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Research Paper

Data-Driven Consolidation Settlement Prediction Using ML: A Step Toward Smarter Geotechnical Design

Deepanshu[1], Sahil Rana[2], Divyansh[3], Kunal[4], Sarita Yadav[5]
[1]*(Student, Delhi Technological University, Delhi)*
[2]*(Student, Delhi Technological University, Delhi)*
[3]*(Student, Delhi Technological University, Delhi)*
[4]*(Student, Delhi Technological University, Delhi)*
[5]*(Research Scholar, Amity University Haryana)*
Corresponding Author: Sarita Yadav

ABSTRACT: *Consolidation settlement prediction is an important aspect of geotechnical engineering, which influences the performance and stability of various civil engineering structures. Traditional methods rely heavily on empirical correlations and time-consuming laboratory tests, often lacking in accuracy and efficiency. This research examines the use of machine learning (ML) techniques for predicting consolidation settlement in civil engineering, encompassing both one-dimensional (1D) and three-dimensional (3D) consolidation processes. The principal aim is to illustrate the integration of AI/ML methodologies into geotechnical engineering, aiming to optimize prediction tasks while minimizing human intervention and potential errors. Various ML models such as Decision Tree Regressor, Gradient Boosting Regressor, Linear Regression, Random Forest Regressor, ARIMA, GRU, and LSTM, were harnessed to forecast settlement outcomes. Additionally, an innovative approach was adopted, utilizing a perforated consolidation ring to gather data for 3D consolidation settlement. The results of the study showcase promising accuracy levels, with R-squared values of 0.9942 and 0.9876 values achieved for Gradient Boosting Regressor and Random Forest Regressor, respectively, in 1D settlement prediction. These findings highlight the substantial potential of AI/ML techniques in strengthening predictive capabilities within geotechnical engineering which leads to more efficient and precise settlement predictions in civil infrastructure projects. By using advanced ML algorithms and novel data acquisition methodologies, this research underscores the transformative impact of AI/ML integration in enhancing the reliability and efficacy of geotechnical analyses. Such advancements not only facilitate improved decision-making processes but also hold promise for optimizing resource allocation and mitigating risks associated with settlement-related challenges in civil engineering projects.*

KEYWORDS: *Consolidation settlement; ML algorithms; Gradient Boosting Regressor; Random Forest regressor; Decision Tree regressor*

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I. INTRODUCTION

Soil consolidation is a fundamental process in geotechnical engineering, wherein soil gradually settles under applied loads, impacting the stability and performance of civil engineering structures. In other words, consolidation is the slow compression/settlement of soil caused by pore water outflow under constant pressure. In contrast to consolidation, compaction is an instantaneous process. Consolidation is a gradual process. - The soil is unsaturated during compaction but saturated during consolidation. There are numerous methods for compaction. The soil should be loaded with static loading over time for consolidation. In the event of compaction, the volume of air spaces is reduced. However, pore water ejection happens during consolidation.

II. EXPERIMENTALMETHODOLOGY

The aim of this experimental study is to assess the soil settlement under various consolidation scenarios. Specifically, the experiments try to investigate both the conventional 1D consolidation settlement observations with loading over time and 3D consolidation as well. The experimental procedure involves systematically recording the applied pressure, dial reading, compression (change in height), Specimen height over time and collecting a dataset of values.

Upon completing the data collection, the gathered measurements will be utilized to develop different machine learning models. The obtained results will then be collected and processed in a way that can be used to train the ML Models. The experimental work was carried out at the Soil Mechanics Laboratory, Delhi Technological University, located in Shahbad Daulatpur Village, Rohini, Delhi, 110042. This facility is equipped with advanced instrumentation and resources necessary for conducting high precision Geotech experiments. The choice of this laboratory underscores the commitment to obtaining accurate and reliable data using state-of-the art equipment.

In conducting this experiment, several critical aspects were considered to ensure the validity and reproducibility of the results. These include the calibration of dial gauge and other meters for proper readings, the meticulous setup of the apparatus for 3D consolidation using a perforated consolidometer ring. This research seeks to enhance the current understanding in geotechnical engineering by emphasizing precise machine learning models that either corroborate or challenge theoretical frameworks, thus improving our comprehension of soil consolidation.

Experimental Setup

The experiment was conducted using the following apparatus:

A. Consolidometer: The consolidometer is a specialized apparatus utilized in geotechnical engineering for conducting consolidation tests on soil specimens. It comprises a container designed to accommodate a consolidation ring containing the soil specimen, sandwiched between porous stones positioned at the top and bottom ends. The container is equipped to be filled with water, allowing the specimen to be submerged to a level higher than the top of the upper porous stone. Additionally, the consolidometer is capable of applying an axial, vertical load to the top of the specimen, facilitating the application of pressure representative of field conditions. This load application is essential for inducing consolidation settlement within the soil specimen.

