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Prediction of Strength Properties of Soft Soil Using Machine Learning Techniques

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Abstract **Original Research Article**

In civil engineering projects, the strength of soil, particularly its cohesion, is pivotal for the stability of building foundations and slopes. Traditionally, determining cohesion (c) involves labor- intensive methods such as unconfined compression tests, direct shear tests, and triaxial tests, which require collecting soil samples. However, these methods are often constrained by time and cost considerations, exacerbated by the diverse nature of soil types. This research initiative aims to introduce a simplified approach for assessing the cohesion strength parameter of cohesive soil. Our proposal entails leveraging statistical correlations and machine learning techniques to establish connections between soil properties such as liquid limit, plastic limit, moisture content, % fine particle content, and the strength parameter. These laboratory tests are comparatively straightforward, rapid, and cost-effective when juxtaposed with conventional methodologies.

Keywords: Cohesion, Machine Learning Techniques, Prediction of strength of soil Properties Background.

INTRODUCTION

Soft soil is a common geotechnical challenge faced in many construction projects. The strength properties of soft soil are crucial for designing foundations, determining bearing capacities, and ensuring the stability of structures. Soft soil exhibits low strength characteristics, which can lead to settlement, instability, and failure of structures. Traditional methods of determining the strength properties of soft soil are time-consuming and expensive. Therefore, there is a need to develop a reliable and efficient prediction model that can estimate the strength properties of soft soil using easily measurable soil parameters. Important soil parameters for assessing geotechnical properties are SPT-N value, Dry Density, Moisture content, Particle size distribution (Cu, Cc), Liquid limit, Plastic Limit etc. The resistance property of soil can be measured by its SPT-N value during the soil penetration test. Dry Density refers to the mass of soil per unit volume when it is completely in a dry state. Moisture content, expressed as a percentage of the dry weight of soil, indicates the amount of water present in the soil. Particle size distribution provides in- formation about the distribution and composition of soil particles across different size ranges. Atterberg limits such as Liquid limit which is the moisture con- tent at which fine grained soil transitions from a liquid- like to a plastic state and Plastic limit which is the moisture content at which fine-grained soil transitions from a plastic state to a semi-solid state. The stability and capability of a soil to adjust when facing overburden loads and loading from structures, are greatly impacted by the shear strength of soil. This shear strength parameter is important in terms of soil stability which denotes how much shear stress a soil can take before sliding down. The shear strength parameter, especially the cohesion value of soil is of prime importance in the case of different foundation designs.

In the field of civil engineering, accurately predicting cohesion strength parameters in soft soils is crucial for ensuring the stability of various structures, including foundations and embankments. Traditionally, determining cohesion requires complex and expensive laboratory tests, such as unconfined compression tests and triaxial tests, which are time-consuming and resource intensive. To address these challenges, this research aims to propose a more efficient approach for estimating cohesion strength parameters in cohesive soils, with a specific focus on the city of Bangladesh (Dhaka). By leveraging statistical correlations and machine learning techniques, this approach seeks to establish relationships between soil properties such as liquid limit, plastic limit, moisture content, and the percentage of fines, and cohesion strength. By utilizing simpler and more cost- effective laboratory tests, this research endeavors to provide civil engineers with a practical tool for accurately assessing cohesion strength parameters, ultimately contributing to the stability and safety of civil engineering projects in the Bangladesh.

Soil parameter assessments are crucial for geotechnical engineers and builders, guiding decisions related to soil bearing capacity, slope stability, foundation design, and other critical aspects of construction. These parameters serve as fundamental indicators of soil behavior and directly influence the safety and stability of structures.

Key soil parameters include dry density, moisture content, particle size distribution (Cu and Cc), liquid limit, plastic limit, and SPT-N value. The SPT-N value, obtained from soil penetration tests, offers insights into soil resistance properties, while dry density and moisture content reflect soil composition and water content. Particle size distribution provides valuable information about soil particle distribution, while Atterberg limits (liquid and plastic limits) characterize soil behavior at different moisture levels.

Problem Statement

Soft soil poses a challenge for construction because it lacks the strength needed for stability. Before building on it, we must accurately predict its strength. However, traditional testing methods are slow and expensive.

To address this, we aim to develop a computer program that can predict soil strength quickly and affordably. We'll use advanced math techniques like Support Vector Machine (SVM), Long Short- Term Memory (LSTM), and Artificial Neural Networks (ANN) to build this program. These techniques are like special tools that help us make accurate predictions while saving time and money.

By creating this program, we hope to make construction on soft soil safer and more cost-effective. Builders can use it to make informed decisions, reducing the risks associated with soft soil construction projects."

Significance

Cost and Time Efficiency

Traditional methods for assessing soil strength properties often involve extensive laboratory testing, which can be time-consuming and costly. By utilizing simple soil parameters, engineers can develop predictive models that offer quick and cost-effective assessments of soil strength properties. This efficiency can lead to reduced project timelines and lower overall costs.

Improved Site Characterization

Soft soils pose unique challenges due to their low bearing capacity and high compressibility. Understanding the strength properties of these soils is critical for site characterization and foundation design. By incorporating simple soil parameters into predictive models, engineers can gain valuable insights into soil behavior, enabling more accurate site assessments and foundation designs.

Research Organization

Predicting the strength properties of soft soil entails a systematic process relying on empirical correlations or mathematical models derived from experimental data. Here's a breakdown of the steps involved in predicting soil strength properties using easily obtainable soil parameters.

