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ASSESSMENT OF GEOTECHNICAL PROPERTIES OF FINE-GRAINED SOIL FOR SUB GRADE BY USING ARTIFICIAL INTELLIGENCE

Abhinav Saxena PG Student, Department of Civil Engineering, Samrat Ashok Technological Institute, Vidisha, Madhya Pradesh, India
Dr. Rajeev Jain Professor, Department of Civil Engineering, Samrat Ashok Technological Institute, Vidisha, Madhya Pradesh, India Corresponding Author: abhinavsaxena.email@gmail.com

ABSTRACT
The present research work is carried out to predict the geotechnical properties (consistency limits, OMC, and MDD) of soil using AI technologies, namely regression analysis (RA), support vector machine (SVM), Gaussian process regression (GPR), artificial neural networks (ANNs), and relevance vector machine (RVM). The models of machine learning (SVM, GPR), hybrid learning (RVM), and deep learning (ANNs) are constructed in MATLAB R2020a with different configurations. The models of RA are built using the Data Analysis Tool of Microsoft Excel 2019. The input parameters of AI models are gravel, sand, silt, and clay content. The correlation coefficient is calculated for pair of soil datasets. The correlation shows that sand, silt, and clay content play a vital role in predicting soil's liquid limit and plasticity index. The performance of constructed AI models is compared to determine the optimum performance models. The limited datasets of soil are used in this study. Therefore, artificial neural networks and relevance vector machines could not perform well. Based on the performance of AI models, the Gaussian process regression outperformed the RA, SVM, ANNs, and RVM AI technologies. Hence, the GPR AI approach can predict the geotechnical properties of soil by gravel, sand, silt, and clay content. The Monte-Carlo global sensitivity analysis is also performed, and it is observed that the prediction of geotechnical properties of soil is affected by sand and clay content.

Keywords: Consistency limits, Geotechnical Properties, Hybrid Learning, Machine Learning, Geotechnical Engineering, AI & ML Techniques, Soil Properties.

1.0 INTRODUCTION

The integration of AI in geotechnical engineering not only improves prediction accuracy but also enhances efficiency, providing a significant advantage over traditional approaches. By utilizing AI, engineers can quickly evaluate soil properties such as liquid limit, plastic limit, maximum dry density, and specific gravity. This capability is critical for ensuring the safety and success of construction projects. As AI continues to evolve, its application in geotechnical engineering promises to further advance the field, leading to more robust, data-driven engineering solutions.

Artificial intelligence (AI) is transforming geotechnical engineering by offering advanced methods for predicting the geotechnical properties of fine-grained soils. Traditional approaches, such as laboratory testing and empirical correlations, often involve extensive time, labor, and costs. These methods can also struggle with the inherent variability and complexity of fine-grained soils, which include clays like illite, kaolinite, and montmorillonite. These soils are characterized by properties such as liquid limit, plastic limit, maximum dry density, and specific gravity, which are crucial for understanding soil behavior under different conditions.

AI, particularly machine learning, provides a powerful alternative by harnessing computational models that learn from data to identify patterns and make predictions. These models excel at processing large datasets, capturing complex relationships that may not be evident through traditional methods. AI techniques enable engineers to predict soil properties with greater accuracy and efficiency, facilitating faster decision-making in project planning and risk management. The ability of AI to integrate diverse data sources and continuously improve through learning algorithms further enhances its predictive capabilities.

In recent years, the development of robust machine learning models has been supported by advancements in data collection technologies and computational power. Tools like neural networks, support vector machines, and decision trees have been effectively applied to model soil behavior, achieving high levels of precision. AI's ability to predict critical parameters such as compressibility, permeability, and shear strength provides valuable insights for geotechnical design and analysis.

1.1 AI Techniques in Geotechnical Engineering

AI techniques can be employed to predict and analyze the geotechnical properties of fine-graded soils. Commonly used AI methods include:

1. Artificial Neural Networks (ANNs)
- Functionality: ANNs can model complex relationships between input variables (e.g., soil properties) and outputs (e.g., geotechnical characteristics).
- Applications: Predicting soil classification, Atterberg limits, shear strength, and compaction characteristics.
- Advantages: High accuracy and ability to learn from data.