Figure 1: Consolidometer Apparatus Set Up

Figure 2: Consolidometer rings

1.1 *Experimental Procedure*

1. Sample Preparation:

Sampling: Obtain an undisturbed soil sample from the field using a sampling tube or other appropriate method.
Trimming: Prepare the soil sample to fit the consolidation ring perfectly, making sure it has a uniform, smooth surface. The ring dimensions are usually standardized (e.g., 50 mm in diameter and 20 mm in height).
Saturation: Ensure the sample is saturated with water if the test requires it. This is done by submerging the sample in water and allowing it to saturate.

2. *Setup:*

Placement: Place the trimmed soil sample into the consolidometer ring.

Assembly: Assemble the consolidometer apparatus, placing the ring with the soil sample in the consolidometer cell.
Porous Stones: Place porous stones on both sides (top and bottom) of the soil sample to allow drainage.

Figure 3: Sampling and trimming

Figure 4: Shows Step2 Setup

3. *Initial Measurement:*

Height Measurement: Measure and record the initial height of the soil sample within the ring.
Loading: Apply a small seating load to the sample to ensure proper contact between the sample, the porous stones, and the loading cap.

4. *Loading and Measurement:*

Incremental Loading: Apply incremental loads to the soil sample. Each load increment is typically doubled from the previous load (e.g., 25 kPa, 50 kPa, 100 kPa, etc.).
Deformation Recording: **R**ecord the deformation (settlement) of the soil sample at specific time intervals (e.g., 1, 2, 4, 8, 15, 30 minutes, 1 hour, 2 hours, 4 hours, etc.) for each load increment**,** until primary consolidation is considered complete (24 hours per load increment).

5. *Unloading:*

Incremental Unloading: After the final load increment, unload the sample in stages, similarly recording the rebound deformation at each stage.

6. *Final Measurements:*

Final Height Measurement: Measure and record the final height of the soil sample.
Moisture Content: Determine the moisture level of the sample post-test by taking a small amount of the sample and drying it in an oven.

7. *Data Analysis:*

Settlement Data: Plot the settlement data against time for each load increment to analyze the consolidation behavior.
Pressure-Settlement Curve: Develop a curve that plots pressure against void ratio or pressure against settlement to establish consolidation parameters including the compression index, recompression index, and the coefficient of consolidation.

8. *Reporting:*

Result Compilation: Compile all the recorded data, plots, and calculated parameters into a comprehensive report.
Interpretation: Interpret the results to assess the consolidation characteristics of the soil, which are essential for geotechnical engineering and foundation design.

B. *Safety and Quality Control:*

Calibration: Ensure all equipment is calibrated and functioning correctly before the test.

Standard Procedures: Follow standardized procedures (e.g., ASTM D2435) to maintain consistency and accuracy in test results.
Safety Precautions: Adhere to laboratory safety protocols to avoid any accidents or sample contamination.

III. ML Model Training

3.1 *Data Collection & Processing:* To train and validate the ML models for soil settlement prediction, a comprehensive data collection and processing approach was employed:

Experimental Setup: Laboratory experiments were conducted using a consolidometer apparatus to simulate 1D consolidation scenarios. Various geotechnical parameters such as sample depth bulk density, plasticity index, and moisture content were measured.
Data Preprocessing: The gathered data went through preprocessing procedures to guarantee its compatibility with machine learning algorithms. This process involved normalization, feature scaling, and addressing missing values to improve the quality and dependability of the dataset.
3.2 *Model Selection*
Nature of the Data: The first consideration in selecting the AI/ML model is the nature of the data available for training and prediction. For example, since the data exhibits complex nonlinear relationships, ensemble learning techniques such as Gradient Boosting Regressor or Random Forest Regressor may be more suitable.

Complexity of the Problem: For more complex problems with nonlinear relationships or high-dimensional data, more sophisticated models may be necessary.

Desired Predictive Performance: If the goal is to achieve the highest possible accuracy in predicting soil settlement, models with strong predictive capabilities and robustness to overfitting, may be preferred.
Model Evaluation and Comparison: Different evaluation metrics, are utilized to evaluate the predictive accuracy of each model on a validation dataset. The model that demonstrates the highest predictive accuracy and generalization performance across multiple evaluation metrics is ultimately selected for predicting soil settlement in this study.
3.3 *Prediction of settlement using ML Models:* Once the data was prepared, the trained ML models were deployed to predict soil settlement based on the collected data:

Model Training: Every ML model was developed with the processed data to understand the fundamental patterns and connections between the input characteristics and the outcomes of settlement. Prediction: The trained models were subsequently utilized to produce forecasts for soil settlement. These forecasts were evaluated against the real settlement values to determine the effectiveness and precision of each model. Evaluation Metrics: To measure the performance of the machine learning models, we computed evaluation metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R2). These metrics offered valuable insights into the predictive abilities and efficiency of each model.