Identify Simple Soil Parameters

Begin by pinpointing straightforward soil parameters that are readily accessible or easily measurable. These parameters encompass factors like grain size distribution, Atterberg limits (including liquid limit, plastic limit, and plasticity index), soil moisture content, density (both bulk and dry density), pH level, organic matter content, and soil classification (such as clay, silt, or sand).

Collect Experimental Data

Compile a comprehensive dataset containing both the identified simple soil parameters and corresponding strength properties. This dataset should cover a diverse range of soil types and conditions representative of soft soils under examination. Data collection may involve conducting laboratory tests, field investigations, or utilizing existing databases.

Develop Empirical Correlations or Mathematical Models

Utilize statistical analysis techniques or machine learning algorithms to establish empirical correlations or mathematical models. These models elucidate the relationships between the simple soil parameters and soil strength properties. Common modeling approaches encompass Artificial Neural Network (ANNs), Lasso Regression Method, Recursive Features Elimination, LSTM.

Verify the constructed models by employing separate datasets that were not involved in the model creation process. The validation of models aims to assess their precision, dependability, and ability to generalize, facilitating the detection of any potential constraints and uncertainties associated with them.

Validate the Models

Validate the developed models using independent datasets that were not utilized in the model development phase. Model validation serves to gauge the accuracy, reliability, and generalization capacity of the predictive models, aiding in identifying potential limitations and uncertainties associated with them.

MATERIAL AND METHODS

Study Area

Our research focused on the collection of soil samples from various sites within Dhaka city (Bangladesh), where we identified the prevalence of silty clay soil. These samples were primarily sourced from locations exhibiting a predominance of fine particles, surpassing other soil components by a factor of 8 to 9. Emphasis was placed on obtaining undisturbed soil samples. Collection was carried out at varying depths, including 2.5 m, 5 m, 10 m, and 15 m below the surface. Following collection, samples were carefully placed in sturdy, labeled, and sealed polythene bags before transport to the laboratory for analysis.

Methods

Support Vector Machine

Support Vector Machine (SVM) stands out as one of the most powerful machine learning algorithms for both regression and classification tasks. It operates by identifying the optimal hyperplane that best separates different classes within a high-dimensional space, effectively delineating data points. The key objective of SVM is to maximize the margin, which represents the distance between the hyperplane and the nearest data points from each class. This margin optimization strategy enhances the algorithm's ability to generalize well to new, unseen data. SVM finds extensive applications across various domains, including image recognition, text classification, and bioinformatics, thanks to its remarkable performance, especially with complex datasets. The versatility of SVM is further amplified by the incorporation of kernel functions, which empower it to handle intricate non-linear relationships with ease.

Long Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN), are increasingly recognized as invaluable tools in civil engineering due to their unique ability to capture temporal dependencies and handle sequential data. Within the realm of civil engineering, where understanding and forecasting temporal trends are crucial, LSTM models find applications across a spectrum of tasks. Whether it's predicting structural behavior over time, forecasting traffic flow patterns, or optimizing energy consumption in buildings, LSTM models excel at extracting meaningful patterns from sequential data, thereby empowering engineers to make more informed decisions and optimize the performance of infrastructure systems.

By leveraging LSTM models, civil engineers can gain deeper insights into the dynamic behavior of infrastructure systems and make proactive decisions to enhance their efficiency, resilience, and sustainability. These models enable engineers to analyze historical data, identify trends, and forecast future scenarios with greater accuracy. For instance, in transportation engineering, LSTM models can predict traffic congestion patterns based on historical traffic data, allowing for better traffic management strategies. Similarly, in structural engineering, LSTM models can forecast the deterioration of bridges or buildings over time, facilitating timely maintenance and ensuring structural integrity. In essence, LSTM models offer a powerful computational framework that equips civil engineers with the tools needed to address the complex temporal dynamics inherent in civil infrastructure systems.

Artificial Neural Networks (ANNs)

In civil engineering, Artificial Neural Networks (ANNs) have found various applications due to their ability to learn complex patterns and relationships from data. Here's how ANNs are utilized in civil engineering;

Predictive Modeling

ANNs are used for predictive modeling in civil engineering tasks such as estimating structural loads, predicting material properties, and forecasting environmental factors like rainfall and temperature. These models help engineers make informed decisions during the design and construction phases of projects.

Application in Geotechnical Engineering

ANNs are utilized in geotechnical engineering for tasks such as predicting soil behavior, slope stability analysis, and groundwater modeling. By analyzing historical data on soil properties, ANNs can assist in site characterization, risk assessment, and optimization of construction processes.

Overall, ANNs offer a powerful tool for analyzing complex data in civil engineering applications, enabling engineers to make more accurate predictions, optimize designs, and improve the efficiency and safety of civil infrastructure projects. In civil engineering, Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN), can be applied to various tasks due to their ability to capture temporal dependencies and handle sequential data. Top of Form.

Recursive Feature Elimination

Recursive Feature Elimination (RFE) is a technique used for feature selection, particularly in machine learning tasks where there are a large number of features or predictors.

Recursive Feature Elimination

Recursive Feature Elimination (RFE) is a technique used for feature selection, particularly in machine learning tasks where there are a large number of features or predictors. Its primary goal is to identify the most relevant features that contribute the most to the predictive performance of a model.

The key idea behind Recursive Feature Elimination is that by iteratively removing the least important features and re-evaluating the model's performance, it progressively identifies and retains only the most relevant features for the task at hand. This helps in reducing the dimensionality of the feature space, improving model interpretability, and potentially enhancing predictive performance by focusing on the most informative features.

