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Predicting Resilient Modulus of Subgrade Soil Using Deep Learning Technique

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ABSTRACT

The evaluation of subgrade hardness generally depends on the utilisation of the M_R (resilient modulus) of the subgrade soils, which is a crucial factor to examine. This study is based on the use of Deep Learning technique (ANN) and machine learning equations, for determination the M_R of soil uses in subgrade layers which is an effective and reliable manner. According to AASSTO, A-4 group of soil is selected for this research. The research database has been developed based on 119 experimental test results. MR acts as an output parameter, including Liquid Limit, Plastic Limit, Optimum Moisture Content, Maximum Dry Density, and California Bearing Ratio as input factors. Machine learning algorithm and ANN model is created using Python programming language in Google Colab. Multiple machine learning (ML) techniques, such as linear regression, lasso regression, ridge regression, and K-nearest neighbours (KNN), are used along with the deep learning (DL) technique of BPNN (backpropagation neural network) and optimizer (Adam) is used for predicting M_R. The precision of the predicted data is evaluated using evaluation metrics such as MSE (mean squared error), R2 (R-squared), MAE (mean absolute error), and MAPE (mean absolute percentage error). The utilisation of Adam optimizers in BPNN results in a high level of precision when predicting MR findings, as seen by its high values of R2 and negligible error rates.

KEYWORDS: ANN (Artificial Neural Network), Machine Learning, M_R (Resilient Modulus)

1 INTRODUCTION

The assessment of M_R to describe subgrade soil is essential to flexible pavement design. This phenomenon is evaluated by estimating the deviator stress-recoverable strain ratio. The AASHTO (American Association of State Highway and Transportation Officials) requires the MR to test pavement layer material strength [1].

The Mechanistic-Empirical Pavement Design Guide (MEPDG) included the principles of resilient modulus (M_R) into the design of flexible pavements. Several researchers have examined the M_R performance of subgrade soils, with particular focus on the effects of several factors such as dry density, deviatoric stress, gradation (moisture content), shape, fines material, and stress state [2]– [4].

Resilient Modulus determination for subgrade soil is commonly conducted through the utilization of the Repetitive Load Triaxial (RLT) test. However, this examination necessitates the expertise of highly skilled individuals and the utilization of costly scientific apparatus. Furthermore, it is widely acknowledged that this task is relatively time-consuming. In recent decades, researchers have utilized empirical equations derived from prior work to ascertain the resilient modulus. Subgrade resilient modulus (M_R) is influenced by numerous factors, containing the support of soil value, R-value, CBR, Dynamic Cone Penetration Index and the physical characteristics of the soil [5]. The term "M_R" refers to the mechanical property known as the modulus ratio. It is mathematically expressed as the ratio between the ε_r (resilient strain) and σ_d (deviatoric stress), as depicted in Equation 1[6].

$$M_R = {}^{\sigma_d}/_{\varepsilon_r} \ldots\ldots\ldots\ldots\ldots (1)$$

The subgrade soils resilience is influenced by several factors, including the state of stress, MC (moisture content) fluctuations, variations of matric suction, and fundamental properties soil such as shape of particles, sieve analysis, size, LL (liquid limit), PL (plastic limit), PI (plasticity index), and percentage of fines (passing through sieve No. 200) [7]– [11]. According to prior study, it has been proved that the stress state and MC (moisture content) are the most influential components that affect the magnitude and modulus of rigidity of soil. Over the past five decades, numerous researchers have conducted investigations into the notable influence of stress levels on the modulus of resilience (M_R) of subgrade soils [12]– [14]. It showed that bulk stress has no appreciable effect on M_R at lower shear stress values, while at higher shear stress levels, bulk stress causes an increase in M_R. Numerous studies, however, have shown that shear stress (octahedral) has a substantial validity on the resilient modulus of delicate materials [15], [16]. The optimal solution can be found by using ANNs because they can combine and associate data from both literature and exploratory research. In a nutshell, ANNs can be used for forecasting, modelling, and simulation, as well as for recognizing patterns and making predictions. It is stated that such supervised interconnected networks can replace more traditional prediction methods when used with paving materials[17]–[19].

