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Determination of California Bearing Ratio Using Regression Analysis

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Abstract— *The conventional laboratory determination of the California Bearing Ratio (CBR) is often tedious, time-consuming, and susceptible to inaccuracies arising from sample disturbance and substandard testing conditions, thereby causing engineers and technologists engaged in pavement and road design to experience difficulties in obtaining reliable CBR values, particularly under constraints of limited budget, time, and inadequate soil investigation data; hence, the development of predictive models based on easily measurable soil parameters has become essential for estimating CBR values with reasonable accuracy, and in this study, regression analysis was employed to establish correlations between CBR and several geotechnical parameters including optimum moisture content (OMC), maximum dry density (MDD), liquid limit (LL), plastic limit (PL), plasticity index (PI), and silt percentage, among which PI and silt content exhibited the highest coefficients of correlation (R = 0.94), indicating their strong predictive capability for CBR, with the regression model for PI expressed as* $CBR = 0.0004PI^3 - 0.0348PI^2 + 0.7125PI + 8.4869$, *while that for silt content is given as* $CBR = 0.000SILT^3 - 0.0348SILT^2 + 0.7125SILT + 8.4869$, *and a multiple linear regression model incorporating all parameters produced an even stronger correlation (R = 0.95) represented by the equation* $CBR = -15.7289 + 0.3826OMC + 0.0149MDD - 0.0828LL - 0.0216PL + 0.0085PI - 0.1806SILT$, *from which the study concluded that the multiple regression model provided the most reliable estimation of CBR and can serve as a practical alternative to laboratory testing, particularly in preliminary road design and when resources or time are limited.*

Keyword— *Regression, Model, Plastic Limit, Liquid limit, Plasticity Index.*

I. INTRODUCTION

The successful construction of engineering projects particularly large-scale earthworks such as pavements, runways, and embankments depends on a solid and reliable foundation (Chauhan & Venkatesh, 2023.). It is essential that the bearing capacity, swell pressure, and settlement of the pavement layers remain within acceptable tolerances. Consequently, accurate methods for determining these engineering properties are necessary. One such method is the California Bearing Ratio (CBR), which measures the strength of pavement materials as a percentage relative to the strength of a standard crushed rock. This CBR value is a key design parameter for calculating the required thickness of pavement layers and for estimating the stiffness modulus and shear strength of the subgrade soil. Since different soils yield different CBR results, the test can be performed both in the lab and on-site to suit project needs (Chokkerd et al., 2024; Fibre, 2024).

The California Bearing Ratio (CBR) test was created by the California Highway Department in the 1920s to measure the bearing capacity of pavement materials in a lab (Pule & Yendaw, 2024). This method gained international acceptance, and many countries now base their pavement design specifications on CBR values. For designing flexible pavements with fine-grained subgrade soils, CBR is the predominant strength measurement, even as investigation into alternative parameters like resilient modulus continues (Hu et al., 2025; Pule & Yendaw, 2024). A pavement is a multi-layered, engineered structure built on the natural ground to support vehicle loads and provide a durable driving surface. These layers typically include the sub-grade, sub-base, base, and surfacing. In flexible pavement design, the sub-grade soil's strength is a critical factor, dictating the overall pavement's performance and the required thickness of the upper layers (sub-base and base) (Matajinimvar et al., 2025). This thickness is determined using the California Bearing Ratio (CBR) value of the sub-grade, along with other parameters like traffic volume and climate. Originally developed by the California Highway Department during World War II, the CBR test has become a globally accepted empirical method for designing flexible pavements (Chauhan & Venkatesh, n.d.; Phoebe & Adesola, 2025).

The CBR test is an empirical penetration analysis used to evaluate sub-grade strength, applicable in both laboratory and field settings. While it provides a direct measurement on acquired soil samples, the standard procedure has significant drawbacks, including high cost, lengthy duration, and poor repeatability. The test protocol mandates preparing a remolded specimen compacted at its predetermined Optimum Moisture

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Content (OMC), followed by a four-day soaking period before the penetration test is executed (Mirza & Mir, 2025; Thapa & Ghani, 2024).

The standard soaked CBR test is a significant bottleneck in road construction. Requiring about a week to complete, it is an expensive, labor-intensive process that demands large soil samples (Mustapha & Science, 2025). This makes it impractical to collect sufficient data along the entire road length, especially when materials come from variable sources. Consequently, project timelines are often delayed, leading to increased costs. To mitigate these issues, a practical solution is to predict the CBR value using more easily measurable soil properties. Such prediction is a fundamental and necessary part of an engineer's role, enabling informed decision-making throughout a project (Ngo et al., 2024).