It's worth noting that the choice of the initial model and the stopping criterion are crucial aspects of the RFE process, and they may vary depending on the specific problem and the chosen algorithm. Additionally, RFE can be computationally expensive, especially with a large number of features, but it often provides a powerful and interpretable feature selection method.

Lasso Regression Method

Lasso regression, short for Least Absolute Shrinkage and Selection Operator, is a regularization technique used in linear regression models to prevent overfitting and improve model performance. It achieves this by introducing a penalty term to the standard linear regression objective function, which encourages the model coefficients to be sparse (i.e., many coefficients become exactly zero). This sparsity feature of lasso regression makes it useful for feature selection, where only the most important predictors are retained in the model. Mathematically, lasso regression minimizes the following objective function:

Lasso regression is particularly useful when dealing with datasets containing a large number of predictors, as it can automatically select the most relevant features while discarding the irrelevant ones. However, it is important to tune the regularization parameter λ carefully to balance between model simplicity and predictive performance. Cross-validation techniques are often employed to find the optimal value of λ.

Performance Evaluators

R-Square

A statistical metric known as R-squared, or the coefficient of determination, quantifies the extent to which the independent variables in a regression model account for the fraction of the dependent variable's variance that is explained. The R-squared value can be anywhere from 0 to 1, with larger values suggesting that the model fits the data better. It is a measure of how much of the total variation in the dependent variable can be explained by the regression model. Although R-squared shows how well the model accounts for the data, it doesn't show whether the model was accurate or whether there is a causal relationship between the variables.

Root Mean Square Error

When gauging the accuracy of a predictive model, the Root Mean Squared Error (RMSE) is frequently utilized in statistics and machine learning domains. It serves a similar function to Mean Absolute Error (MAE) by quantifying the average discrepancy between predicted and actual values. However, RMSE accentuates larger errors by squaring the average squared deviations. Lower RMSE values indicate superior model performance, reflecting the model's ability to predict numerical outcomes effectively. RMSE proves particularly useful in evaluations where larger errors should be penalized more severely.

Relative Root Mean Square Error

In statistical analysis, assessing the performance of a predictive model often involves considering its RRMSE, or relative root mean squared error, especially in regression tasks. RRMSE offers a normalized version of the RMSE by dividing it by the mean of the observed values. This metric proves valuable for comparing models across different datasets or scales due to its percentage form and relative assessment of model performance. A lower RRMSE indicates a better fit of the model to the data, taking into account the magnitude of the observed values.

Mean Average Error

The Mean Average Error (MAE), also referred to as Mean Absolute Error, serves as a measure to assess the accuracy of a predictive model. It quantifies the average absolute disparity between the predicted values and the actual values. Mathematically, it computes the average of the absolute discrepancies between predicted and actual values: MAE offers a straightforward evaluation of the Proximity between predictions and actual outcomes, with smaller MAE values indicating higher accuracy. It is especially beneficial when the errors need to be interpreted directly in the units of the target variable.

RESULTS AND DISCUSSION

This study is centered around utilizing two advanced machine learning techniques, Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN), to predict the undrained shear strength of soft soil in Dhaka, Bangladesh. Soft soil presents unique challenges in construction and engineering due to its low bearing capacity and susceptibility to settlement, making accurate predictions of its strength crucial for ensuring the stability and safety of structures built upon it.

To begin the research process, the input data related to soft soil characteristics, including wet basis, liquid limit (LL), plastic limit (PL), and fines, undergoes preprocessing. This step involves cleaning the data, handling missing values, and standardizing or normalizing the features to ensure uniformity and optimal performance during modeling. Furthermore, feature engineering techniques may be applied to extract relevant information from the dataset, potentially uncovering hidden patterns or relationships that can enhance the predictive capabilities of the models. For instance, combining certain features or creating new features based on domain knowledge can contribute to the overall effectiveness of the predictive models.

Subsequently, both LSTM and ANN models are implemented and trained using the preprocessed data. These models are then evaluated based on their ability to accurately predict the undrained shear strength of soft soil. Through rigorous experimentation and analysis, the performance of the models is assessed across various metrics such as R^2, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Hyperparameter tuning plays a pivotal role in optimizing the performance of the LSTM and ANN models. Parameters such as the number of hidden layers, number of nodes in each layer, choice of activation functions (e.g., sigmoid, tanh, ReLU), and optimization algorithms (e.g., Adam, RMSprop, SGD) are systematically adjusted and fine-tuned to achieve the best possible predictive accuracy.

By focusing exclusively on LSTM and ANN techniques, this study aims to provide a thorough understanding of their applicability in predicting the undrained shear strength of soft soil. The insights gleaned from this research can prove invaluable for engineers, geotechnical experts, and researchers involved in construction, infrastructure development, and urban planning, facilitating better decision-making processes and ultimately contributing to the safety and stability.

Results of the Long-Short Term Memory (LSTM)

The LSTM model is built with an input layer, a single LSTM layer, and an output layer. The input data is reshaped to fit the LSTM's format with one time step and three input features (Wet basis, Liquid Limit, Plastic Limit, and Fines). The hidden layer consists of 64 neurons with a Leaky ReLU activation function, and the output layer has a single unit.

Performance metrics such as R^2, MSE, NSE, and RMSE are used for evaluation, with Mean Squared Error (MSE) as the selected loss function due to its easy interpretability. The model is evaluated across 28 combinations of activation functions (Relu, tanh, sigmoid, ELU, SoftMax, and leaky Relu) and optimizers (Adam, Sgd, Rmsprop, Adagrad, and Nadam), varying the number of hidden layers, nodes in each layer, batch size, and epochs.