IV. RESULTS

The experimental study of soil consolidation, including both one-dimensional and three-dimensional aspects, provided valuable information regarding the settlement and properties of soil samples. This section presents a detailed examination of the data collected during the experiments, including the applied pressure, dial readings, compression (change in height), Specimen Height, void ratio and coefficient of consolidation.

Load (Kg/cm2)	Applied Pressure P (Kpa)	Dial Reading mm	Height of Sample (H)	Void Ratio (e)
0	0	10	19	0.529
0.5	27.5	9.7	18.7	0.505
1	54.9	9.48	18.48	0.487
2	109.9	9.205	18.21	0.465
4	219.8	8.85	17.85	0.437
8	439.5	8.36	17.36	0.397
16	879	7.885	16.89	0.359
32	1758.1	7.35	16.35	0.316
8	439.5	7.455	16.46	0.324
2	109.9	7.63	16.63	0.339
0.5	27.5	7.75	16.75	0.348
0	0	8	17	0.368

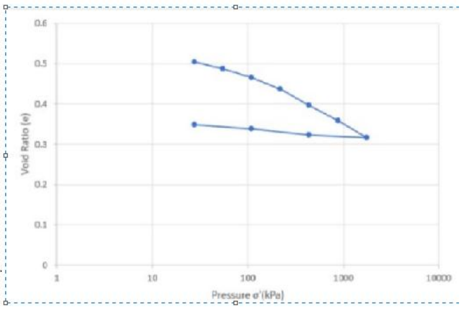

Table 1: Consolidation result of soil sample 1

Load (Kg/cm2)	Applied Pressure P (Kpa)	Dial Reading mm	Height of Sample (H)	Void Ratio (e)
0	0	0	19	0.818
0.5	25	0.32	18.68	0.787
1	50	0.55	18.45	0.766
2	100	0.81	18.19	0.741
4	200	1.13	17.87	0.71
8	400	1.52	17.18	0.673
16	800	2.14	16.86	0.613
32	1600	2.64	16.36	0.566
8	400	2.61	16.39	0.568
2	100	1.52	17.48	0.673
0.5	0	1.07	17.93	0.716

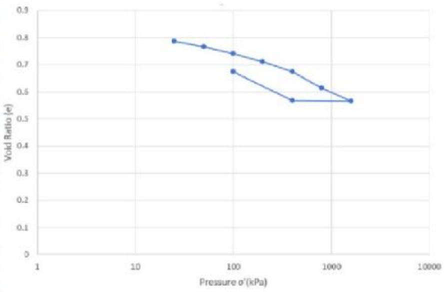

Table 2: Consolidation result of soil sample 2

Load (Kg/cm2)	Applied Pressure P (Kpa)	Dial Reading mm	Height of Sample (H)	Void Ratio (e)
0	0	7.06	25.4	0.816
3.23248	10	8.74	24.97328	0.785
8.0812	25	9.65	24.74214	0.769
16.1624	50	10.93	24.41702	0.745
32.3248	100.01	12.75	23.95474	0.712
64.6496	200.01	15.05	23.37054	0.671
129.2992	400.03	18.15	22.58314	0.614
258.5984	800.06	21.97	21.61286	0.545
129.2992	400.03	21.49	21.73478	0.554
32.3248	100.01	19.81	22.1615	0.584
3.23248	10	16.45	23.01494	0.645

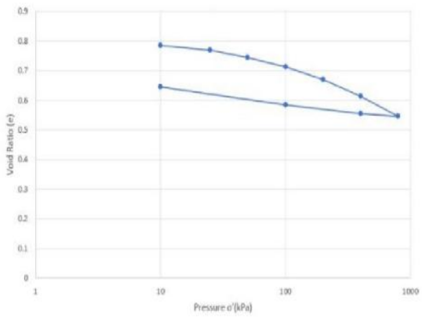

Table 3: Consolidation result of soil sample 3

Load (Kg/cm2)	Applied Pressure P (Kpa)	Dial Reading mm	Height of Sample (H)	Void Ratio (e)
0	0	20	19.77	0.615283
0.5	9.8	19.95	19.72	0.611198
1	19.6	19.75	19.52	0.594857
2	49	19.29	19.06	0.557273
4	98	18.81	18.58	0.518055
8	196	18.24	18.01	0.471484
16	392	17.68	17.45	0.42573
32	784	17.12	16.89	0.379976

