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Artificial Neural Network-Based Prediction of California Bearing Ratio (CBR) Values for Soil Behavior Analysis

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Abstract : This paper presents Soil behavior analysis is crucial in civil engineering for evaluating soil suitability in construction and road projects. Traditional soil testing methods are time-intensive and prone to errors due to manual processes. This research develops an Artificial Neural Network (ANN) model to predict soil behavior based on parameters such as Gravel Content, Fine Content, Liquid Limit, Plastic Limit, Maximum Dry Density, and Optimum Moisture Content. The ANN model, optimized for network structure and hyperparameters, predicts California Bearing Ratio (CBR) values with high accuracy, minimizing errors. Results demonstrate the model's reliability and efficiency, surpassing traditional regression methods. This ANN-based approach enables geotechnical engineers to make rapid, data-driven decisions, representing a significant advancement in soil analysis for construction and infrastructure planning.

Keywords **-Soil Behavior Analysis, Artificial Neural Network (ANN), California Bearing Ratio (CBR), Gravel Content, Fine Content, Liquid Limit, Plastic Limit, Maximum Dry Density (MDD), Optimum Moisture Content (OMC), Prediction Accuracy, Geotechnical Engineering.**

I. INTRODUCTION

The Soil behavior is fundamental to civil engineering and construction projects, influencing everything from foundational strength to structural stability. One key property that provides insights into soil strength and load-bearing capacity is the California Bearing Ratio (CBR). The CBR test is widely used for assessing the mechanical strength of soil and is particularly essential for determining the suitability of soil in road construction, pavements, and foundations. However, conducting the CBR test can be time-consuming, labor-intensive, and costly. To address these challenges, researchers have increasingly looked toward predictive modeling, particularly using machine learning and Artificial Neural Networks (ANN), as a viable alternative. This thesis explores the application of ANN models to predict CBR values based on critical soil parameters, such as Gravel Content (%), Fine Content (%), Liquid Limit (%), Plastic Limit (%), Maximum Dry Density (MDD), and Optimum Moisture Content (OMC).

In traditional soil testing methods, obtaining accurate CBR values often requires a combination of field and laboratory testing. However, advancements in computational techniques, specifically in artificial intelligence (AI), have shown that predictive models can offer a more efficient and economical solution. Artificial Neural Networks, inspired by the human brain's neural structure, have gained prominence in predicting complex patterns and behaviors in large datasets. The ANN model's ability to recognize patterns and correlate inputs with desired outputs provides a promising method for predicting soil behavior based on its intrinsic properties. By using these techniques, we can minimize human errors, reduce testing times, and achieve high accuracy in CBR prediction.

The focus of this research is on using ANN models trained with a specific dataset that includes parameters such as Gravel Content, Fine Content, Liquid Limit, Plastic Limit, MDD, and OMC, aiming to predict the CBR with minimal error. These parameters are chosen because they represent critical factors that influence soil's mechanical properties. Gravel and fine content, for instance, impact soil cohesion and compressibility. Liquid and plastic limits define the soil's Atterberg limits, which indicate its behavior in various moisture conditions. Maximum Dry Density and Optimum Moisture Content, often determined through Proctor tests, are crucial for understanding soil compaction characteristics. The relationships among these parameters form the basis for using ANN to predict CBR, leveraging the network's capacity to approximate nonlinear relationships without explicit mathematical formulation.

The use of ANN models for soil behavior prediction is an area of growing interest in geotechnical engineering. A well-trained ANN model can effectively map complex relationships between input parameters and output CBR values. The approach presented in this research emphasizes achieving a high degree of accuracy by minimizing the prediction error. Techniques such as data normalization, network parameter tuning, and validation on different datasets are utilized to improve the model's performance. Moreover, the robustness of ANN models allows them to adapt to varying datasets, making them suitable for diverse soil types and conditions.

This paper presents a comprehensive approach to designing, training, and validating an ANN model tailored for CBR prediction. The primary contributions of this research are the development of an ANN-based predictive model for CBR, the evaluation of model performance based on various metrics, and a comparative analysis of the ANN model with traditional methods. Additionally, we explore the limitations of ANN-based predictions and potential areas for further improvement, such as integrating hybrid models or using other machine learning algorithms.