The results of all trials were ranked using compromise programming, which identified Leaky ReLU as the optimal activation function and Adam as the optimal optimizer, with 1000 epochs and a batch size of 128. Graphs are utilized to visualize the outcomes, including scatter plots, line plots, and swarm plots. The scatter plots show the relationship between predicted and actual undrained shear strength values for both training and testing datasets, highlighting the model’s ability to capture the general trend with some deviation at higher values.

The LSTM model's performance was evaluated using key statistical metrics: R^2, MSE, RMSE, and MAE. These metrics provide insights into the model's accuracy and reliability in predicting the undrained shear strength of soil. The performance evaluation metrics for both training and testing phases are summarized in the table below:

Table 3.1 Performance evaluation metrics of LSTM model

Performance Metrics	Training	Testing
R^2	0.628	0.529
MSE	5044.00	7563.15
RMSE	71.02	86.97
MAE	51.03	66.91

The results indicate that the LSTM model has a moderate level of accuracy in predicting the undrained shear strength of soil. The R^2 values suggest a reasonable fit for both training and testing datasets, with a slightly higher accuracy during the training phase. The lower values of MSE, RMSE, and MAE during training demonstrate the model's ability to learn the underlying patterns in the data effectively. However, the increased error metrics in the testing phase highlight the challenges in generalizing the model to unseen data, suggesting potential areas for further optimization and refinement.

These metrics underscore the importance of careful hyper parameter tuning and model validation to enhance predictive performance. The findings from this study indicate that while the LSTM model is robust, incorporating additional data and refining model parameters could further improve its accuracy and reliability in practical applications.

This scatter plot visualizes the predictions made by the LSTM model developed as part of this thesis. Each point on the plot represents a data point from the testing dataset, with the x-axis indicating the actual values and the y-axis showing the corresponding predicted values by the LSTM model.

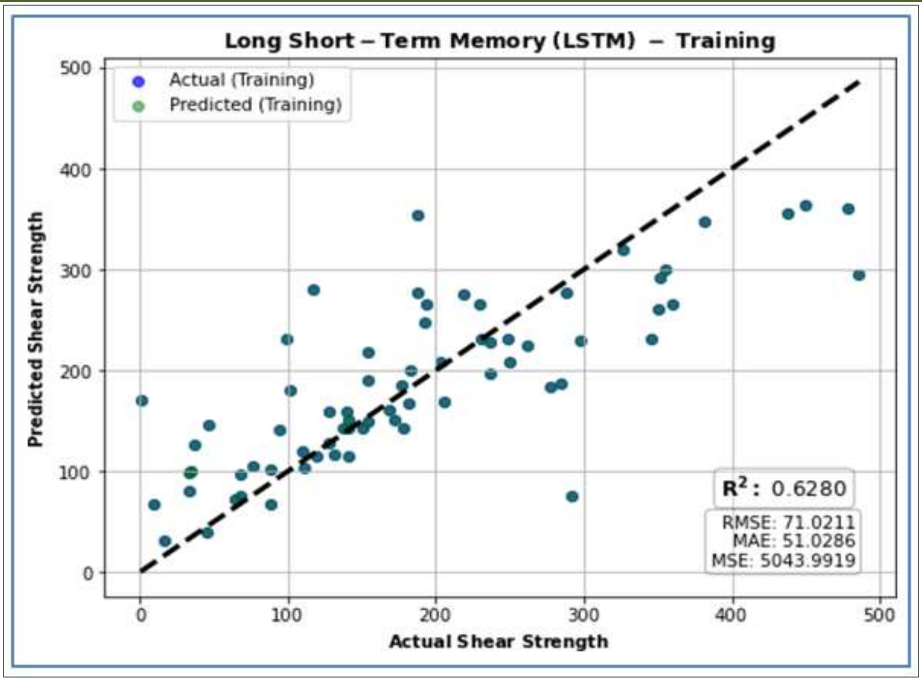

Figure 3.1: LSTM model's training scatter plot for undrained shear strength prediction

The scatter plot showcases the relationship between the predicted and actual values of the target variable on the testing dataset. Each point on the plot represents a data point from the testing dataset, with its position reflecting the model's prediction and the actual value. The distribution of points relative to the diagonal line (y = x) offers insights into the generalization ability of the model to unseen data. Close alignment between predicted and actual values suggests effective model performance on the testing dataset.