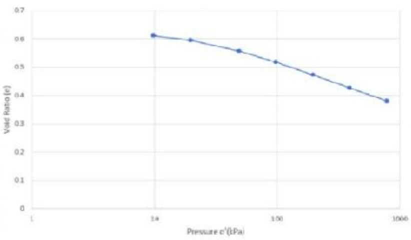

Table 4: Consolidation result of soil sample 4

Now, for the data with time considerations to train the model basis time series as well, we took reading at various time periods as well. As below:

Load	0.1 kg/cm2

Time (mins)	H (mm)
0	20
0.25	19.99
1	19.98
2	19.98
4	19.97
8	19.97
15	19.97
30	19.97
60	19.97
120	19.97
240	19.96
480	19.96
1440	19.95

Load	0.2 kg/cm2

Time (mins)	H (mm)
0	19.95
0.25	19.91
1	19.89
2	19.88
4	19.86
8	19.84
15	19.83
30	19.8
60	19.79
120	19.78
240	19.77
480	19.76
1440	19.75

Load	0.5 kg/cm2

Time (mins)	H (mm)
0	19.75
0.25	19.56
1	19.49
2	19.46
4	19.43
8	19.41
15	19.38
30	19.36
60	19.34
120	19.32
240	19.32
480	19.3
1440	19.29

Load	1 kg/cm2
Time (mins)	**H (mm)**
0	19.29
0.25	19.08
1	19.01
2	18.98
4	18.95
8	18.93
15	18.91
30	18.9
60	18.86
120	18.85
240	18.84
480	18.82
1440	18.81

Load	2 kg/cm2
Time (mins)	**H (mm)**
0	18.81
0.25	18.49
1	18.42
2	18.39
4	18.37
8	18.35
15	18.33
30	18.31
60	18.3
120	18.28
240	18.26
480	18.26
1440	18.24

Load	4 kg/cm2
Time (mins)	**H (mm)**
0	18.24
0.25	17.89
1	17.84
2	17.81
4	17.79
8	17.77
15	17.76
30	17.74
60	17.73
120	17.72
240	17.7
480	17.69
1440	17.68

Load	8 kg/cm2
Time (mins)	**H (mm)**
0	17.68
0.25	17.31
1	17.27
2	17.25
4	17.23
8	17.21
15	17.2
30	17.19
60	17.17
120	17.16
240	17.15
480	17.14
1440	17.12

Table 5: Change in H w.r.t. time at constant load

The integration of a perforated ring into the experimental setup to facilitate 3D consolidation readings represented a novel approach. However, the Machine Learning (ML) predictions based on these readings fell short of expectations, resulting in decreased accuracy. Further enhancements to the apparatus are warranted to acquire more precise and comprehensive readings for 3D consolidation. These insights highlight the necessity for advancements in the apparatus to streamline and optimize data collection processes, ultimately fostering more efficient ML model training and yielding superior results. Such advancements are crucial for advancing the affordability and usability of 3D consolidation apparatus, thereby driving progress in this field of study.

In conclusion, the study demonstrates that settlement of soil under various loads over time is influenced by both the pressure applied and the saturation of soil. In this detailed analysis, the plot comparing actual and predicted values serves as a visual tool to assess how well a Machine Learning (ML) model performs. In this graph, the true values of the target variable (often referred to as ground truth or observed values) are compared to the values predicted by the model.

In the context of Machine Learning (ML), a residual plot serves as a visual tool to evaluate how well a regression model fits the data. It shows the discrepancies between the actual values and the predicted values of the target variable plotted against the predictor variables.

Residual=Observed value−Predicted value

First let's look at the distribution curve which refers to a graphical representation of the distribution of a particular variable within a dataset. This curve is often used to visualize the spread or dispersion of values and to understand their frequency or likelihood of occurrence.