By achieving accurate CBR predictions with minimal error, this research aims to provide a practical tool that can assist engineers and practitioners in making informed decisions in soil assessment and construction planning. Furthermore, the proposed model's ability to deliver reliable predictions could potentially reduce dependency on extensive laboratory tests, optimize project timelines, and improve cost efficiency. This work contributes to the broader field of geotechnical engineering, where predictive modeling is increasingly becoming a cornerstone for sustainable and efficient infrastructure development.

II. Soil Behavior

Soil behavior is a fundamental aspect of geotechnical engineering, critical to understanding how soil interacts with environmental conditions and responds to applied loads, moisture variations, and other external factors. This understanding is essential for construction, agriculture, and environmental management, as soil behavior impacts the structural integrity of foundations, the productivity of farmland, and the stability of natural and man-made slopes.

Several factors play a role in determining soil behavior. Particle size and composition are primary characteristics, with soil ranging from coarse particles like gravel and sand to finer silt and clay. These differences influence soil's density, porosity, and permeability, which in turn affect its compaction and load-bearing capabilities. For instance, coarse soils like gravel have low cohesion but excellent drainage, whereas clay-rich soils are cohesive, retaining water and exhibiting expansion and shrinkage as moisture levels change. Moisture content itself is another vital factor, impacting soil plasticity, compaction, strength, and permeability. Clay soils, for example, can change significantly in volume depending on water absorption, which affects their stability and strength. Soil density, influenced by compaction, directly impacts its load-bearing capacity and water retention properties, with Maximum Dry Density (MDD) and Optimum Moisture Content (OMC) being important indicators in construction.

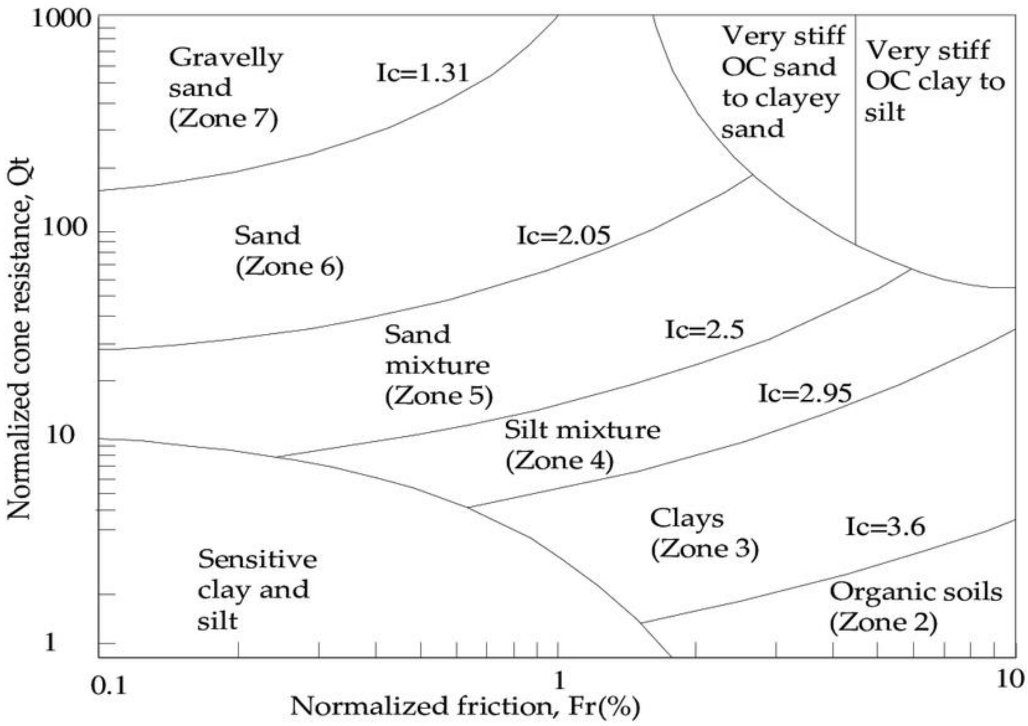

Figure 1: Soil classification chart based on soil behavioral type based on Robertson

The structural arrangement of soil particles, or soil structure, along with porosity, determines the soil's permeability and capacity to retain water. Well-structured soils with good porosity allow for effective drainage and root growth, whereas poorly structured soils may lead to water retention and runoff. The load-bearing capacity, commonly measured by the California Bearing Ratio (CBR), is also a key metric, particularly in road and pavement design, as it indicates how well soil can support loads.