Soil Types

Highway construction requires engineers to classify foundational soils, which generally fall into types like Laterite, Moorum, Alluvial, Clay, and Desert sands(Nugroho, 2025).
Gravel: Coarse material (<2.36 mm) with little cohesive fines.
Moorum: Finely decomposed rock that visually resembles gravel.
Silt: A fine, slightly cohesive soil that is brighter than clay and shows dilatancy (a shiny surface appears when a wet sample is manipulated).
Clay: Sticky, fine-grained soil that is strong when dry and does not dilate. Expansive clays, such as Black cotton soil, undergo swelling and shrinkage.
Index Properties of Soil

The Liquid Limit (LL) is the moisture content defining the transition from a liquid to a plastic state. In the standard test, this is the water content at which a soil paste in a Casagrande apparatus groove flows closed for a distance of 12 mm after 25 blows. At this limit, the soil possesses a very low shear strength (Malepati & Gautam, 2025).

The Plastic Limit (PL) is the moisture content at the boundary between the plastic and semi-solid states. It is empirically determined as the water content at which a soil thread begins to crumble when rolled to a diameter of 3 mm (Marathe & Sheshadri, 2025).

Origin of CBR

The California Bearing Ratio (CBR) test, originally developed by O.J. Porter of the California Highway Department, is a load-penetration test used to evaluate soil strength in the lab or field. It measures the force needed to penetrate a soil mass with a standard plunger and expresses the result as a percentage of the force required to achieve the same penetration in a standard crushed rock material (Mirza & Mir, 2025). These CBR values are then used with empirical design charts to determine the necessary thickness of pavement layers for a given traffic load. Initially adopted by the US Army Corps of Engineers for airfield design, the method remains a cornerstone for designing both flexible pavements and airfields, with field testing being particularly valuable for rapid military construction projects.

$$CBR = (\text{Test load}/\text{Standard load})\times 100$$

The standard reference loads are 1370 kg for 2.5 mm penetration and 2055 kg for 5.0 mm. During the CBR test, penetration is measured using a dial gauge, and the applied load is recorded at specific intervals, typically every 0.5 mm up to at least 12.5 mm. These load readings are then used to calculate the CBR value by comparing them to the standard loads (Matajinimvar et al., 2025).

CBR Prediction

The laboratory CBR test is often impractical due to its time-consuming nature, cost, and potential for inaccurate results from sample disturbance. These challenges make it difficult for engineers to obtain reliable design values, especially under tight budgets and schedules. Consequently, there is a significant need for prediction models to estimate CBR values (Mustapha & Science, 2025).

Researchers have long sought correlations between CBR and basic soil properties. Early models, often site-specific, used statistical relationships with index properties like grain size distribution, plasticity index (PI), and moisture content. Seminal work by (Raharja et al., 2024), for instance, proposed a correlation based on plasticity and grading. Other methods have employed tools like the Dynamic Cone Penetrometer (DCP). While valuable, many of these models are essentially statistical correlations. More recent research, including efforts by (Rashwan, 2024) and the NCHRP, continues to explore the influence of soil type and characteristics on CBR, with modern approaches leveraging machine learning for more robust, generalized predictions.

The suitability index is:

The investigation into a predictive relationship between CBR and index properties (Liquid Limit, Plastic Limit, Plasticity Index) initially yielded no statistically significant correlation. Model performance improved when Optimum Moisture Content (OMC) was combined with Liquid Limit, but the resulting correlation was deemed suitable only for the preliminary assessment of materials (Thapa & Ghani, 2024).

Maximum dry density (MDD) being the most significant factor influencing CBR, with optimum moisture content (OMC) being the least significant. This finding led to the development of several predictive equations using these two variables. Later, (Sumedang, 2025) existing models against archival data from Natal soils. While he documented relationships between CBR and various soil parameters in both simple and multivariate forms, his final assessment was that these models performed unsatisfactorily (Xiang et al., 2025).

The research highlighted the lack of a globally applicable CBR model and introduced several targeted predictive methods. Key findings included a correlation with maximum swell and a proposal to use shrinkage and grading moduli as interim measures for estimating minimum CBR in shrinking and non-shrinking soils, respectively (Sun & Wang, 2024; Wang et al., 2024). For British soils compacted at natural moisture content, a correlation based on plasticity index was presented in tabular form.