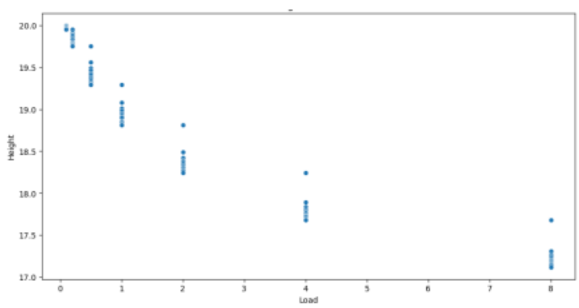

Figure 5: Distribution curve for Height vs Load

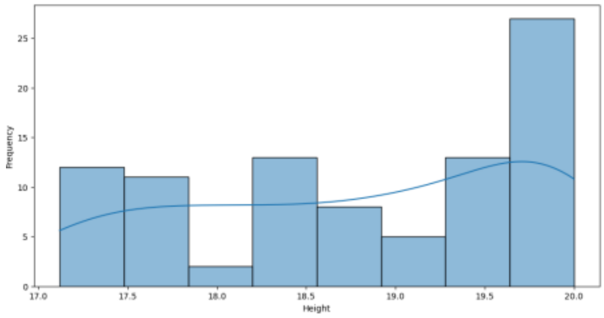

Figure 6: Distribution curve for Height vs Frequency

Gradient Boosting Regressor Model

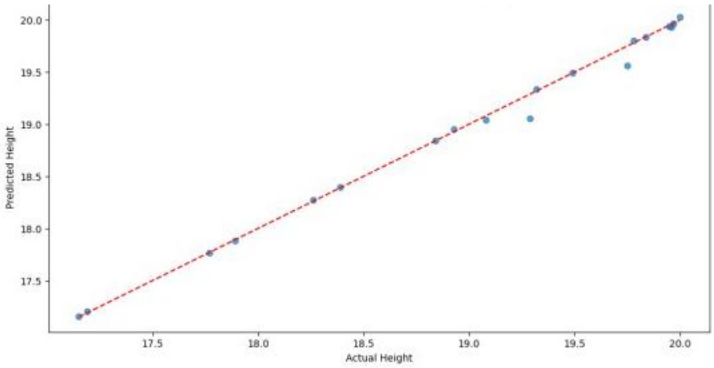

Figure 7: Actual vs Predicted Height for soil sample plot for Gradient Boosting Regressor Model

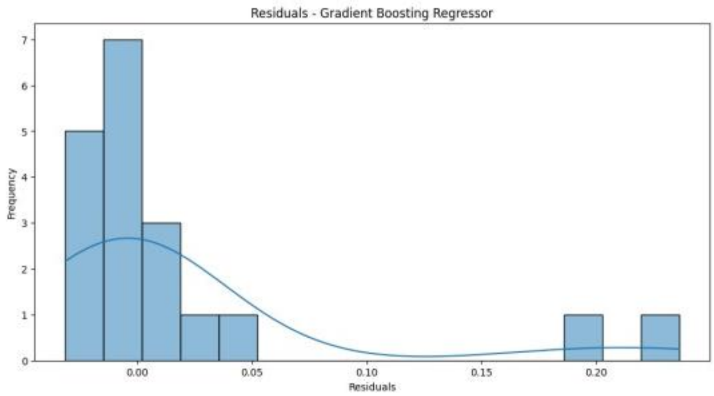

Figure 8: Residuals plot for Gradient Boosting Regressor Model

Random Forest Regressor Model

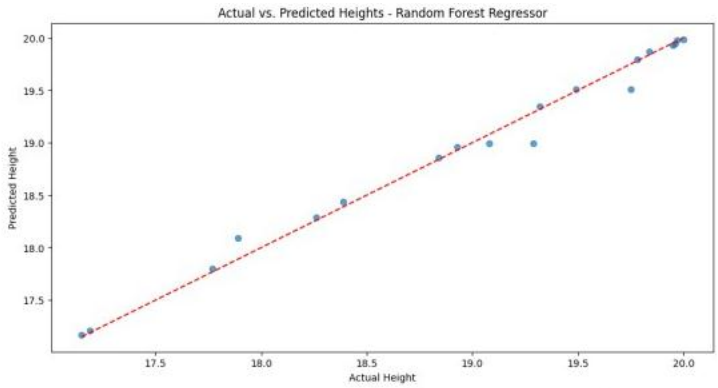

Figure 9: Actual vs Predicted Height for soil sample plot for Random Forest Regressor Model

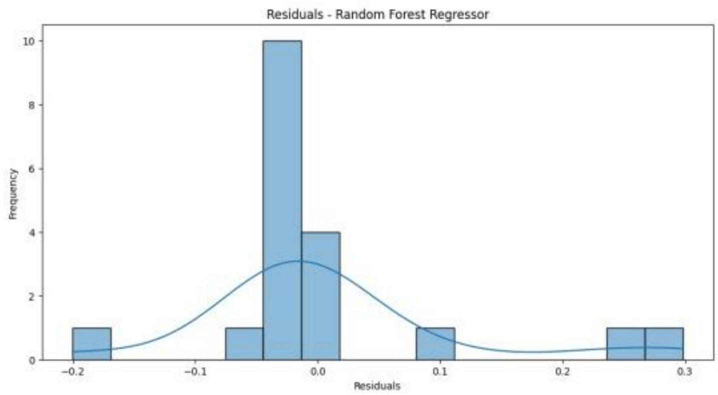

Figure 10: Residuals plot for Random Forest Regressor Model

Decision Tree Regressor Model

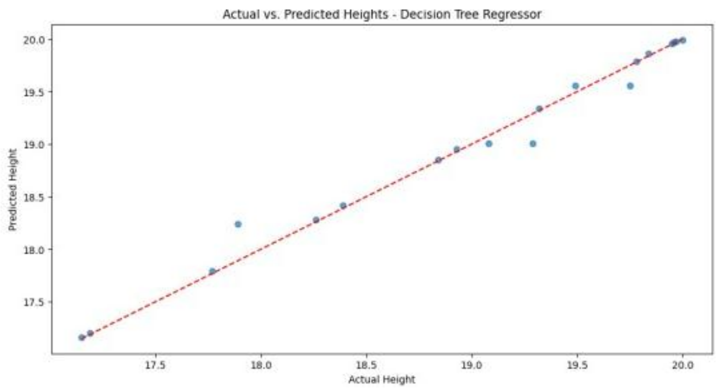

Figure 11: Actual vs Predicted Height for soil sample plot for Decision Tree Regressor Model