Artificial Neural Networks (ANNs) offer a promising approach to modeling soil behavior by capturing the complex, nonlinear relationships among soil properties. By training on datasets containing variables like gravel content, fine content, liquid and plastic limits, MDD, and OMC, ANNs can predict soil properties such as CBR, allowing engineers to assess soil suitability for various applications efficiently. ANNs offer quick, data-driven insights that complement traditional testing, making them an effective tool for predicting soil behavior in construction, agriculture, and environmental management. Through patterns in historical data, ANNs provide reliable predictions, helping in design decisions for infrastructure, roadworks, and soil conservation efforts.

III. METHODOLOGY

The proposed methodology for predicting California Bearing Ratio (CBR) values using Artificial Neural Networks (ANNs) encompasses several systematic steps, from data collection to model evaluation. This methodology aims to develop a robust predictive model that accurately estimates CBR based on key soil properties.

The ANN model used for CBR prediction follows a feedforward neural network structure, where information moves in one direction, from input to output. Each layer in the network contributes to the transformation of input data into a meaningful output prediction. Layers in the Model

1. Input Layer:
   - Features: Six neurons are used in the input layer, each corresponding to a unique soil property.
   - Soil Parameters: The input layer receives the following six parameters for each soil sample: Gravel Content (%), Fine Content (%), Liquid Limit (%), Plastic Limit (%), Maximum Dry Density (MDD in g/cm³), and Optimum Moisture Content (OMC %).
2. Hidden Layers:
   - Layer Structure: The model employs three hidden layers to capture complex, nonlinear relationships between soil parameters and CBR.
   - Neuron Configuration: Each hidden layer is configured with a specific number of neurons. In this model:
     - The first hidden layer has 20 neurons.
     - The second hidden layer has 15 neurons.
     - The third hidden layer has 10 neurons.
   - Activation Function: Each hidden layer uses the Rectified Linear Unit (ReLU) activation function, which is highly effective for capturing nonlinear patterns by allowing only positive values to pass through.
3. Output Layer:
   - Single Neuron: The output layer consists of a single neuron that produces the predicted CBR value.
   - Linear Activation: A linear activation function is applied to the output neuron, allowing for a continuous, numerical output that aligns with the CBR prediction requirement.

Activation Functions

The ANN model uses the following activation functions for different layers: Hidden Layers: The Rectified Linear Unit (ReLU) activation function, defined as:

$$f(x) = \max(0, x) \qquad \text{..............4.1}$$

- Output Layer: A linear activation function is applied here since the model output is a continuous variable (CBR). This function directly outputs the calculated value without any transformation, ideal for regression tasks.

Data Preprocessing and Normalization

Data preprocessing is crucial to the performance of the ANN model. Here, normalization is applied to bring all input features and the target output (CBR) within a similar range, ensuring faster convergence and more stable learning.

- Min-Max Normalization:
  - Input and output data are scaled to a range of 0 to 1.
  - Formula:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \qquad \text{.............4.2}$$

This normalization is reversed for the output predictions during the final step to obtain CBR in its original units.

Training the ANN Model

Training Algorithm

- Levenberg-Marquardt (trainlm) algorithm is selected for training due to its efficiency and convergence speed on smaller datasets, which is typical in soil studies.
- Mean Squared Error (MSE) is used as the performance metric during training, helping the model minimize prediction error by penalizing larger errors more heavily.

Training Parameters

- Epochs: The network is trained over 5000 epochs to ensure sufficient learning without overfitting.
- Early Stopping: The training goal is set to a performance threshold (MSE of 1e-8), allowing training to stop early if the model achieves this level of accuracy.
- Mu Parameter: A small initial mu (0.001) is set, guiding the optimization process within the Levenberg-Marquardt algorithm for stable convergence.