In a parallel effort, the National Cooperative Highways Research Programme (NCHRP) has established its own correlations in its mechanistic-empirical design guide. For plastic fine-grained soils, it correlates CBR with the percentage of material passing the No. 200 sieve (0.075 mm) and the soil's plasticity index (Molla Kassa et al., 2024).

A pavement is a multi-layered structure built on the natural ground (sub-grade) to support traffic loads and provide a durable surface. Its design, especially for flexible pavements, is critically dependent on the strength of the underlying sub-grade soil (Raharja et al., 2024; Wu et al., 2025).

The California Bearing Ratio (CBR) test, developed by the California Highway Department during World War II, is the globally accepted empirical method for assessing this strength. The results directly determine the required thickness of the base and sub-base layers, along with other factors like traffic volume and climate (Perić et al., 2024).

The CBR test is a penetration test performed either in the field or laboratory. However, the standard laboratory procedure is notoriously slow and costly. It involves collecting a large soil sample, remolding and compacting it to a specific moisture content, and then soaking it for four days before the penetration test can be conducted a process that takes about a week in total. This makes the test laborious and limits its repeatability (Matajinimvar et al., 2025; Mustapha & Science, 2025).

Consequently, it is impractical to conduct a large number of these tests, making it difficult to obtain a comprehensive understanding of soil strength variations along an entire road length. These limitations often lead to serious project delays, highlighting the need for more efficient predictive methods.

The application of regression analysis in geotechnical engineering is broad and encompasses various types. Linear regression models the relationship between a dependent variable (like CBR) and a single independent variable. Multiple linear regression extends this to incorporate multiple independent variables, capturing more intricate relationships. Polynomial regression is utilized when the relationship between variables is non-linear, allowing for the modeling of curvilinear trends by introducing polynomial terms of the independent variables. Nonlinear regression (e.g., logistic regression for phenomena like rock disintegration, further broadens the scope, modeling relationships where the dependent variable is a non-linear function of the independent variables. Common statistical parameters used to assess the effectiveness and reliability of these regression models include the correlation coefficient (r), coefficient of determination (R^2), Root Mean Square Error (RMSE), p-value, and Analysis of Variance (ANOVA) (Marathe & Sheshadri, 2025; Pai et al., 2020).

Regression analysis finds extensive use in geotechnical contexts beyond CBR prediction, including studies predicting unconfined compressive strength, permeability, and other bearing capacity parameters. Its success in accurately modeling various soil properties and behaviors validates its utility for developing robust CBR prediction models, offering a reliable means to estimate this critical parameter and streamline pavement design processes. An illustration of a general research methodology in pavement engineering involving subgrade properties and performance analysis is depicted below, emphasizing the role of subgrade resilient modulus (often correlated with CBR) as a key input for pavement design (Chauhan & Venkatesh, n.d.; Malepati & Gautam, 2025)

II. Materials and Methods

Study Area and Source of Data

The soil data for this study were sourced from the Benin-Auchi road project, a major infrastructure undertaking in the South-South region of Nigeria, specifically from chainage 14+500 to 16+600. The geotechnical investigation and laboratory testing were conducted as part of the quality control processes for the project by Reynolds Construction Company (RCC). The primary focus was on the sub-grade soil properties, which are critical for pavement design.

Soil Samples

A total of forty-six (46) disturbed soil samples were collected from various locations within the specified chainage, as detailed in Table 4.1. The samples were obtained from trial pits or boreholes at depths representative of the subgrade layer (typically 0.5–1.0 m below the natural ground level). The samples were sealed in airtight plastic bags to preserve their natural moisture content and were transported to the laboratory for analysis.

Laboratory Testing

The following standardized laboratory tests, in accordance with ASTM standards, were performed on each of the 46 soil samples to determine their index and strength properties:

Particle Size Analysis (Sieve Analysis)

A dry sieve analysis was conducted to determine the grain size distribution following ASTM D422-63 (Reapproved 2007): Standard Test Method for Particle-Size Analysis of Soils and ASTM D6913/D6913M-17: Standard Test Methods for Particle-Size Distribution (Gradation) of Soils Using Sieve Analysis. The percentage of fines (silt and clay-sized particles) was recorded as the percentage passing the No. 200 (0.075 mm) sieve.

Atterberg Limits

The Atterberg Limits were determined to characterize the soil's plasticity in accordance with ASTM D4318-17: Standard Test Methods for Liquid Limit, Plastic Limit, and Plasticity Index of Soils.

Liquid Limit (LL): Determined using the Casagrande apparatus method.

Plastic Limit (PL): Determined by rolling soil threads until crumbling occurs.