2. Support Vector Machines (SVMs)
- Functionality: SVMs classify data into different categories and can handle nonlinear relationships.
- Applications: Soil classification, predicting permeability and consolidation behavior.
- Advantages: Effective in high-dimensional spaces and robust to overfitting.

3. Decision Trees and Random Forests
- Functionality: These methods use tree-like models to make decisions based on input data.
- Applications: Predicting compaction parameters, shear strength, and soil classification.
- Advantages: Easy to interpret and implement.

4. Genetic Algorithms (GAs)
- Functionality: GAs optimize solutions based on natural selection principles.
- Applications: Parameter optimization for soil models and improving the performance of other AI techniques.
- Advantages: Useful for complex optimization problems.

5. Fuzzy Logic Systems
- Functionality: These systems handle uncertainty and imprecision by using fuzzy sets.
- Applications: Predicting soil behavior under varying conditions.
- Advantages: Can model the inherent uncertainties in geotechnical data.

2.0 LITERATURE REVIEW

- Park et al. (2021): This research focused on the use of AI techniques, particularly convolutional neural networks (CNNs), for analyzing soil images to predict soil properties. The study demonstrated that AI could effectively process image data to extract meaningful geotechnical information, offering new avenues for soil property assessment.
- Khodayar et al. (2020): This study explored the integration of AI techniques with geographic information systems (GIS) to predict landslide susceptibility. The research highlighted the potential of

AI for geospatial analysis and risk assessment, demonstrating how AI can be combined with other technologies to enhance geotechnical evaluations.

- Jain and Kumar (2020): Jain and Kumar investigated the use of deep learning techniques for predicting soil compaction parameters. Their study found that deep learning models provided superior prediction performance compared to conventional methods, demonstrating the advantages of AI in modeling complex geotechnical properties.
- Bui et al. (2018): Bui and colleagues conducted a comparative study of various machine learning algorithms, such as ANNs, SVMs, and decision trees, for predicting soil shear strength parameters. The study concluded that AI models generally outperformed traditional methods in terms of accuracy and efficiency, underscoring the versatility of machine learning techniques.
- Zhang and Goh (2016): Zhang and Goh applied decision tree-based models, including random forests, to predict soil permeability. Their research demonstrated that ensemble methods could enhance prediction accuracy by reducing variance and improving model robustness, highlighting the potential of AI to improve geotechnical property assessments.
- Samui and Kothari (2011): Samui and Kothari applied ANNs to estimate soil shear strength parameters. Their findings indicated that AI techniques could achieve high prediction accuracy, emphasizing the potential of neural networks to handle complex soil behavior data.
- Pal and Deswal (2011): This research investigated the use of support vector machines (SVM) for predicting the unconfined compressive strength of soils. The study found that SVM models provided reliable and accurate predictions, showcasing the technique’s effectiveness in handling non-linear relationships in soil data.
- Shahin et al. (2002): This study utilized artificial neural networks (ANNs) to predict settlement in shallow foundations. The research demonstrated that ANNs could model complex, non-linear relationships in geotechnical data, providing more accurate predictions than traditional empirical approaches.

3.0 METHODOLOGY ADOPTED

In the methodology for assessing geotechnical properties of fine-graded soil using AI techniques, several specific properties of the soil need to be determined. These properties are critical for understanding the soil's behaviour and are typically evaluated through a series of laboratory tests. The primary properties to assess include:

- Particle Size Distribution (PSD)
- Atterberg Limits (Liquid Limit & Plastic Limit)
- Compaction Characteristics (OMC & MMD)

4.0 EVALUATION TECHNIQUES

4.1. Data Collection

4.1.1 Soil Sample Collection

- Collect soil samples from diverse locations to capture variability in soil properties.