A developed a program called WESDEF that uses ANN models to retroactively determine moduli of pavement layers. Field data from a Falling Weight Deflectometer was used to teach ANN models to calculate the moduli of layers in a flexible pavement[20]. To relate with typical subgrade soil stress states and other parameters seen in pavement design. A system (neuro-fuzzy adaptive interface system) to make predictions regarding the behaviour of flexible pavements include subgrade soils. The estimation of compressed subgrade soils using the utilization of genetic programming and artificial neural networks [21]– [27]. The determination of this work is to establish and examine the current state of data on the M_R behaviour of subgrade soils using ANN and machine learning equation.

1.1 Problem Statement

This paper discusses the challenges associated with determining the strength properties of subgrade materials and MR values for different types of soil. The current approach involves time-consuming laboratory testing, which can be prone to errors due to variations in settings. This research aims to address these issues by exploring cost-effective methods that maintain accuracy and reliability. The study focuses on developing prediction models based on artificial neural networks (ANNs) to reduce reliance on laboratory testing.

1.2 Research Objectives

The primary objective is to evaluate the predictive capabilities of the ANN model in geotechnical scenarios by analysing its performance. Our aim is to improve the precision of strength characteristic predictions by optimising the structure and variables within the artificial neural network (ANN) model. This objective involves doing sensitivity assessments and fine-tuning parameters using well-established approaches outlined in existing literature. The dataset used in this study was obtained by analysing soil samples that included several variables to attain the intended outcome known as "M_R".

2 METHODILOGY

The methodology framework is shown in Figure A.

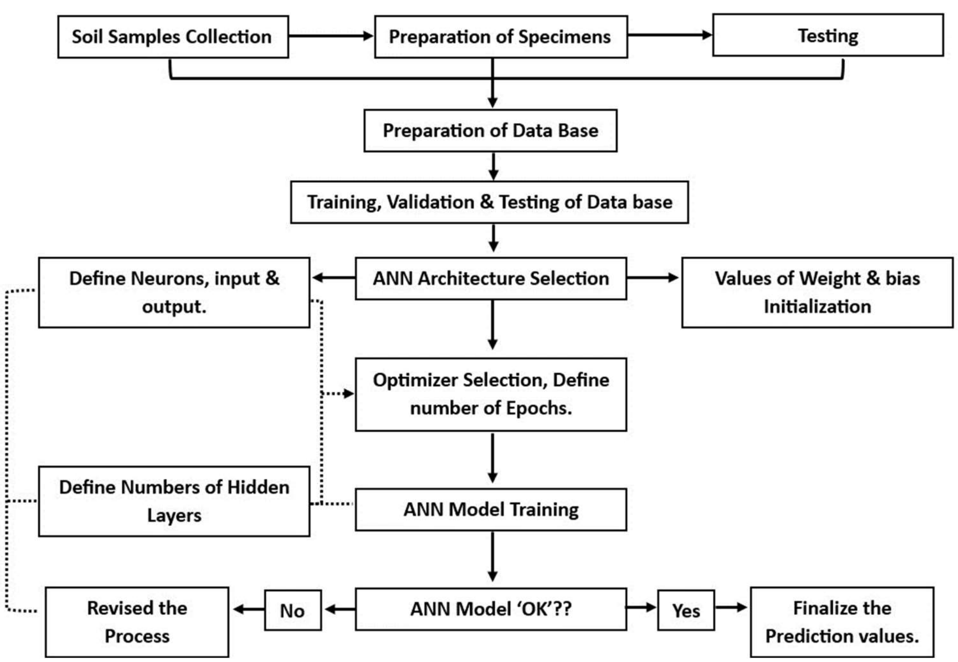

Figure A: Methodology Framework

2.1 Specimens Preparation & Testing

In this study, according to AASTTO, A-4 group soil is used for testing having different plasticity index. In order to define this soil, a series of tests was performed, such as: liquid limit and Plastic limit (ASTM D-4318) and CBR 95% T-193/180 Soaked. Experimental determinations of resilient modulus were carried out in accordance with the AASHTO T-307 standards procedures (AASHTO 2003). The samples were subjected to 1000 cycles of load in accordance with the AASHTO procedure. Performing the tests are shown in Figure 1.