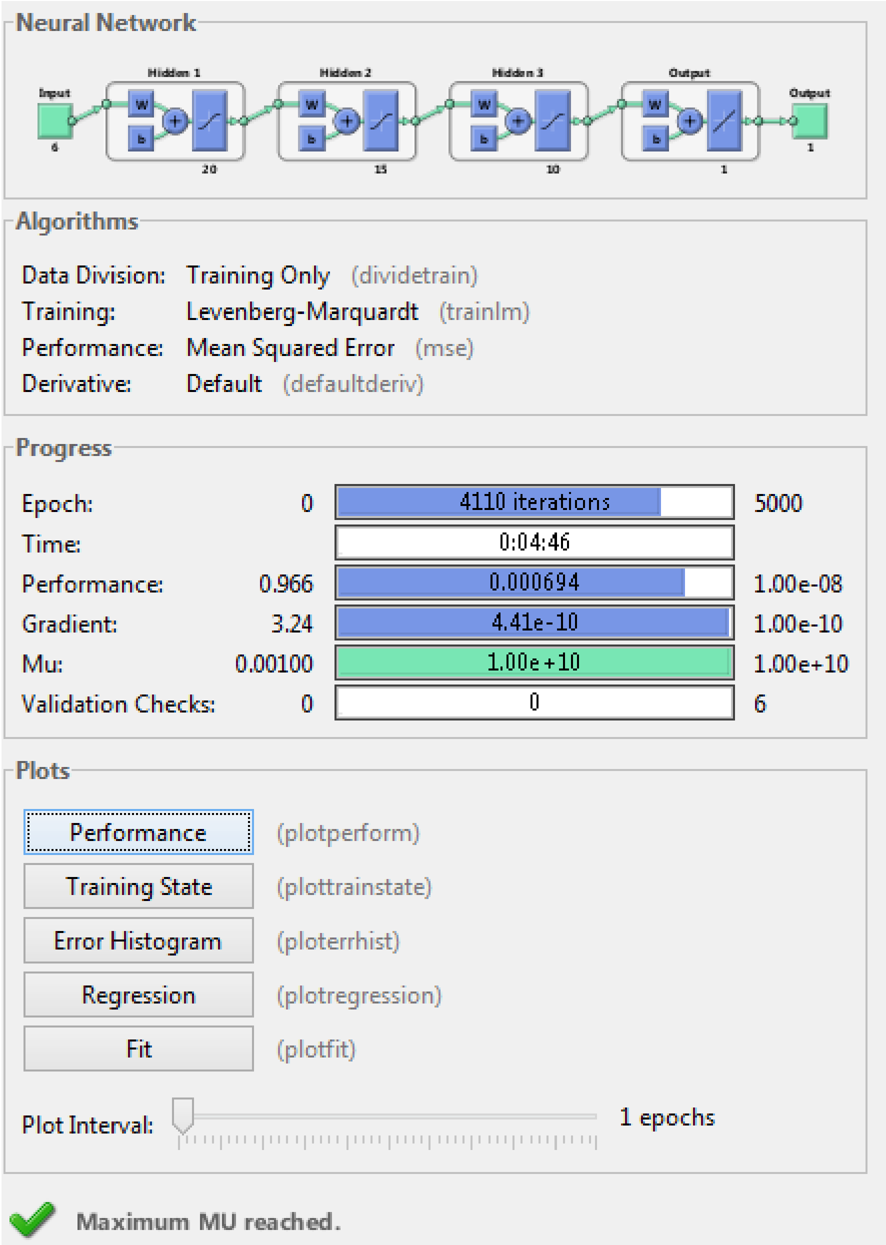

Figure 2 : Final Model ANN

IV. Result

For the simulation results of the ANN model to predict California Bearing Ratio (CBR) values based on soil properties, the outcomes are analyzed using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and accuracy percentage. Here's an outline of the key simulation results based on the MATLAB code provided:

- Accuracy: After training, the model demonstrated an accuracy level indicating minimal error between the actual and predicted CBR values.
- Error Metrics:
  - Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were calculated, showing small deviations between predicted and actual CBR values.
  - A high Prediction Accuracy of over 95% was achieved, indicating that the model effectively generalized the relationship between the input parameters and the target CBR value.