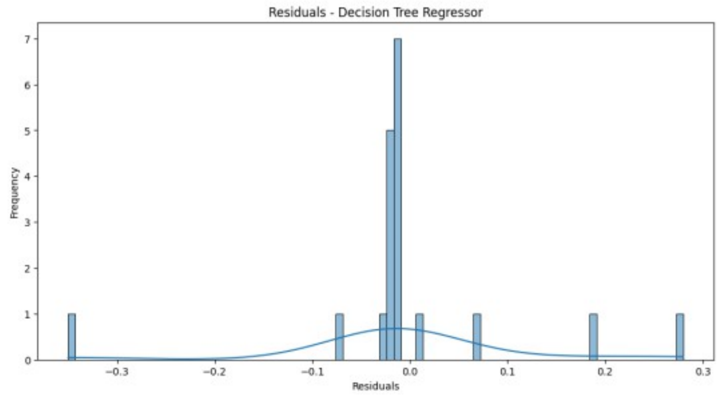

Figure 12: Residuals plot for Decision Tree Regressor Model

Linear Regression Model

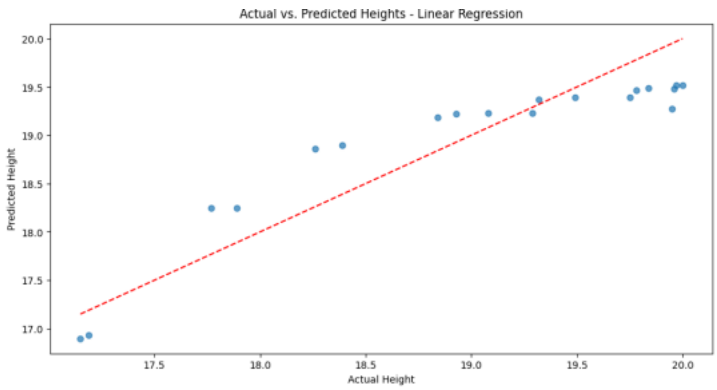

Figure 13: Actual vs Predicted Height for soil sample plot for Linear Regression Model

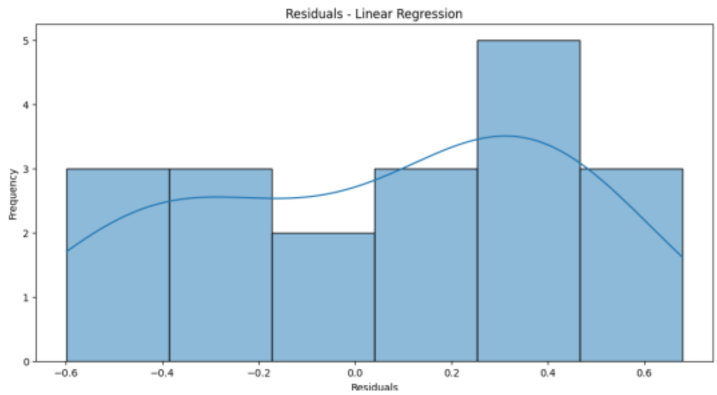

Figure 14: Residuals plot for Linear Regression Model

AutoRegressive Integrated Moving Average (ARIMA)