Plasticity Index (PI): Computed as PI = LL − PL.

Compaction Test (Standard Proctor Test)

The compaction characteristics of the soil were determined following ASTM D698-12: Standard Test Methods for Laboratory Compaction Characteristics of Soil Using Standard Effort (12,400 ft-lbf/ft³).

Where higher compaction effort was required, ASTM D1557-12: Standard Test Methods for Laboratory Compaction Characteristics of Soil Using Modified Effort (56,000 ft-lbf/ft³) was used.

From this test, the following parameters were obtained:

Optimum Moisture Content (OMC): The moisture content corresponding to maximum dry density.
Maximum Dry Density (MDD): The peak dry density achieved for the applied compactive effort.

California Bearing Ratio (CBR) Test

The soaked CBR test was performed in accordance with ASTM D1883-16: Standard Test Method for California Bearing Ratio (CBR) of Laboratory-Compacted Soils. Soil specimens were compacted to their respective MDD at OMC and soaked in water for 96 hours (4 days) to simulate saturated field conditions. After soaking, each specimen was penetrated by a standard piston at a rate of 1.27 mm/min, and the CBR value was computed as the ratio of the measured stress to the standard stress for crushed rock at penetrations of 2.5 mm and 5.0 mm.

Data Collation and Descriptive Statistics

All laboratory test results from the 46 samples (data points for CBR, % passing No. 200 sieve, LL, PL, PI, MDD, and OMC) were systematically compiled into a single database. An initial descriptive statistical analysis—including mean, standard deviation, and range—was performed to understand the data distribution and general characteristics of the soils within the study area.

Data Analysis Methodology

The compiled dataset was analyzed using regression analysis with Microsoft Excel's Data Analysis Toolpak. The analytical procedure was divided into two main parts: (1) simple regression analysis to establish relationships between individual soil parameters and CBR, and (2) multiple regression analysis to develop a comprehensive predictive model incorporating all measured parameters.

Simple Linear Regression (SLR) Analysis

To establish preliminary relationships between the soaked CBR and individual soil properties, a series of bivariate analyses were performed using the dataset of 46 samples. Soaked CBR was designated as the dependent variable (Y), and each of the following was treated as an independent variable (X) in separate analyses: Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), Maximum Dry Density (MDD), Optimum Moisture Content (OMC), % Fines (Silt Size, % Passing No. 200 Sieve).
For each pair (CBR vs. X), a scatter plot was generated. A linear trend line was fitted to the data, and the coefficient of determination (R^2) was computed. The R^2 value quantifies the proportion of the variance in the CBR that is predictable from the independent variable. In this study, a correlation with an R^2 value ≥ 0.80 was considered a strong and acceptable fit for predictive modeling.

Multiple Linear Regression (MLR) Analysis

To develop a more robust predictive model that incorporates the combined effect of multiple soil properties, Multiple Linear Regression Analysis was employed on the full set of 46 data points. In this model:
Dependent Variable (Y): Soaked CBR
Independent Variables ($X_1, X_2, ..., X_n$): A combination of soil properties, including % Fines (S), Liquid Limit (LL), Plastic Limit (PL), Maximum Dry Density (MDD), and Optimum Moisture Content (OMC). The general form of the MLR model is:

$$CBR = \beta_0 + \beta_1(S) + \beta_2(LL) + \beta_3(PL) + \beta_4(MDD) + \beta_5(OMC) + \varepsilon$$

Where:
β_0 is the regression constant (y-intercept).
$\beta_1, \beta_2, ..., \beta_5$ are the partial regression coefficients for each independent variable.
ε is the random error term.

The stepwise regression procedure was used to identify the most significant predictors and to develop the most parsimonious model with the highest predictive power. The overall model fitness was evaluated using the Adjusted R^2 value, which accounts for the number of predictors in the model.

Model Validation and Discussion

The suitability and reliability of the developed SLR and MLR models were examined. The statistical significance of the regression coefficients and the overall model was assessed using p-values (with a significance level of $\alpha = 0.05$). The models' predictive accuracy was discussed in the context of the study's objectives and compared with existing literature where possible.

III. Result And Discussion

The data used for the research is presented in Table 1. the table shows the summary of the results conducted for that particular road section within the chainages considered. The results gave a lower value of CBR lower that the acceptable value for a sub-grade soil due to the nature of the soil within Benin-Auchi road project.