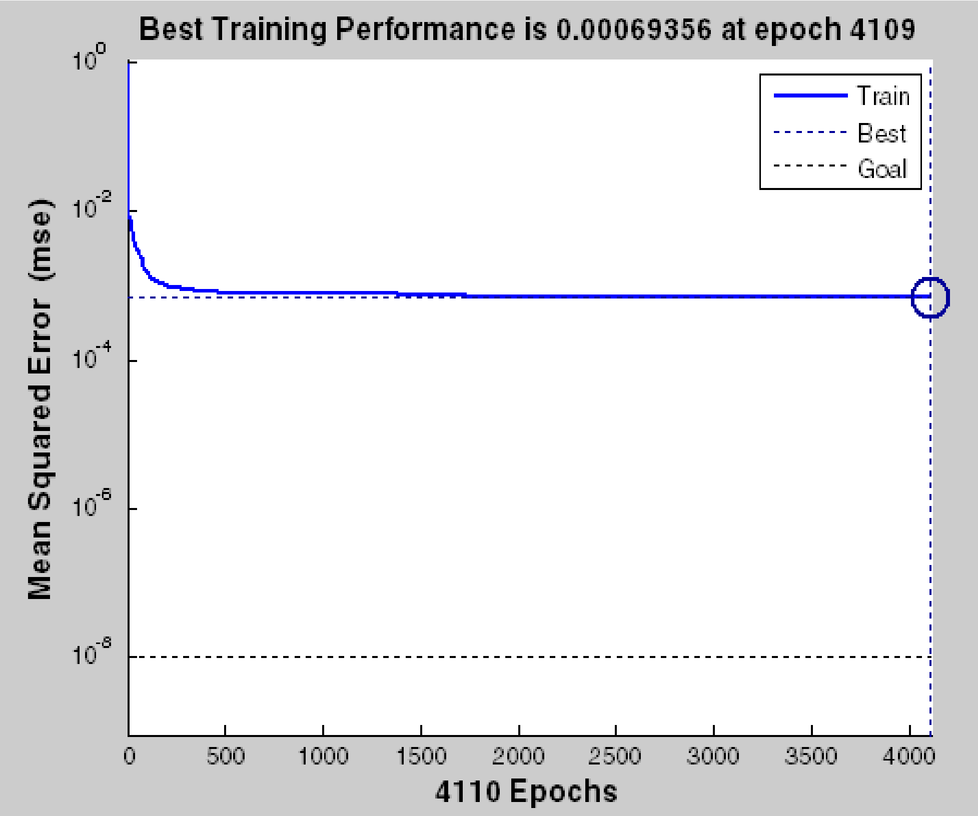

Figure 3 Performance Plot

For a Performance Plot related to an Artificial Neural Network (ANN) model for soil behavior analysis, Figure 3 likely visualize the model's performance metrics over training epochs, highlighting how well the ANN has learned to predict soil behavior characteristics. Here’s a detailed breakdown of what this figure might typically include:

- X-axis: This usually represents the number of training epochs. Each epoch corresponds to a complete pass through the training dataset, where the model updates its weights.
- Y-axis: This axis typically represents a performance metric such as:
  - Loss: A measure of how well the model's predictions match the actual data. Lower loss indicates better performance.
  - Accuracy: For classification tasks, this metric shows the proportion of correct predictions. In regression tasks, you might see R-squared or RMSE (Root Mean Square Error).