4.1.2 Laboratory Testing

- Conduct standard geotechnical tests to determine properties such as:
- Particle size distribution
- Atterberg limits
- Compaction characteristics
- Shear strength parameters
- Permeability
- Consolidation properties

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4.2 Python code

```
print("Cross-validation R² scores for 'c (in kPa)':", cv_scores_c) print("Mean cross-validation R² score for 'c (in kPa)':", cv_scores_c.mean()) print("Training MSE for 'c (in kPa)':", mse_c) print("Training R² for 'c (in kPa)':", r2_c)
```

Results:
- Cross-validation R^2 scores: [0.9115273, 0.88620099, 0.68556788, 0.29512667, 0.85706794]
- Mean cross-validation R^2 score: 0.7270981564214617
- Training MSE: 0.6485039999999992
- Training R^2: 0.987077886883887 Internal Friction Angle (phi in degrees)

Similarly, the cross-validation R^2 scores and the mean cross-validation R^2 score for phi evaluate the model's generalization ability. The training MSE and R^2 score indicate the fit on the training data.

Python code

```
print("\nCross-validation R² scores for 'phi (degree)':", cv_scores_phi) print("Mean cross- validation R² score for 'phi (degree)':", cv_scores_phi.mean()) print("Training MSE for 'phi (degree)':", mse_phi) print("Training R² for 'phi (degree)':", r2_phi)
```

Results:
- Cross-validation R^2 scores: [0.84127069, 0.53378417, 0.62374253, -6.98308333, 0.77118896]
- Mean cross-validation R^2 score: -0.8426193983932313
- Training MSE: 0.3982119615999993
- Training R^2: 0.9573012320757202

5.0 RESULTS & DISCUSSION

5.1 Testing of Soil Sample Data: The table below gives the data of the soil sample in which the test was carried out in the laboratory.

Table1: Testing of Soil Sample Data

Sample. No.	Sand size (%)	Silt size (%) <75 micron	Clay size (%) <2 micron	%age finer 75micron	Coefficient of uniformity	Coefficient of curvature	Sp. Gravity, G	Liquid limit (oven dried), (%)	Plastic limit, (oven dried) (%)	PI=LL -PL (%)	PI (A-line) = 0.73*(L L-20)	PI (U-line) = 0.9*(LL-8)	Clay mineral type
1	2	87	11	98	10	1.4	2.62	35	23	12	10.95	24.3	ILLITE
2	5	83	12	95	14	1	2.64	40	26	14	14.6	28.8	ILLITE
3	6	80	14	94	13	1.1	2.65	43	22	21	16.79	31.5	ILLITE
4	6	81	13	94	15	1.3	2.64	44	24	20	17.52	32.4	ILLITE
5	7	79	14	93	16	1	2.63	45	25	20	18.25	33.3	ILLITE
6	5	83	12	95	14	2	2.63	47	26	21	19.71	35.1	ILLITE
7	6	81	13	94	13	1	2.63	46	27	19	18.98	34.2	ILLITE
8	4	78	18	96	15	3	2.63	50	35	15	21.9	37.8	ILLITE
9	5	75	20	95	16	4	2.63	51	30	21	22.63	38.7	KAOLINITE
10	6	74	20	94	12	4	2.63	55	37	18	25.55	42.3	KAOLINITE