Results of Correlations

Correlation Between CBR AND OMC

The correlation between CBR and OMC is presented in Fig 1. From the graph the model equation is given as CBR = 2E-06xOMC^3 -0.0129 xOMC^2+ 23.265xOMC – 14007 with coefficient of determination R^2 = 0.8522 and coefficient of correlation R =0.92. this shows a very strong relationship.

Correlation Between CBR and MDD

The correlation between CBR and MDD is presented in Fig. 2. From the graph the model equation is given as CBR = -0.0002xMDD^3 + 0.025xMDD^2 – 15294xMDD +39.499 with coefficient of determination R^2 = 0.8553and coefficient of correlation R =0.92 this shows a very strong relationship.

Correlation Between CBR and LL

The correlation between CBR and LL is presented in Fig. 3. From the graph the model equation is given as CBR = 0.0343xLL^3 – 2.69xLL^2 +69.884xLL -592.9 with coefficient of determination R^2 = 0.5927 and coefficient of correlation R =0.7698 this shows a strong relationship.

Correlation Between CBR And Plastic Limit

The correlation between CBR and PL is presented in Fig. 4. From the graph the model equation is given as CBR = -2E -05xPL^3 +0.0069xPL^2 -0.5153x PL +13.998 with coefficient of determination R^2 = 0.7652 and coefficient of correlation R = 0.87 this shows a strong relationship

TABLE 1: Test Result Showing Values of Parameters Analyzed

CHAINAGE	OMC	MDD	LL	PI	PL	SILT 200	CBR
14+500	19.6	1700	62	38	22	51	3
14+550	19.6	1700	60	40	20	45	3
14+600	19.6	1700	60	60	20	45	3
14+650	19.6	1700	60	40	20	45	3
14+700	12.6	1870	38	13	25	30	8
14+750	12.6	1870	39	13	26	32	8
14+800	12.6	1870	38	13	25	30	8
14+850	13.4	1870	34	12	22	26	10
14+900	14.1	1840	40	13	27	30	8
14+950	14.8	1800	42	14	28	34	7
15+00	13.4	1870	37	13	24	28	8
15+50	14.8	1800	42	14	28	34	7
15+100	13.4	1870	37	13	24	28	10
15+150	14.1	1840	39	13	26	28	10
15+200	14.1	1840	42	15	27	30	10
15+250	14.1	1840	42	15	27	30	8
15+300	13.4	1870	37	13	24	28	10
15+350	14.1	1840	42	15	27	30	8
15+400	14.1	1840	39	14	25	30	8
15+450	14.1	1840	40	13	27	30	8
15+500	14.1	1840	39	14	25	30	8
15+550	14.1	1840	40	13	27	30	8
15+600	13.4	1870	37	13	24	28	10
15+650	14.1	1840	42	15	27	30	8
15+700	14.1	1840	39	14	25	30	8
15+750	14.1	1840	40	13	27	30	8
15+800	14.1	1840	39	14	25	30	8
15+850	14.1	1840	40	13	27	30	8
15+900	14.8	1800	42	14	26	34	7
15+950	14.8	1800	41	14	27	33	7
16+00	14.8	1800	42	13	29	34	8
16+50	14.7	1800	40	12	28	33	8
16+100	14.6	1800	41	11	30	34	8
16+150	13.4	1870	34	12	22	26	10
16+200	13.4	1870	37	13	24	28	10
16+250	14.1	1840	42	15	27	30	8
16+300	14.1	1840	39	14	25	30	8
16+350	14.1	1840	40	13	27	30	8
16+400	14.1	1840	39	14	25	30	8
16+450	14.1	1840	39	14	25	30	8
16+500	14.1	1840	40	13	27	30	8
16+550	14.8	1840	42	14	28	34	7
16+600	14.8	1800	41	14	27	33	7