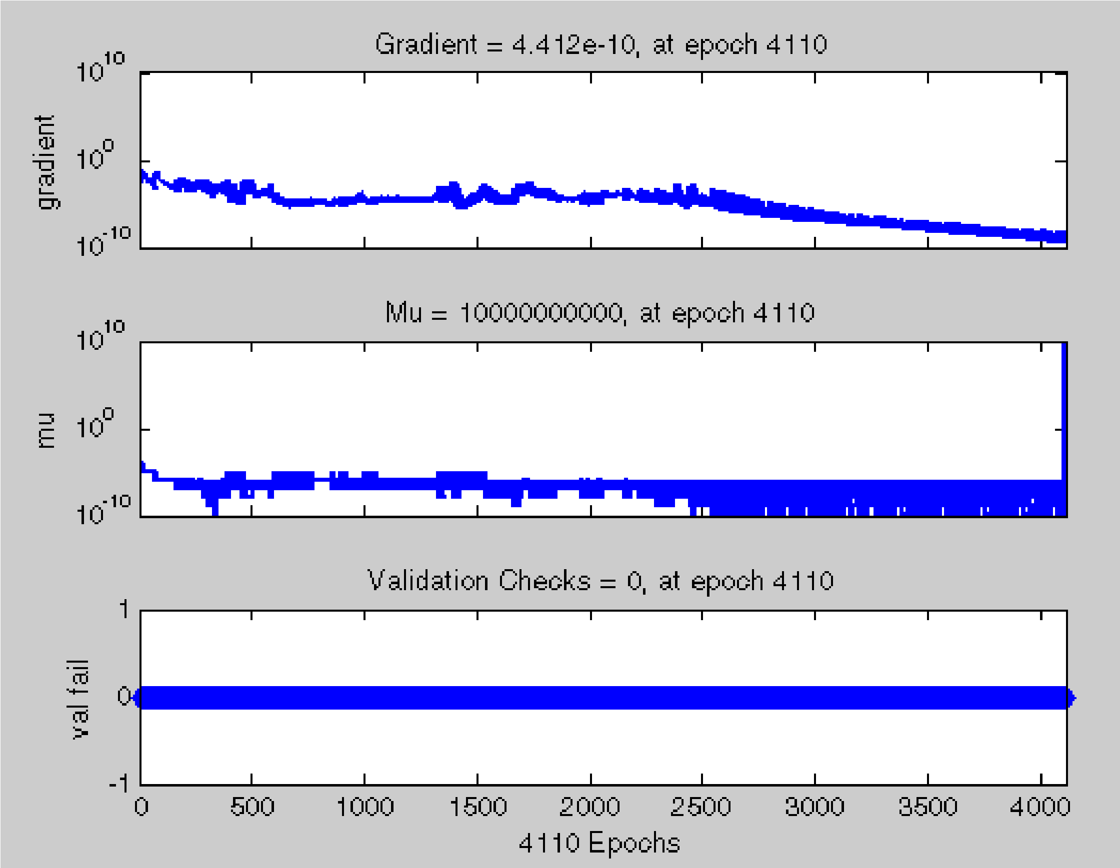

Figure 4 Training State

Figure 4, "Training State," serves as a snapshot of the ANN's training progress and performance at a given moment. It provides essential information for monitoring the training process, helping researchers and practitioners make informed decisions about potential adjustments to improve model performance in the context of soil behavior analysis.