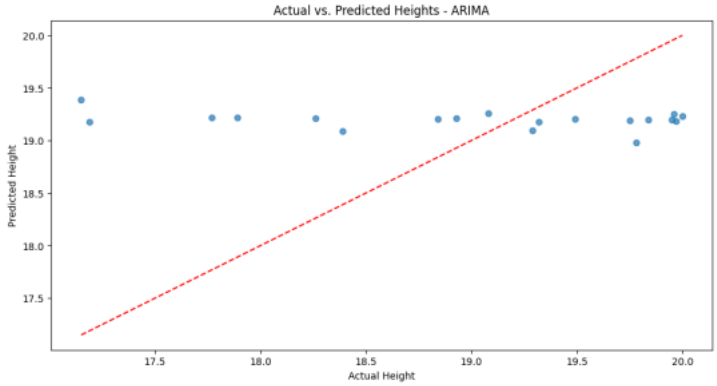

Figure 15: Actual vs Predicted Height for soil sample plot for ARIMA

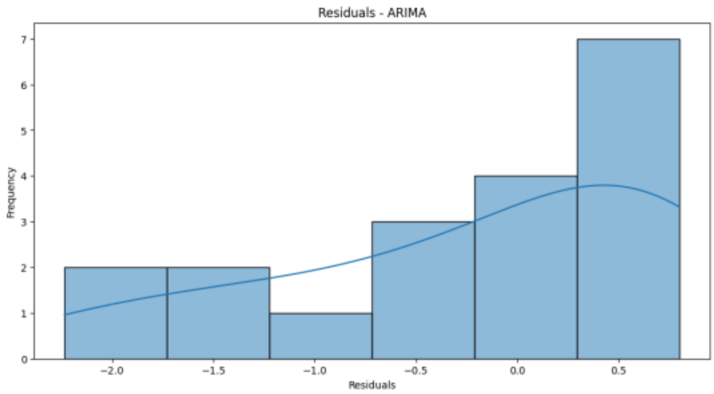

Figure 16: Residuals plot for ARIMA

Long Short-Term Memory (LSTM)

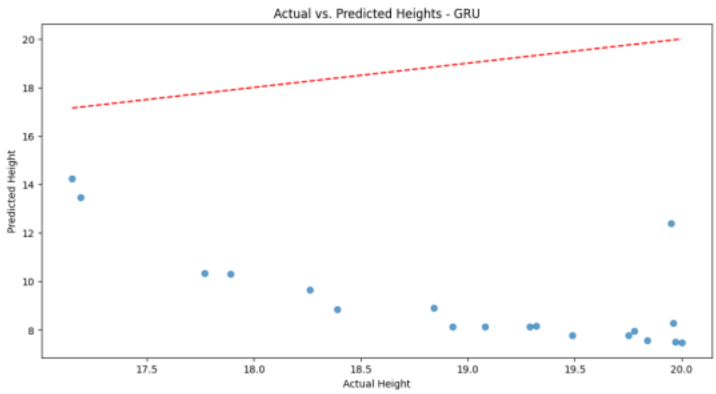

Figure 17: Actual vs Predicted Height for soil sample plot for LSTM

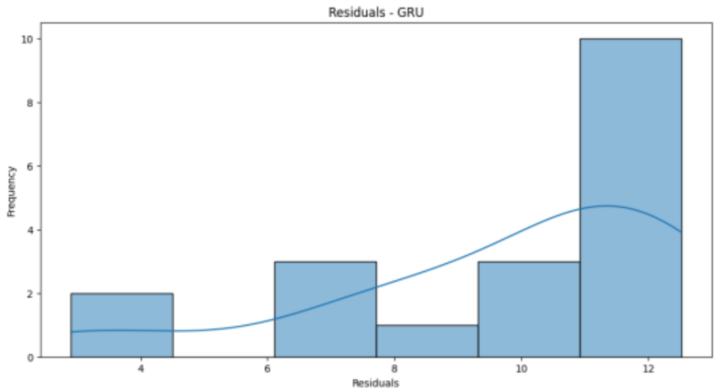

Figure 18: Residuals plot for LSTM

Gated Recurrent Unit (GRU)