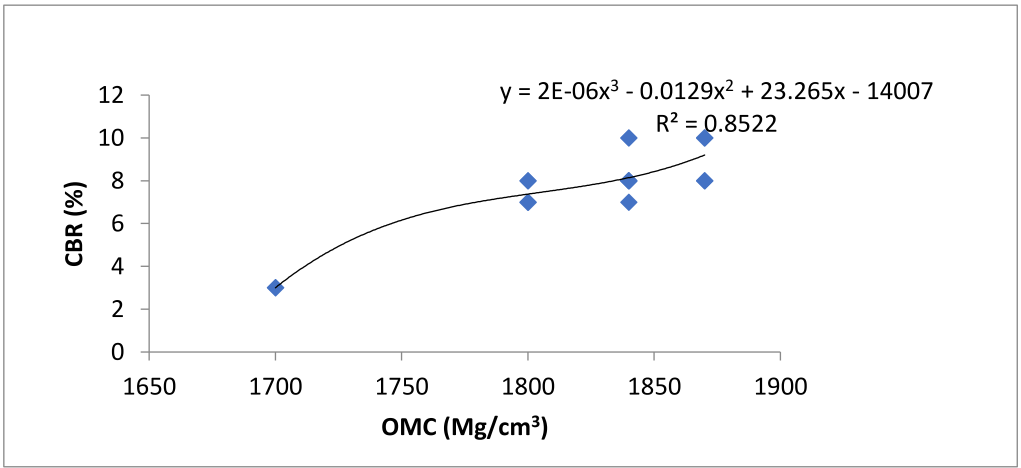

Figure 1: Correlation Between CBR and OMC

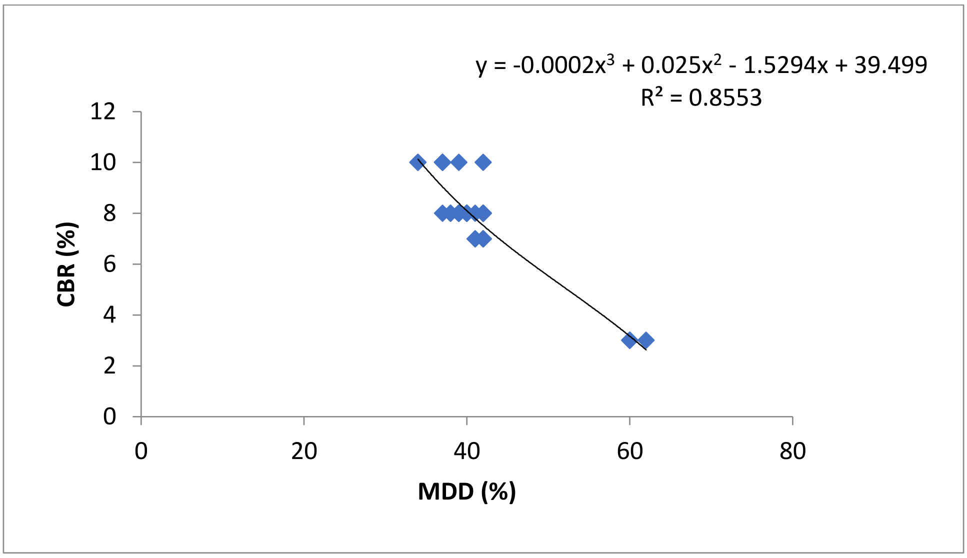

Figure 1: Correlation Between CBR and MDD

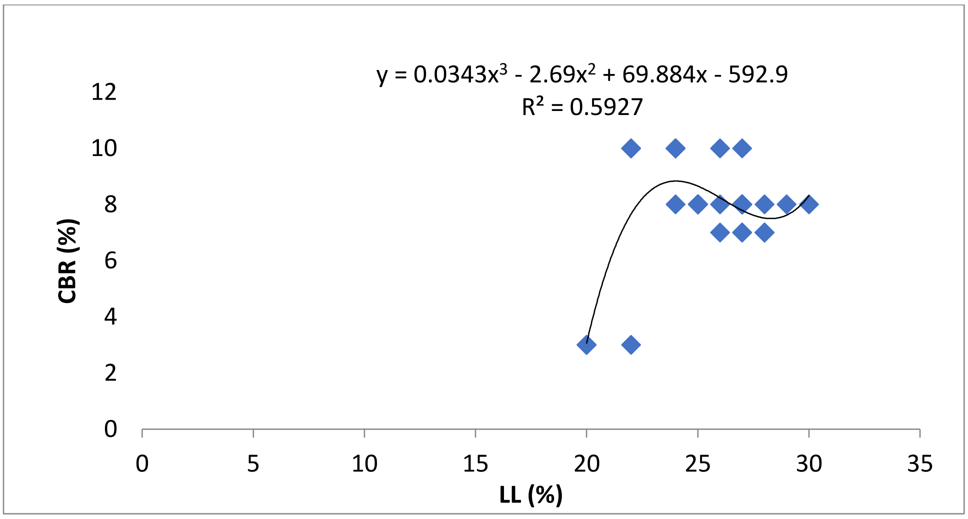

Figure 2: Correlation Between CBR AND LL

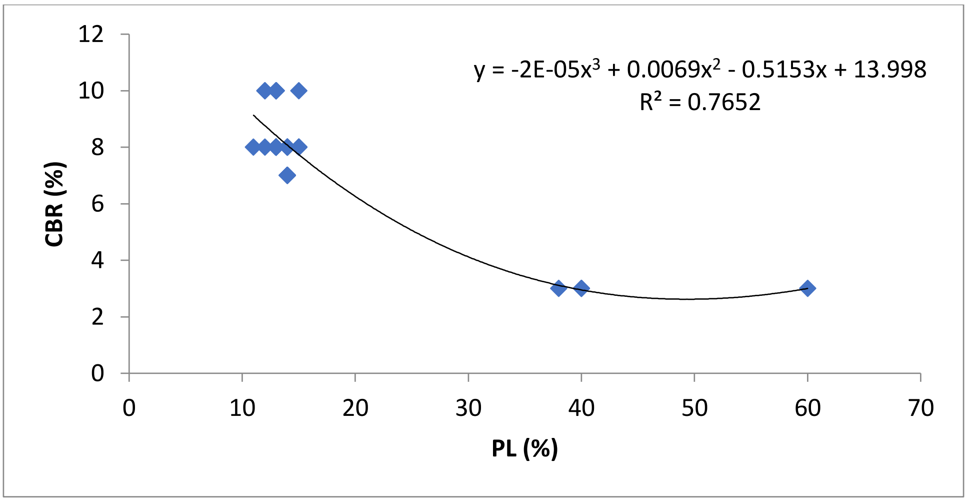

Figure 4: Correlation Between CBR AND PL

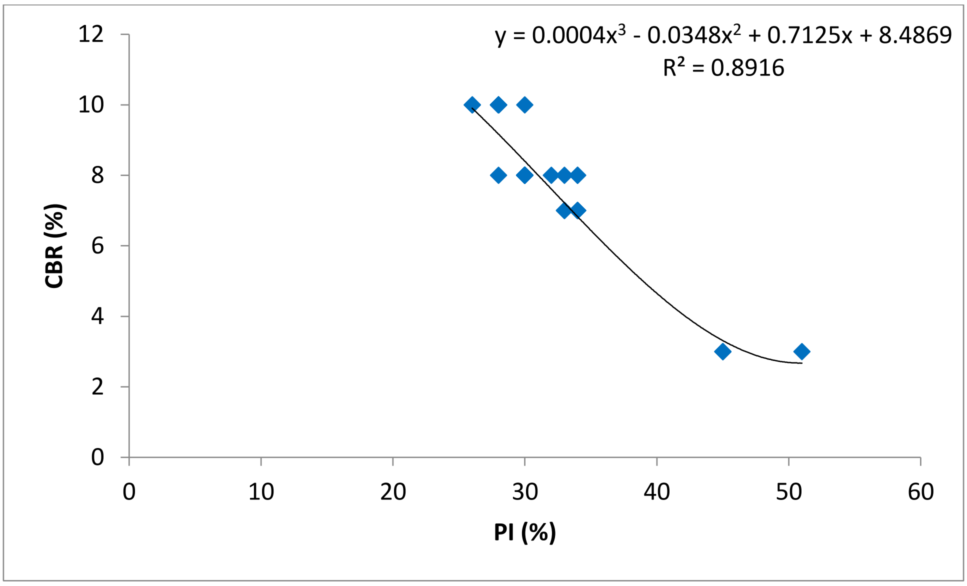

Figure 3: Correlation Between CBR and PI

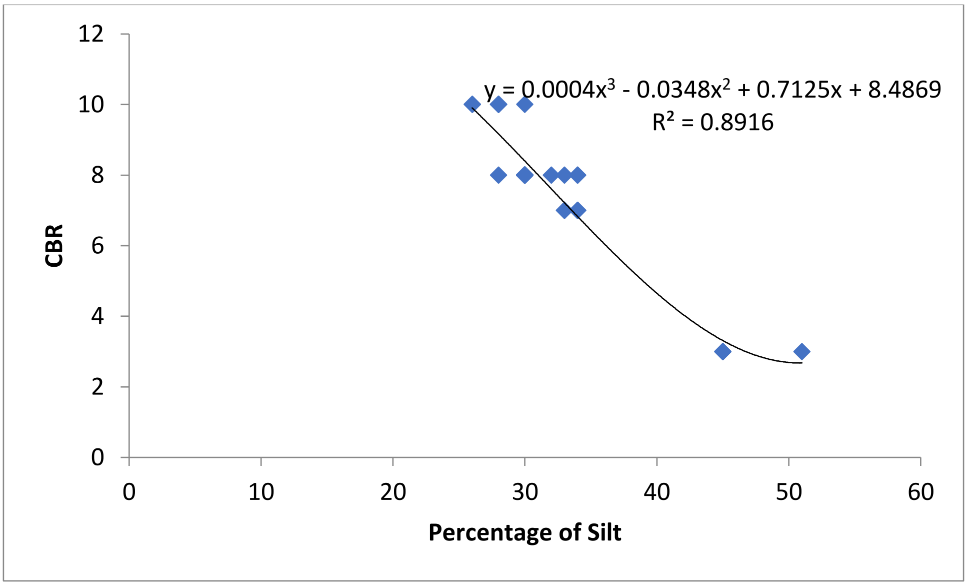

Figure 6: Correlation Between CBR and % SILT

The correlation between CBR and PI is presented in Fig. 5. From the graph the model equation is given as CBR = $0.0004xPI^3$ $-0.0348xPI^2$ $+0.7125xPI$ $+8.486$ with coefficient of determination $R^2 = 0.891$ and coefficient of correlation R = 0.944 this shows a very strong relationship

The correlation between CBR and % Silt is presented in Fig. 6. From the graph the model equation is given as CBR = 0.000x $SILT^3$– 0.0348x $SILT^2$+ 0.7125x SILT +8.4869 with coefficient of determination $R^2 = 0.891$ and coefficient of correlation R = 0.944 this shows a strong relationship

The correlation between CBR and all others parameters being considered in this analysis using the multiple linear equation is given by this equation below

CBR =-15.7289+0.382559OMC +0.014929MDD - 0.08279LL - 0.02161PL + 0.008471PI -0.18061SILT

With a $R^2 = 0.8943$ and R = 0.95 which shows a very strong relationship.

Summary Of Results