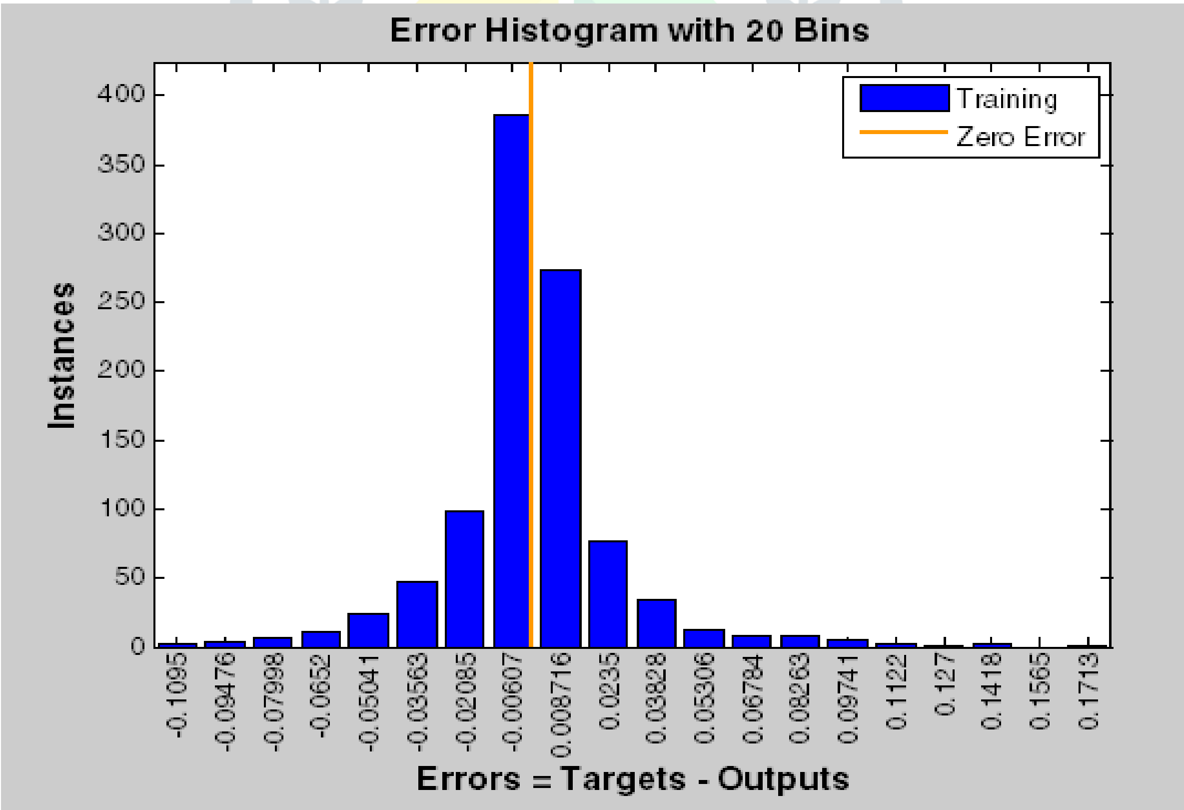

Figure 5 Error Histogram

Figure 5 Error Histogram is a useful diagnostic tool for assessing the ANN's performance in predicting soil behavior, helping identify potential issues with accuracy and guiding refinements to the model.

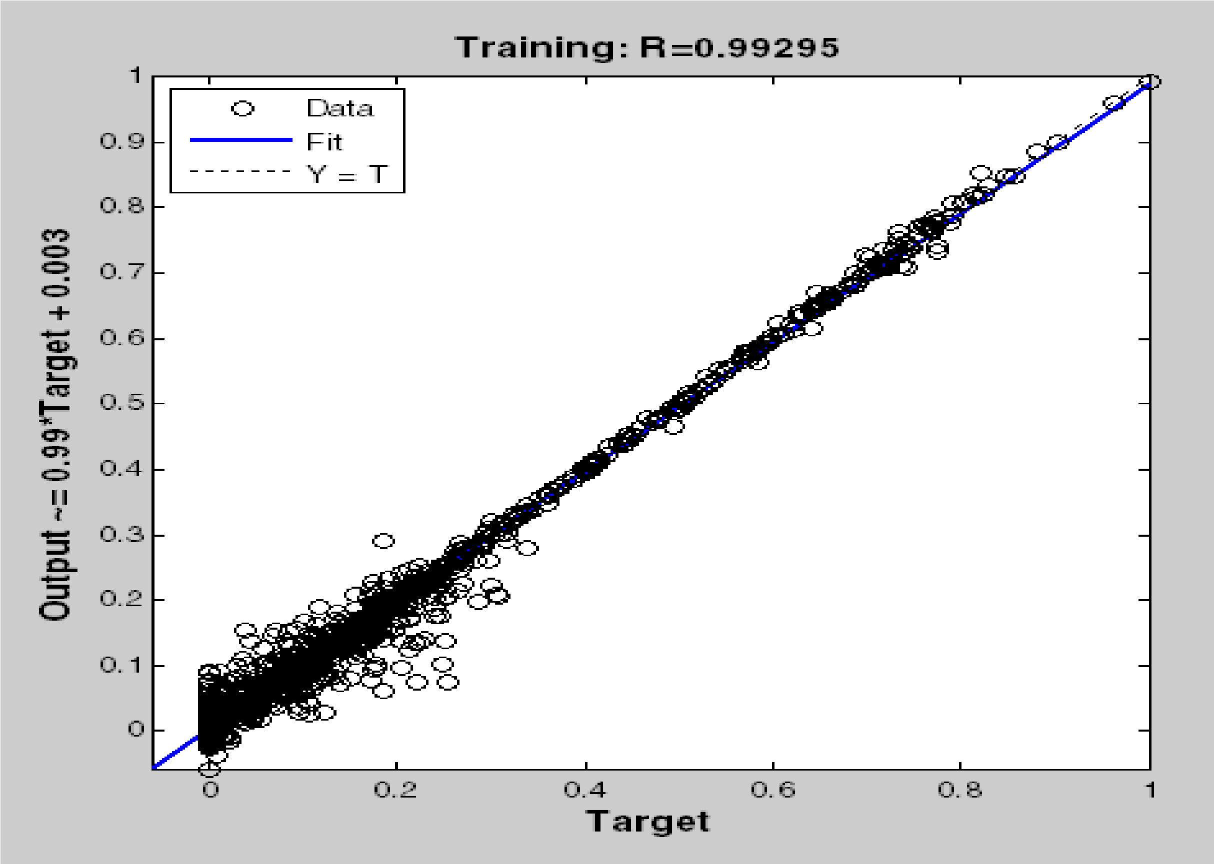

Figure 6 Regression Plot

Figure 6 Regression Plot serves vital tool for visualizing and assessing the performance of the ANN in predicting continuous outcomes related to soil behavior. It helps identify how well the model performs across different ranges of values and where adjustments may be needed for improved accuracy.