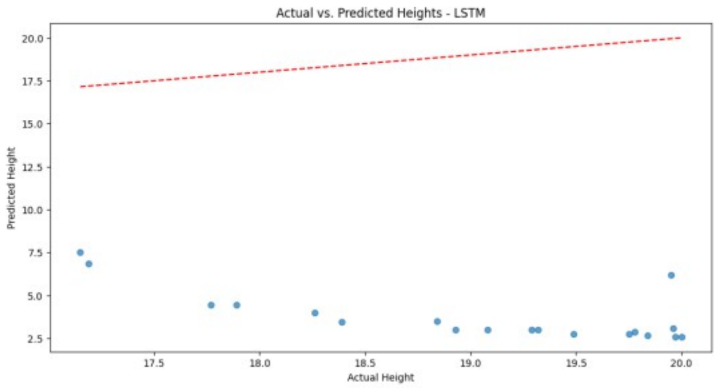

Figure 19: Actual vs Predicted Height for soil sample plot for GRU

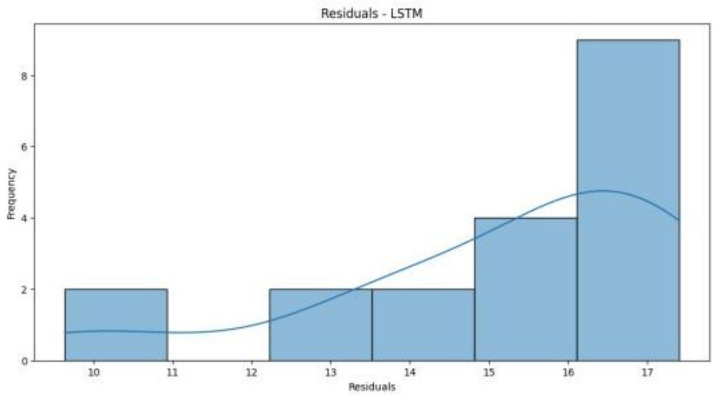

Figure 20: Residuals plot for GRU

The comparison of several ML models' performance is done based on a number of metrics, here we will be looking at R^2, MAE (Mean Absolute Error) and MSE (Means Squared Error) to have a comparison of accuracy of all the models relative to each other.

In conclusion, R-squared indicates the percentage of variance accounted for by the model, while MAE and MSE evaluate prediction accuracy by measuring the size of errors between actual and predicted values. These metrics are vital for assessing the performance of various ML models and determining the most suitable model for a specific task.

V. CONCLUSION

Model	R2	MAE	MSE
Gradient Boosting Regressor	0.9942	0.0344	0.0051
Random Forest Regressor	0.9876	0.0614	0.0107
Decision Tree Regressor,	0.9848	0.0616	0.0132
Linear Regression	0.8288	0.3454	0.1484

Table 6: Comparison of performance of models

In this study, various machine learning models—including Gradient Boosting Regressor (GBR), Random Forest Regressor (RFR), Decision Tree Regressor (DTR), and Linear Regression—were evaluated for predicting soil settlement during consolidation. Among them, the GBR model demonstrated the highest performance with an R^2 value of 0.9942, followed by RFR ($R^2 = 0.9876$) and DTR ($R^2 = 0.9848$), indicating excellent predictive capabilities. The experimental setup and available data were suitable for 1D consolidation analysis, allowing for effective model training and accurate predictions. However, the 3D consolidation data, collected using a perforated ring setup, lacked the precision and reliability required for model training, leading to significant errors and ultimately exclusion from this study. The high accuracy of ML models like GBR not only reduces human error in settlement prediction but also contributes to more reliable and durable infrastructure designs. Looking ahead, advancements in AI/ML hold great potential for geotechnical engineering, particularly through the development of more specialized models capable of addressing complex problems such as 3D consolidation.

REFERENCES

[1] Bekele, Y. W. (2022). Physics-informed deep learning for one-dimensional consolidation. *Rock and Soil Mechanics Group, SINTEF AS, Trondheim, Norway*.

[2] Kolay, P. K., Rosmina, A. B., & Ling, N. W. (2010). Settlement prediction of tropical soft soil by artificial neural network (ANN). *International Journal of Geotechnical Engineering*, *4*(2), 279–288. https://doi.org/10.3328/IJGE.2010.04.02.279-288

[3] Mohammed, M. E., Sharafati, A., Al-Ansari, N., Yaseen, Z. M., & Jasim, H. (2020). Shallow foundation settlement quantification: Application of hybridized adaptive neuro-fuzzy inference system model. *Advances in Civil Engineering*, *2020*, 8836932. https://doi.org/10.1155/2020/8836932

[4] Pham, B. T., Nguyen, M. D., Dao, D. V., Prakash, I., Ly, H.-B., Le, T. T., Ho, L. S., Nguyen, K. T., Ngo, T. Q., Hoang, V., Son, L. H., Ngo, H. T. T., Tran, H. T., Do, N. M., Le, H. V., Ho, H. L., & Bui, D. T. (2019). Development of artificial intelligence models for the prediction of compression coefficient of soil: An application of Monte Carlo sensitivity analysis. *Geoscience Frontiers*, *10*(2), 695–703. https://doi.org/10.1016/j.gsf.2018.08.003

[5] Shahin, M. A. (2014). A review of artificial intelligence applications in shallow foundations. *International Journal of Geotechnical Engineering*, *8*(4), 323–331. https://doi.org/10.1179/1939787914Y.0000000029

[6] Zhai, J. (2022). Machine-learning-based road soft soil foundation treatment and settlement prediction method. *Scientific Programming*, *2022*, 8084791. https://doi.org/10.1155/2022/8084791

[7] Zhang, D.-M., Zhang, J.-Z., Huang, H.-W., Qi, C.-C., & Chang, C.-Y. (2021). Machine learning-based prediction of soil compression modulus with application of 1D settlement. *Mathematics*, *9*(11), 1229. https://doi.org/10.3390/math9111229

[8] Zhang, W., Li, H., Li, Y., & Zhou, W. (2021). Application of deep learning algorithms in geotechnical engineering: A short critical review. *Artificial Intelligence Review*, *54*, 5639–5675. https://doi.org/10.1007/s10462-020-09922-9