Figure 1:(a) Liquid Limit Testing, (b) Plastic Limit Testing, (c) Triaxial Testing

3 RESULTS AND DISCUSSION

This section presents the findings from deep learning and machine learning algorithms, evaluates the errors, and determines the most optimal and effective model for predicting in the present study. Figure 1 presents a brief description of the statistical properties of the Subgrade soil (A-4), emphasizing important measures such as the max, min, standard deviation, range, variance and average values. These statistics provide valuable information on the distribution and average of M_R data. The matrix of correlations related to the database is displayed in Table 2. Additionally, the matrix contains negative correlation values, signifying the inverse relationship between the variables. The same is true for positive correlation, which shows a direct relationship between the two variables.

Table 2: Correlation of all Parameters

PARAMETERS	L.L (%)	P.L (%)	P.I (%)	OMC (%)	MDD (lb/ft³)	CBR (%)	MR (MPa)
L.L (%)	1	0.895813	0.426513	0.162366	-0.3334659	0.095498478	-0.27424345
P.L (%)	0.895813	1	-0.0199	0.065723	-0.2252932	0.032754478	-0.28392352
P.I (%)	0.426513	-0.0199	1	0.231507	-0.2916677	0.148175279	-0.03911875
OMC (%)	0.162366	0.065723	0.231507	1	-0.3068078	0.205607828	0.056718787

MDD (lb/ft³)	-0.33347	-0.22529	-0.29167	-0.30681	1	-0.35207406	-0.0312548
CBR (%)	0.095498	0.032754	0.148175	0.205608	-0.3520741	1	0.361882202
MR (MPa)	-0.27424	-0.28392	-0.03912	0.056719	-0.0312548	0.361882202	1

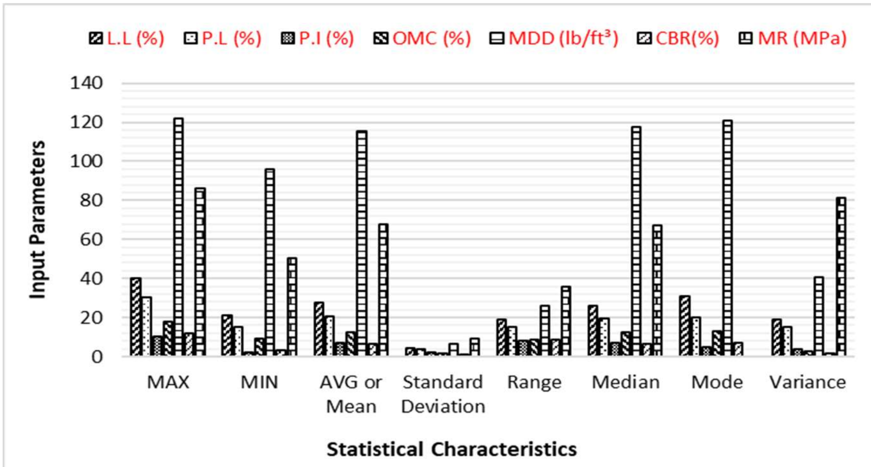

Figure 2: Statistical Properties of Provided Parameters

3.1 Machine Learning Models

This section includes the findings of basic regression models such as Linear, KNN, Lasso and Ridge. The results are shown in Figure 3.