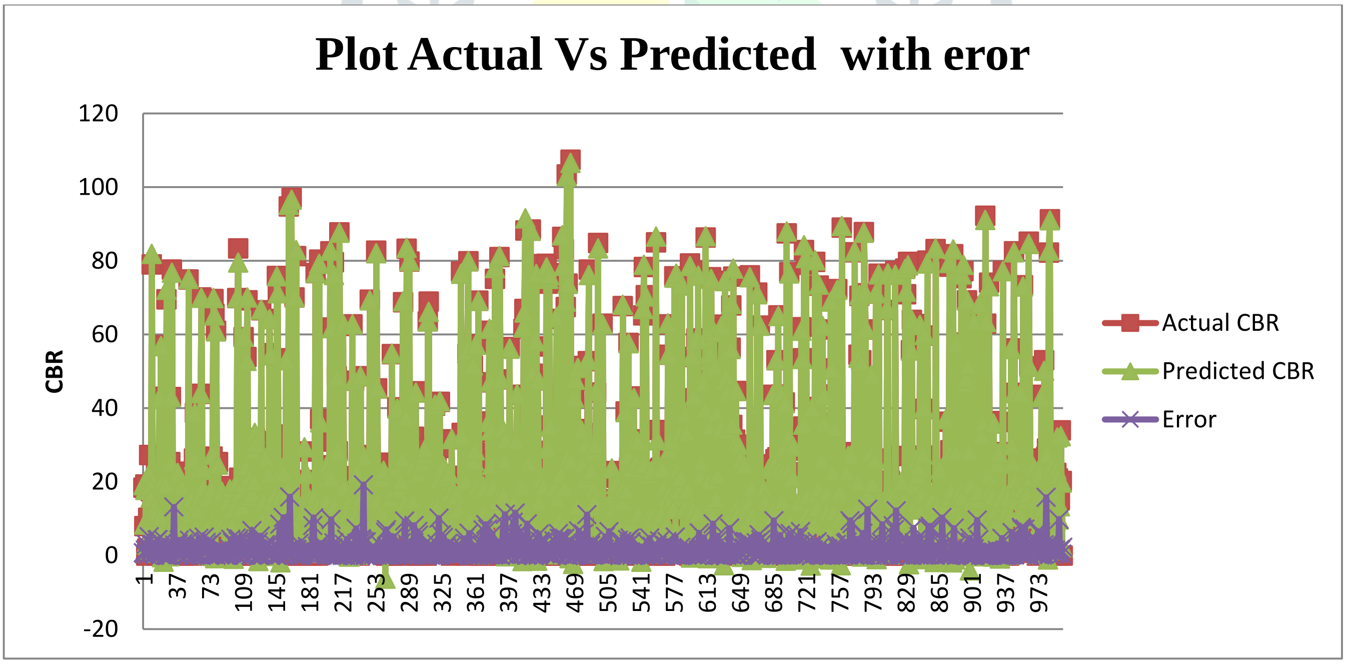

Figure 7 Compare

Figure 7 presents a comparison graph of predicted CBR values versus actual CBR values for a sample size of 1,000 data points. This graph is intended to visualize how closely the model's predictions align with the true CBR measurements, offering insights into the accuracy and reliability of the predictive model.

Sample

IV. Conclusion

This paper soil behavior using an Artificial Neural Network (ANN) has produced highly promising results, demonstrating significant effectiveness in predicting soil properties. The model recorded a Total Error of 1705.59, which, alongside an Average Error of 1.7056 per observation, reflects the model's precision in its predictions. These metrics highlight the ANN's capability to provide accurate estimates, especially when considering the Sum of Actual California Bearing Ratio (CBR) values, which totaled 22661.96.

The ANN's ability to capture complex relationships within soil data is crucial for applications in geotechnical engineering. Accurate predictions of soil behavior are essential for making informed decisions related to construction, design, and safety. This model can assist engineers and practitioners in assessing soil characteristics effectively, thereby facilitating better project planning and risk management. The promising results of this ANN model open avenues for further research and refinement. Future efforts may involve training the model with more diverse datasets to enhance its robustness and generalizability. Additionally, exploring hybrid approaches that integrate ANN with other machine learning techniques could lead to improved predictive performance.

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