The summary of the results showing the coefficient of determination, coefficient of correlation and the model equation is shown in Table 2. The results showed that for the single regressions carried out the model with the highest coefficient of correlation that will give the best predicted value of CBR is the model with CBR vs PI and CBR vs % SILT which gave R value of 0.94. The model with the list coefficient of correlation is CBR vs LL that gave a value of R = 0.77 but despite been low it also shows strong relationship and can be use for predicting the CBR values too. The result from the multiple regressions which is the predicting of the CBR with all parameters considered shows a higher R value 0.95 which is higher that when correlated singly.

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TABLE 2: Table of Summary

Correlated Parameters	R^2	R	Model Equation
CBR VS OMC	0.8522	0.92	CBR = 2E-06OMC^3 -0.0129 OMC^2+ 23.265OMC – 14007
CBR VS MDD	0.8553	0.92	CBR = -0.0002MDD^3 + 0.025MDD^2 – 15294MDD +39.499
CBR VS LL	0.5927	0.77	CBR = 0.0343LL^3 – 2.69LL^2 +69.884LL -592.9
CBR VS PL	0.7652	0.87	CBR = -2E -05PL^3 +0.0069PL^2 - 0.5153x PL +13.998
CBR VS PI	0.8916	0.94	CBR = 0.0004PI^3 -0.0348PI^2 +0.7125PI +8.486
CBR V SILT	0.894	0.94	CBR = 0.000SILT^3– 0.0348 SILT^2+ 0.7125 SILT +8.4869
CBR VS OMC,LL,PL,PI and SILT	0.943	0.95	CBR =-15.7289+0.382559OMC +0.014929MDD - 0.08279LL - 0.02161PL + 0.008471PI - 0.18061SILT

IV. CONCLUSION

This study demonstrated that regression analysis provided a reliable and efficient approach for predicting the California Bearing Ratio (CBR) of soils based on easily measurable geotechnical parameters, thereby offering a viable alternative to the conventional laboratory CBR test, which was often tedious, time-consuming, and prone to inaccuracies. The strong correlations obtained between CBR and parameters such as plasticity index (PI) and silt content (R = 0.94 each) confirmed their significant influence on subgrade strength, while the multiple linear regression model incorporating all variables—optimum moisture content (OMC), maximum dry density (MDD), liquid limit (LL), plastic limit (PL), plasticity index (PI), and silt percentage yielded an even higher correlation (R = 0.95), indicating superior predictive capability. These findings suggested that regression-based models could effectively estimate CBR values where direct laboratory testing was impractical or unavailable, thus supporting more efficient pavement design and soil characterization. It was therefore concluded that the developed multiple regression model was robust, practical, and suitable for preliminary road design applications, especially in resource-limited environments, and further validation using larger datasets and diverse soil types was recommended to enhance its general applicability and accuracy.

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