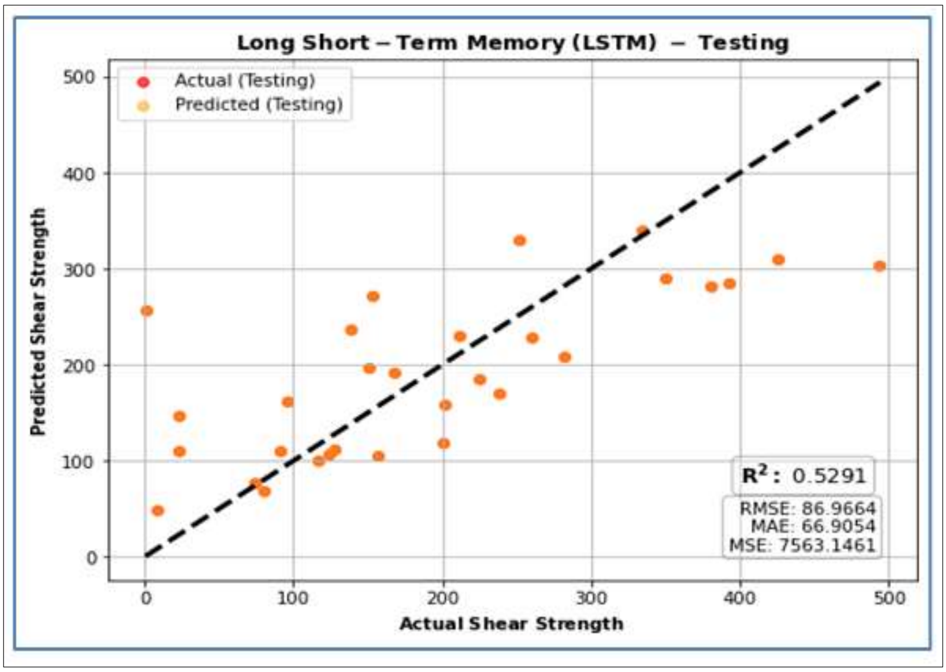

Figure 3.2: LSTM model's testing scatter plot for undrained shear strength prediction

The line plot illustrates the performance metrics of the LSTM model on the training dataset across multiple epochs. The x-axis represents the number of epochs, while the y-axis displays the values of the performance metrics. Performance metrics such as Mean Squared Error (MSE) or Loss are commonly plotted to assess the model's training progress over time. A decreasing trend in the plotted metrics indicates the model's improvement in fitting the training data as training progresses.

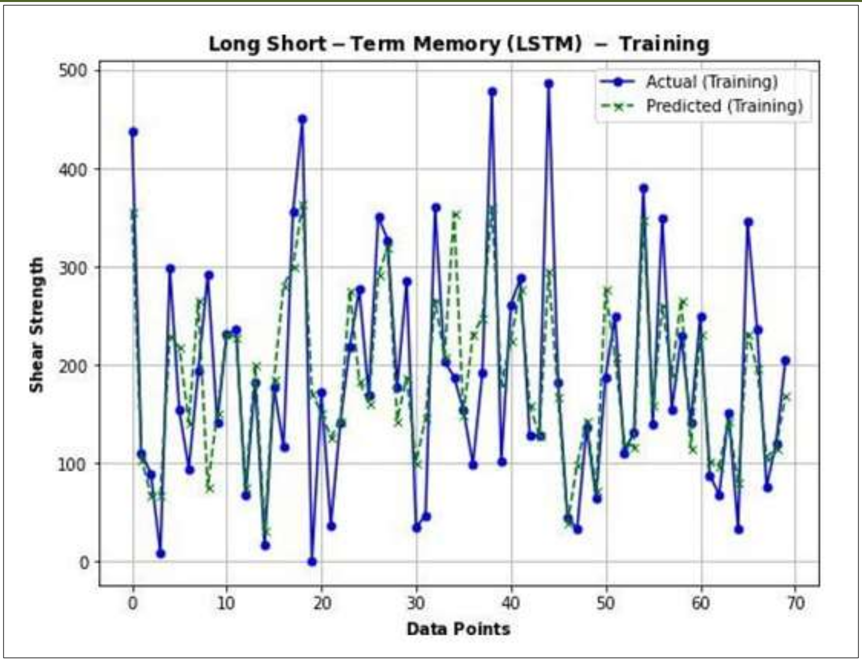

Figure 3.3: LSTM model's training line plot for undrained shear strength prediction

The line plot showcases the performance metrics of the LSTM model on the testing dataset across multiple epochs. Similar to the training plot, the x-axis represents the number of epochs, while the y-axis displays the values of the performance metrics. These metrics provide insights into how well the model generalizes to unseen data as training progresses. Consistent or decreasing trends in the plotted metrics indicate the model's ability to maintain or improve its performance on the testing dataset over time.

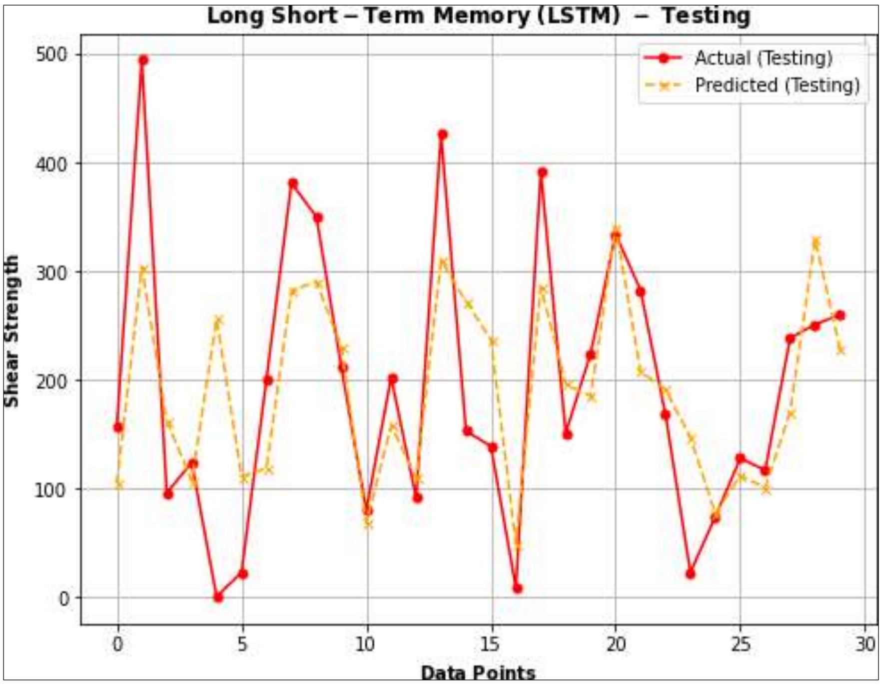

Figure 3.4: LSTM model's testing line plot for undrained shear strength prediction

The swarm plot visually presents the distribution of predicted discharge values generated by the LSTM model developed as part of this study. Each dot on the plot represents a predicted discharge value, with the x-axis representing the range of discharge values and the y-axis indicating the frequency or density of occurrences. The plot provides insights into the model's accuracy in predicting discharge across the entire range of values.

