challenges. Numerous research studies consistently highlight the superior predictive capabilities of Artificial Neural Networks (ANN) when contrasted with statistical and empirical approaches (Bardhan and Samui, 2022; Ebid, 2021; Ghani and Kumari, 2022; Kutanaei and Choobbasti, 2019; Thapa and Ghani, 2023).

The back propagation neural network algorithm was employed to establish a link between input parameters and the CBR value. Training the neural network involved 86 data points, and the model's accuracy was evaluated using the remaining 37 data points. Performance assessment of the AI model relied on metrics such as the R-squared value, R-Pearson’s, root mean squared error (RMSE), mean absolute error (MAE), variance accounted for (VAF) and a20-index.

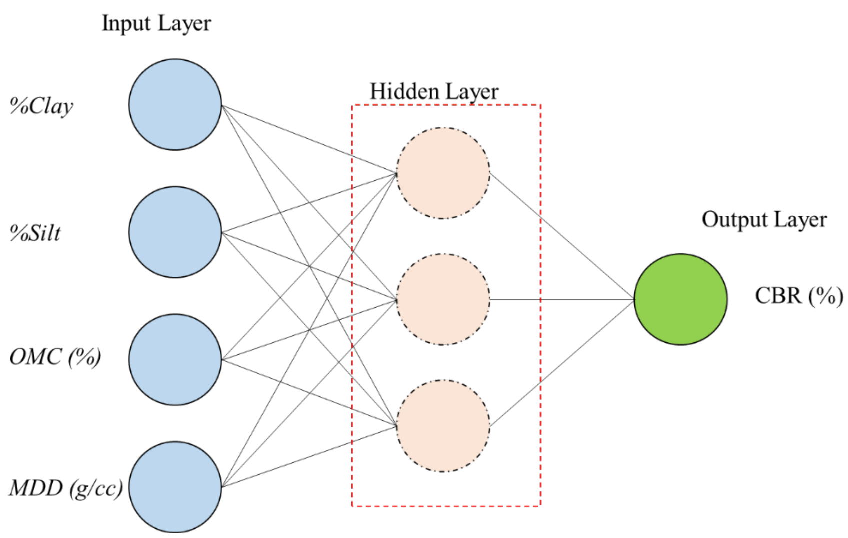


Figure 2: An illustration showing the steps involved in creating the ANN model

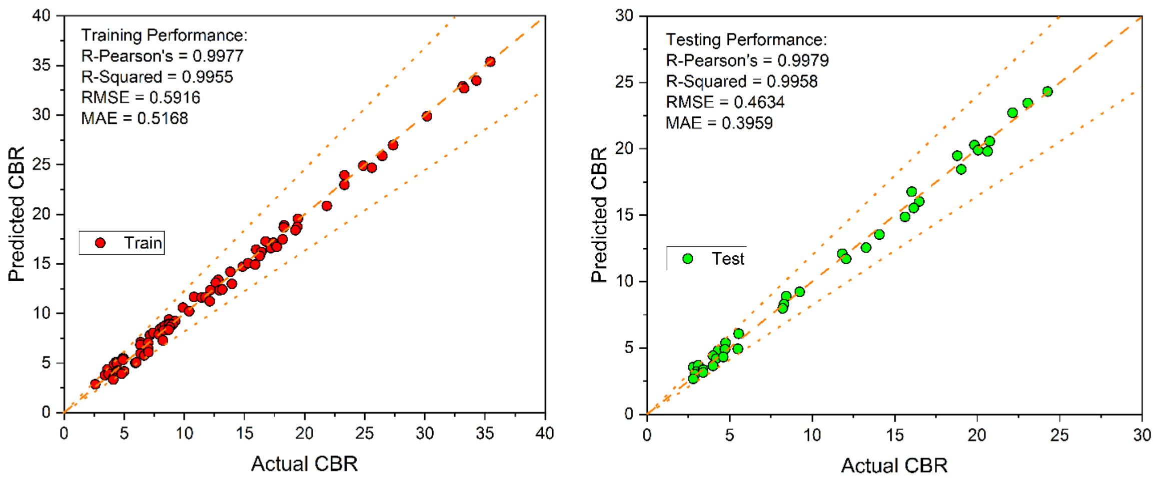
The study used a methodical approach to choose the layers of the ANN, taking into account the quantity of the dataset, computational resources, required accuracy, and the complexity of the CBR prediction task. To prevent overfitting and capture the subtleties of the relationship between input parameters and CBR value, the researcher experimented with several configurations, such as changing the number of neurons (10, 20 and 30) in each layer. The model's architecture has been improved through the use of techniques like cross-validation and regularization, guaranteeing the best performance in predicting CBR values with the selected ANN configuration.