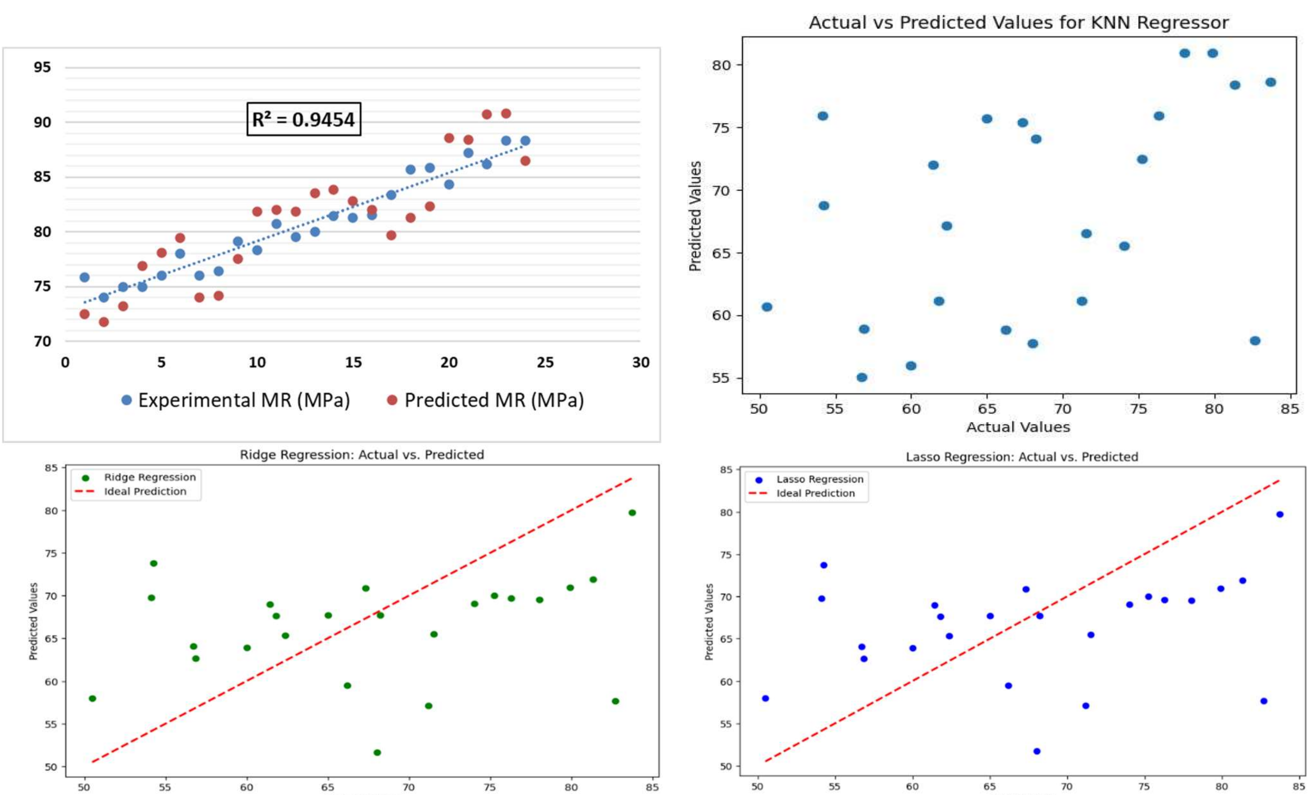

Figure 3. Different Regression model graphs

3.2 BPNN (Back propagation neural network)

The application of the BPNN method in the ANN algorithm's prediction of MR results in a significant correlation between experimental and predicted values. The fundamental operational mechanism of the Artificial Neural Network (ANN) is illustrated in Figure 4 while the results of BPNN are shown in Figure 5. The Model of ANN was developed from 119 datasets of resilient modulus values obtained from laboratory tests.