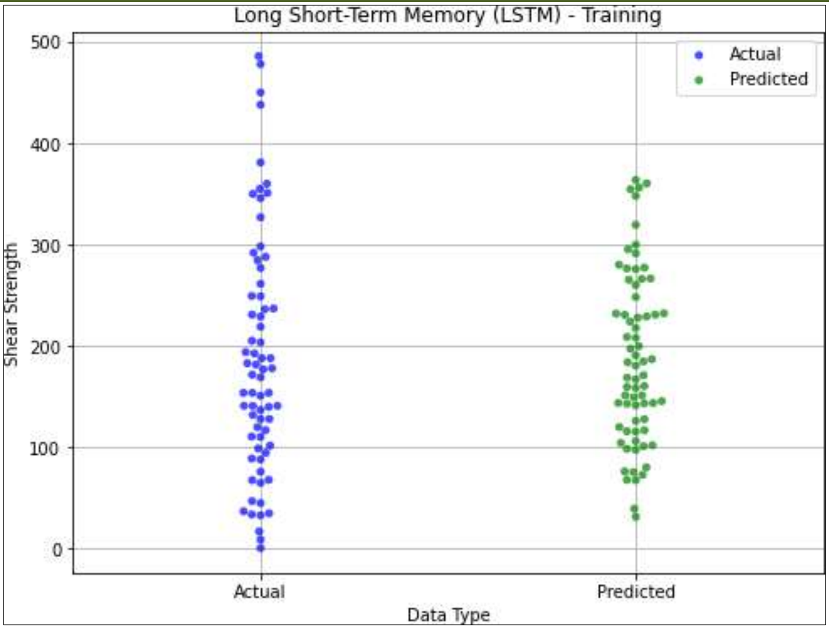

Figure 3.5: LSTM model's training swarm plot for undrained shear strength prediction

Figure 3.6: LSTM model's testing swarm plot for undrained shear strength prediction

The color-coded dots differentiate between observed discharges values from the training and testing datasets. The proximity of the dots to the observed values indicates the model's ability to accurately predict discharge rates. A dense cluster of dots around specific discharge values suggests a high frequency of occurrences in the dataset, while outliers may indicate instances where the model's predictions deviate from the observed values.

Results of the Artificial Neural Networks (ANNs)

The ANN model is constructed with an input layer, a single hidden layer, and an output layer. The input data is formatted to accommodate the ANN's structure with three input features (Wet basis, Liquid Limit, Plastic Limit, and Fines). The hidden layer comprises 64 neurons with Leaky ReLU activation function, while the output layer consists of a single unit.

Evaluation metrics such as R^2, MSE, NSE, and RMSE are utilized, with MSE serving as the chosen loss function due to its interpretability. The model undergoes evaluation across 28 combinations of activation functions (ReLU, tanh, sigmoid, ELU, SoftMax, and Leaky ReLU) and optimizers (Adam, SGD, RMSprop, Adagrad, and Nadam), varying parameters like the number of hidden layers, nodes per layer, batch size, and epochs.

The results of these evaluations are ranked using compromise programming, leading to the identification of Leaky ReLU as the optimal activation function and Adam as the optimal optimizer. The model is trained for 1000 epochs with a batch size of 128. Graphical representations including scatter plots, line plots, and swarm plots are employed to visualize outcomes. Scatter plots depict the relationship between predicted and actual undrained shear strength values for both training and testing datasets, illustrating the model's ability to capture the general trend albeit with some deviation at higher values.

The performance of the ANN model is assessed using key statistical metrics: R^2, MSE, RMSE, and MAE, providing insights into its accuracy and reliability in predicting the undrained shear strength of soil. Performance evaluation metrics for both training and testing phases are summarized in the following table:

Table 3.2: Performance evaluation metrics of ANN model

Performance Metrics	Training	Testing
R^2	0.84	0.46
MSE	2091.55	8657.94
RMSE	34.14	93.04
MAE	45.73	76.39

The scatter plot visualizes the relationship between the predicted and actual values of the target variable during the training phase of the ANN model. Similar to the testing scatter plot, each point represents a data point from the training dataset, with the x-axis indicating the actual values and the y-axis representing the corresponding predicted values by the ANN model. The alignment of the points relative to the diagonal line (y = x) reflects the model's performance in fitting the training data. Ideally, points should cluster closely around the diagonal line, indicating accurate predictions and a good fit of the model to the training data.