3. Results and Discussions

To assemble input parameters for an artificial intelligence (AI) model, laboratory tests were conducted, involving %Clay, %Silt, MDD (g/cc) and %OMC. Subsequently, soaked sub-grade soil samples underwent CBR testing to establish CBR values, crucial for validating the AI model. From a total of 123 data points obtained during the tests, 86 were used for training the AI model, with the remaining 37 reserved for validation. Model performance was assessed based on Pearson's correlation coefficient (R), coefficient of determination (R2) root mean squared error (RMSE), mean absolute error (MAE), variance accounted for (VAF) and a20-index.

As it focuses on forecasting continuous CBR values, the prediction provided requires regression. CBR values from laboratory tests and relevant input features, such as soil qualities (%silt, OMC, and MDD), are used to train the model and determine CBR percentages using an ANN. The ANN learns the intricate correlations between these input features and CBR values during training. Based on the input features, the ANN can be trained to estimate the percentage of CBR in fresh soil samples. As the estimated CBR percentages for the specified soil samples are displayed, the ANN's output yields continuous numerical predictions.

Figures 3 (a) and (b) illustrate the correlation between the actual soaked CBR and the predicted soaked CBR of sub-grade soil using an ANN model. A line plot is employed, with the predicted soaked CBR on the vertical axis and the actual laboratory-soaked CBR value on the horizontal axis. Each data point in the ANN model's training dataset is represented by a dot in the figures. The coefficient of multiple regression (R2) for the actual CBR value versus the predicted CBR value from the ANN model is 0.9955 and 0.9958 for the training and testing dataset respectively, signifying a strong correlation between the two variables.



(a) (b)

Figure 3: Actual vs Predicted Soaked CBR values for sub-grade (a) Training Data and (b) Testing data

Figure 4 shows the variation of workability parameters concerning ideal value in the training and testing phase respectively. The blue bar graph shows how the training dataset's stats differ from the red graph's ideal values, and the green graph does the same for the testing dataset across six models.

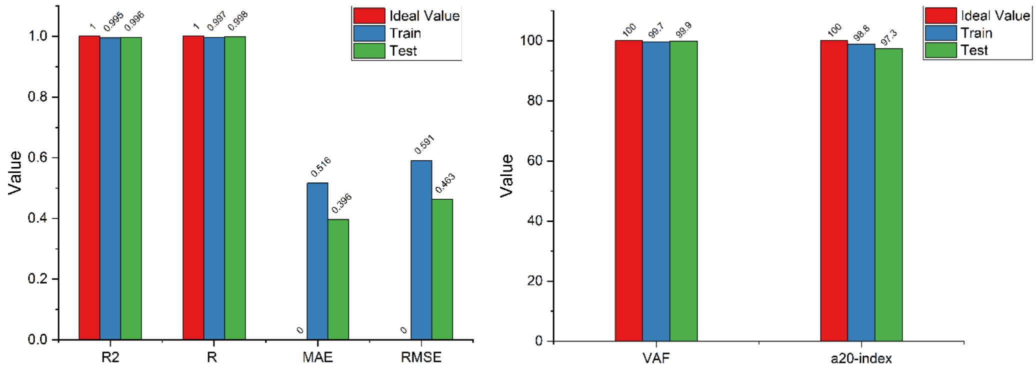


Figure 4: Illustration of workability variation for training and testing dataset of ANN model

4. External Validation

The predictive capability of the ANN model for CBR has proven to be very accurate; in both the training and testing stages, the R-squared value was more than 99%. In this study, ten soil sample sets that were obtained from the vicinity of Sharda University in Greater Noida were analyzed in a controlled laboratory environment to conduct experiments and test the model externally. Table 3 provides specific details about these samples. The accuracy and error analysis of the CBR values predicted by the ANN model in comparison to experimental data is shown in Figure 5. Interestingly, there is significant agreement between the experimental and projected CBR values. These results highlight how well input factors work to predict CBR for fine-grained soil, and the graphical representation provides strong proof of the model's accuracy. This validation highlights the usefulness of the ANN model in geotechnical engineering applications by indicating that they can accurately predict CBR values for fine-grained soil.