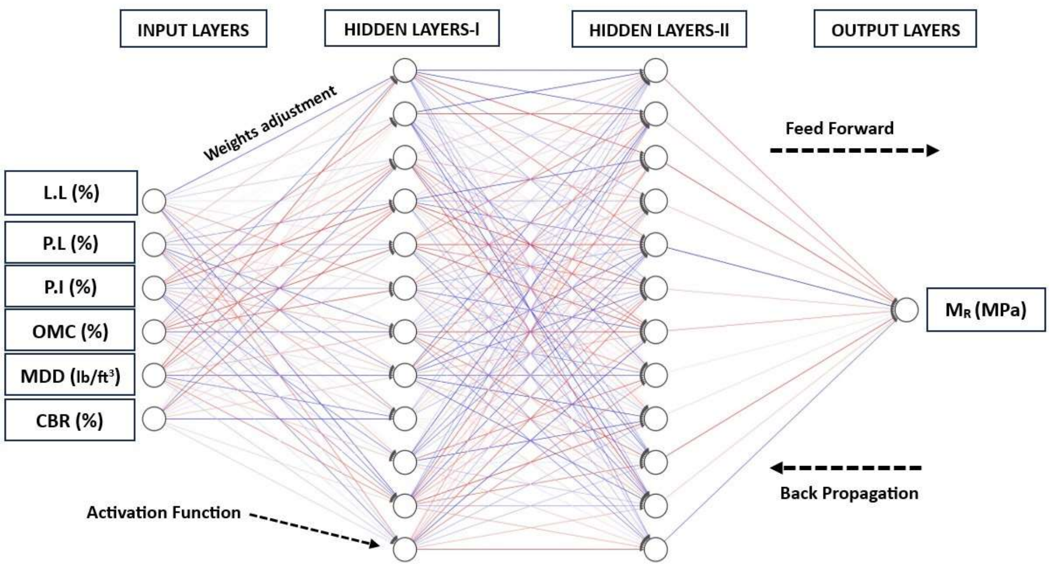

Figure 4: Architecture of ANN Model

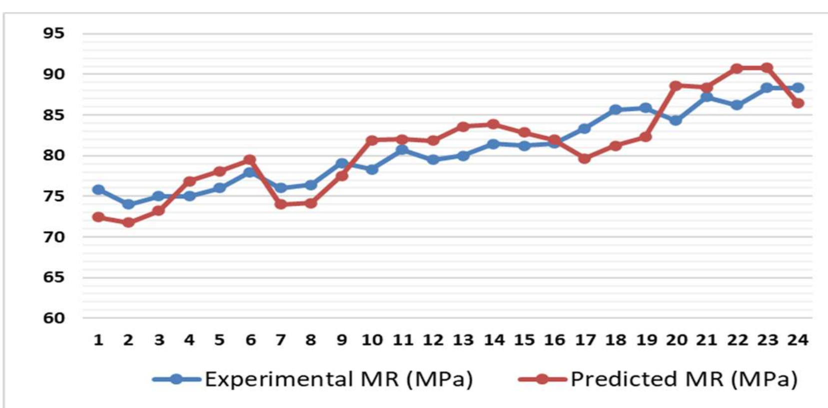

Figure 5: Back Propagation Results

4 PRACTICAL APPLICATION

ANNs predict resilient modulus to optimise pavement, selection of materials and structural integrity. Use resilient modulus predictions to evaluate in-place materials for real-time building quality control. Infrastructure planning benefits from ANNs' geotechnical structure stability and resilience assessments. This helps climate impact studies predict how environmental influences affect resilient modulus. ANNs advise on new projects and optimise loose material characteristics for economical construction in feasibility studies.

5 CONCLUSION

- The regression analysis and correlation matrix revealed the relationships and impacts among different factors present in the database.
- The values obtained from experiments revealed an accurate association between them. The statistical measures, such as the experimental-to-predicted MR ratio, served as indicators of the precision of the algorithms used in M_R prediction.
- The artificial neural network (ANN) models exhibited their effectiveness in accurately predicting MR readings, displaying exceptional performance. These models are highly significant resources in geotechnical construction for estimating the magnitude of risk, facilitating more efficient and accurate decision-making in various building projects.

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