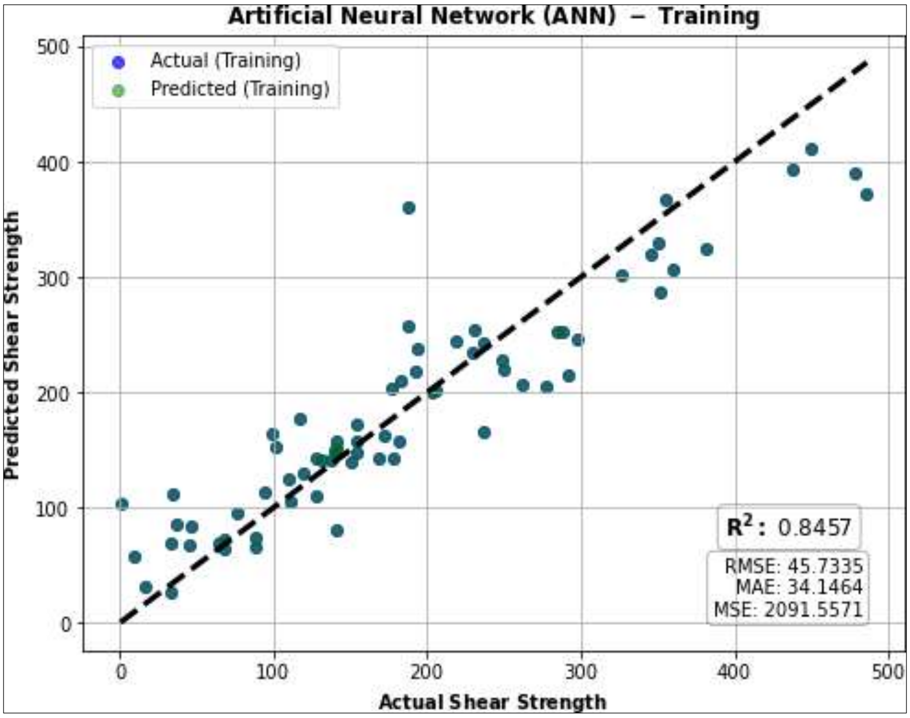

Figure 3.7: ANN model's training scatter plot for undrained shear strength prediction

The scatter plot illustrates the relationship between the predicted and actual values of the target variable during the testing phase of the ANN model. Each point on the plot represents a data point from the testing dataset, with the x-axis indicating the actual values and the y-axis representing the corresponding predicted values generated by the ANN model. The proximity of the points to the diagonal line (y = x) provides insights into the accuracy of the model's predictions. Points that cluster closely around the diagonal line indicate accurate predictions, while deviations from the line suggest discrepancies between the predicted and actual values.

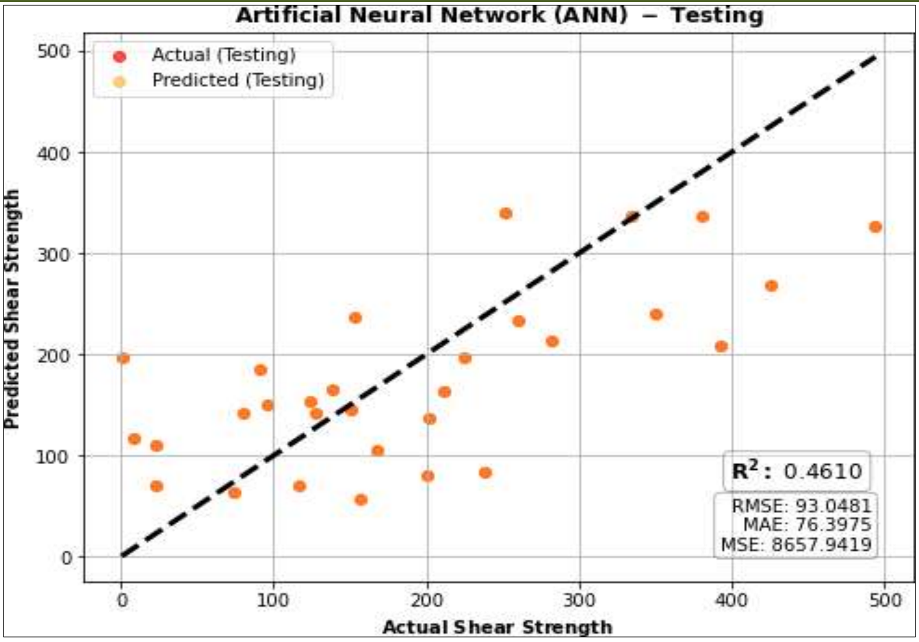

Figure 3.8: ANN model's testing scatter plot for undrained shear strength prediction

The line plot illustrates the performance metrics of the ANN model on the training dataset across multiple epochs. The x-axis represents the number of epochs, while the y-axis displays the values of the performance metrics such as Mean Squared Error (MSE) or Loss. The plot demonstrates how these metrics evolve over the course of training, providing insights into the model's learning process. A decreasing trend in the plotted metrics indicates improvement in the model's performance as training progresses.