Table 3: Experimental datasets for external validation of the best AI models

S.N.	% Clay	% Silt	OMC (%)	MDD (g/cc)	CBR	ANN
1	36.66	27.32	22.70	1.50	25.80	24.75
2	33.05	17.68	17.27	1.20	4.75	5.06
3	36.96	47.10	39.90	1.65	6.89	6.30
4	22.91	66.80	6.15	1.34	11.19	10.12
5	29.15	58.25	38.20	1.92	23.75	24.94
6	25.95	19.70	19.13	1.73	32.21	34.01
7	11.21	56.86	51.84	1.54	28.33	29.97
8	65.14	19.93	38.52	1.85	14.05	13.65
9	24.62	21.72	6.43	1.20	13.29	12.15
10	15.74	61.73	46.32	1.68	4.65	4.21

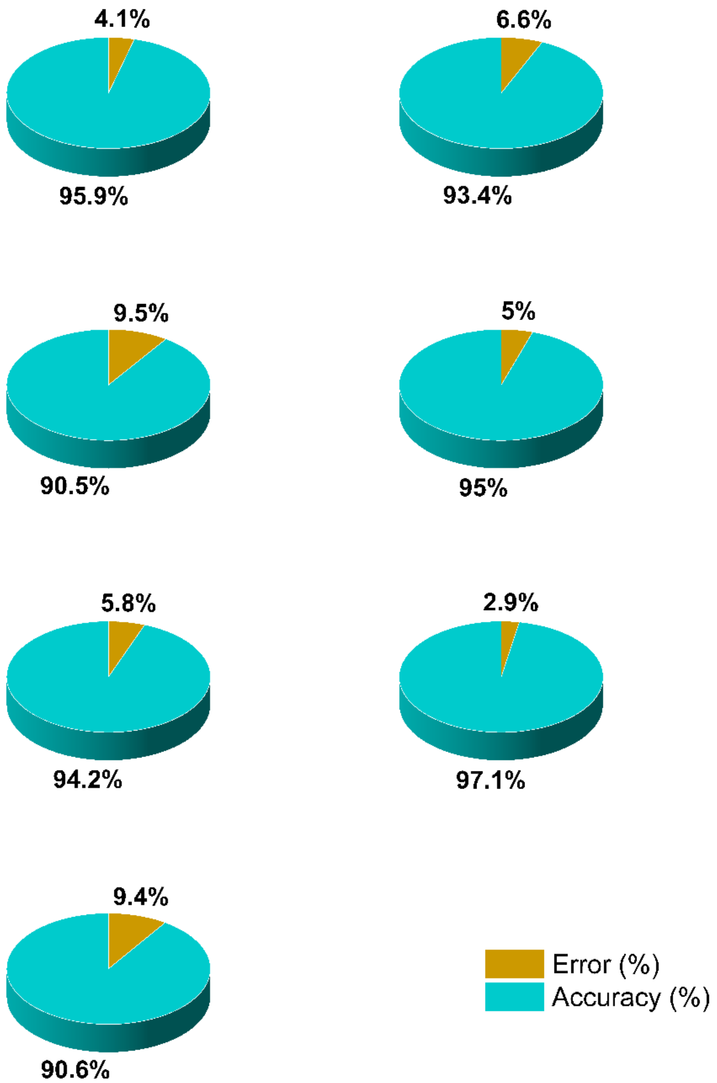


Figure 5: Illustration of error and accuracy of ANN model for experimental validation

5. Conclusions

The importance of comuter-assisted prediction of NS stabilized soaked CBR in pavement design becomes evident when comparing laboratory-calculated values to an ANN model. The ANN model demonstrates efficiency, providing predictions for NS stabilized soaked CBR in sub-grade soil much more quickly than traditional laboratory experiments, delivering results within minutes as opposed to hours or days. Cost-effective advantages arise as the resource-intensive and time-consuming nature of laboratory tests is alleviated by the quicker and more resource-efficient ANN model. With high accuracy, the ANN model effectively estimates NS stabilized soaked CBR values for sub-grade soil, proving particularly advantageous for evaluating sub-grade strength and stability with extensive training data. Impressively accurate, the ANN model achieves R2=0.9955 for training data and R2=0.9958 for testing data in predicting soaked CBR values for sub-grade soil. Consistently providing NS stabilized soaked CBR predictions, the ANN model remains unaffected by variables that may impact laboratory tests, such as sample quality, testing environment, and equipment. Analyzing large datasets with ANN models reveals trends and patterns not immediately apparent, aiding in the identification of potential issues and offering insights into sub-grade soil characteristics. By incorporating input parameters like soil composition, moisture content, and density, the ANN model is trained to swiftly predict NS stabilized soaked CBR values, identifying areas requiring attention to meet specified sub-grade requirements and saving time in the design and construction phases.

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