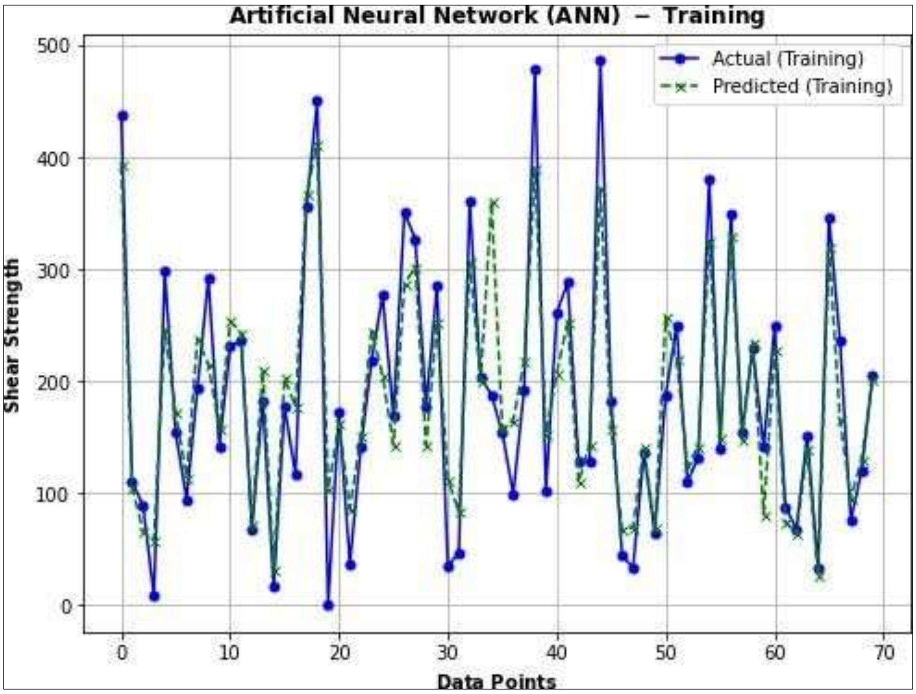

Figure 3.9: ANN model's training line plot for undrained shear strength prediction

The line plot showcases the performance metrics of the ANN model on the testing dataset across multiple epochs. Similar to the training plot, the x-axis represents the number of epochs, while the y-axis displays the values of the performance metrics. These metrics offer insights into how well the model generalizes to unseen data as training progresses. Consistent or decreasing trends in the plotted metrics indicate the model's ability to maintain or improve its performance on the testing dataset over time.

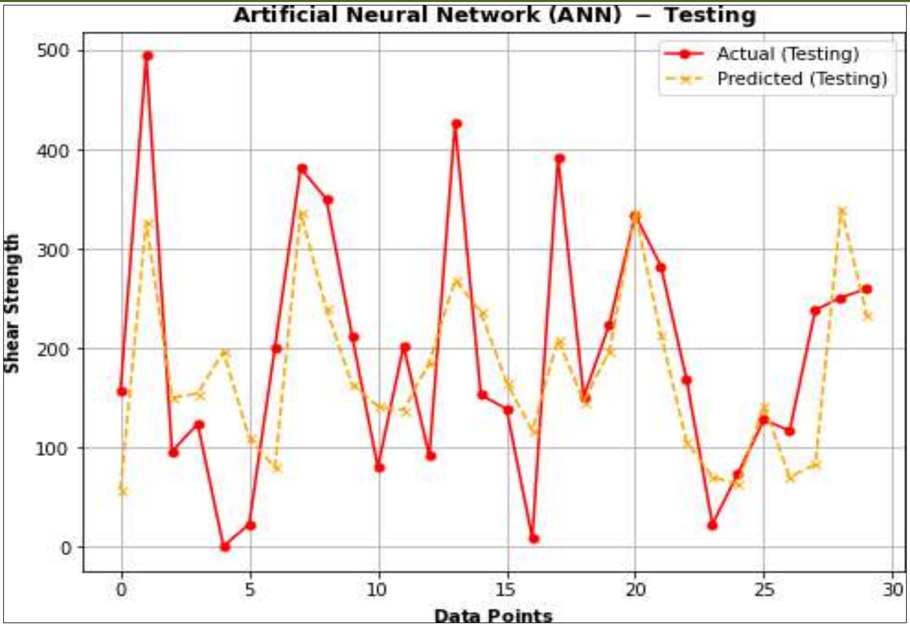

Figure 3.10: ANN model's testing line plot for undrained shear strength prediction

CONCLUSION

The outcome of this research provides valuable insights into the behavior of soft soil in Dhaka and the potential for accurately predicting its strength properties using advanced machine learning techniques. By developing prediction models and establishing correlations among various soil parameters and their shear strength, we aimed to enhance the understanding of soil behavior in this region. This study employed three machine learning techniques: Support Vector Regression (SVR), Artificial Neural Networks (ANNs), and Long Short-Term Memory (LSTM) networks. Through rigorous experimentation and evaluation, LSTM emerged as the most accurate model for predicting the undrained shear strength of soil.

The LSTM model was developed using inputs that included wet basis, liquid limit, plastic limit, and fines content. These inputs were selected due to their significant influence on soil properties. The model's output was the undrained shear strength (cu) of the soil. Initially, individual correlations between soil index properties and undrained cohesion were found to be insignificant. However, when these parameters were combined, the LSTM model significantly improved in predictive accuracy.

The LSTM model demonstrated superior performance with higher R^2 values, indicating its robustness in capturing the nonlinear relationships between the input features and the target variable. The model performance indicators such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were also lower for the LSTM model compared to SVR and ANN, further validating its accuracy.

These findings suggest that the LSTM model can effectively predict the undrained shear strength of soil using plasticity properties and moisture content, potentially reducing the need for extensive strength testing. This can facilitate faster and more cost-effective soil analysis for civil engineering projects.

Despite the promising results, this study was conducted with data from 100 boreholes in a specific region, focusing on silty clay soil. Future research should extend this approach to a broader range of soil types, including sandy soils, and incorporate data from deeper bore logs and larger geographical areas. Additionally, incorporating other machine learning methods such as LASSO Regression, Recursive Feature Elimination (RFE), and further exploration of ANN models could strengthen the correlations established in this study. Long-term monitoring and data collection from diverse soil conditions will enhance the predictive capabilities and generalizability of the models. By implementing these steps, the findings of this research can be applied to various civil engineering projects, improving the accuracy of soil strength predictions and aiding in the design and construction of stable structures.

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