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11	8	72	20	92	10	3	2.63	56	36	20	26.28	43.2	KAOLINITE
12	7	69	24	93	8	2	2.63	58	34	24	27.74	45	KAOLINITE
13	6	65	29	94	6	1	2.63	47	35	12	19.71	35.1	KAOLINITE
14	4	78	18	96	10	2	2.63	54	38	16	24.82	41.4	KAOLINITE
15	3	62	35	97	15	1	2.63	55	39	16	25.55	42.3	KAOLINITE
16	2	60	38	98	14	2	2.63	56	40	16	26.28	43.2	KAOLINITE
17	4	62	34	96	15	3	2.63	58	37	21	27.74	45	KAOLINITE
18	5	59	36	95	19	1	2.63	60	37	23	29.2	46.8	MONTMORILLONITE
19	6	57	37	94	14	2	2.63	62	41	21	30.66	48.6	MONTMORILLONITE
20	4	56	40	96	8	3	2.63	64	40.94	23.06	32.12	50.4	MONTMORILLONITE
21	3	55	42	97	18	4	2.63	65	31.38	33.62	32.85	51.3	MONTMORILLONITE
22	5	58	37	95	21	2	2.63	68	33.64	34.36	35.04	54	MONTMORILLONITE
23	6	54	40	94	19	3	2.63	70	35.29	34.71	36.5	55.8	MONTMORILLONITE
24	10	52	38	90	16	2	2.63	71	35.98	35.02	37.23	56.7	MONTMORILLONITE
25	11	50	39	89	14	3	2.63	72	51.57	20.43	37.96	57.6	MONTMORILLONITE

Sam ple. No.	Sand size (%)	Silt size (%) <75mi cron	Clay size (%) <2mi cron	%age finer 75mic ron	Coeffi cient of unifor mity	Coeffi cient of curvat ure	Sp. Gravit y, G	Liquid limit (oven dried), (%)	Plastic limit, (oven dried) (%)	PI=LL -PL (%)	PI (A-line) = 0.73*(LL-20)	PI (U-line) = 0.9*(LL-8)	Clay mineral type
26	3	86	11	97	10	1.4	2.62	35	23	12	10.95	24.3	ILLITE
27	5	82	13	95	14	1	2.64	40	26	14	14.6	28.8	ILLITE
28	4	81	15	96	13	1.1	2.65	43	22	21	16.79	31.5	ILLITE
29	6	82	12	94	15	1.3	2.64	44	24	20	17.52	32.4	ILLITE
30	7	79	14	93	16	1	2.63	45	25	20	18.25	33.3	ILLITE
31	5	82	13	95	14	2	2.63	47	26	21	19.71	35.1	ILLITE
32	6	80	14	94	13	1	2.63	46	27	19	18.98	34.2	ILLITE
33	4	78	18	96	15	3	2.63	50	35	15	21.9	37.8	ILLITE
34	5	75	20	95	16	4	2.63	51	30	21	22.63	38.7	KAOLINITE
35	6	76	18	94	12	4	2.63	55	37	18	25.55	42.3	KAOLINITE
36	8	74	18	92	10	3	2.63	56	36	20	26.28	43.2	KAOLINITE
37	7	69	24	93	8	2	2.63	58	34	24	27.74	45	KAOLINITE
38	6	65	29	94	6	1	2.63	47	35	12	19.71	35.1	KAOLINITE
39	4	78	18	96	10	2	2.63	54	38	16	24.82	41.4	KAOLINITE
40	3	65	32	97	15	1	2.63	55	39	16	25.55	42.3	KAOLINITE

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41	2	60	38	98	14	2	2.63	56	40	16	26.28	43.2	KAOLINITE
42	4	64	32	96	15	3	2.63	58	37	21	27.74	45	KAOLINITE
43	5	59	36	95	19	1	2.63	60	37	23	29.2	46.8	MONTMORILLO NITE
44	7	56	37	93	14	2	2.63	62	41	21	30.66	48.6	MONTMORILLO NITE
45	8	54	38	92	8	3	2.63	64	40.94	23.06	32.12	50.4	MONTMORILLO NITE
46	8	56	36	92	18	4	2.63	65	31.38	33.62	32.85	51.3	MONTMORILLO NITE
47	9	52	39	91	21	2	2.63	68	33.64	34.36	35.04	54	MONTMORILLO NITE
48	9	54	37	91	19	3	2.63	68	33.64	34.36	35.04	54	MONTMORILLO NITE
49	10	52	38	90	16	2	2.63	70	35.29	34.71	36.5	55.8	MONTMORILLO NITE
50	11	50	39	89	14	3	2.63	71	35.98	35.02	37.23	56.7	MONTMORILLO NITE

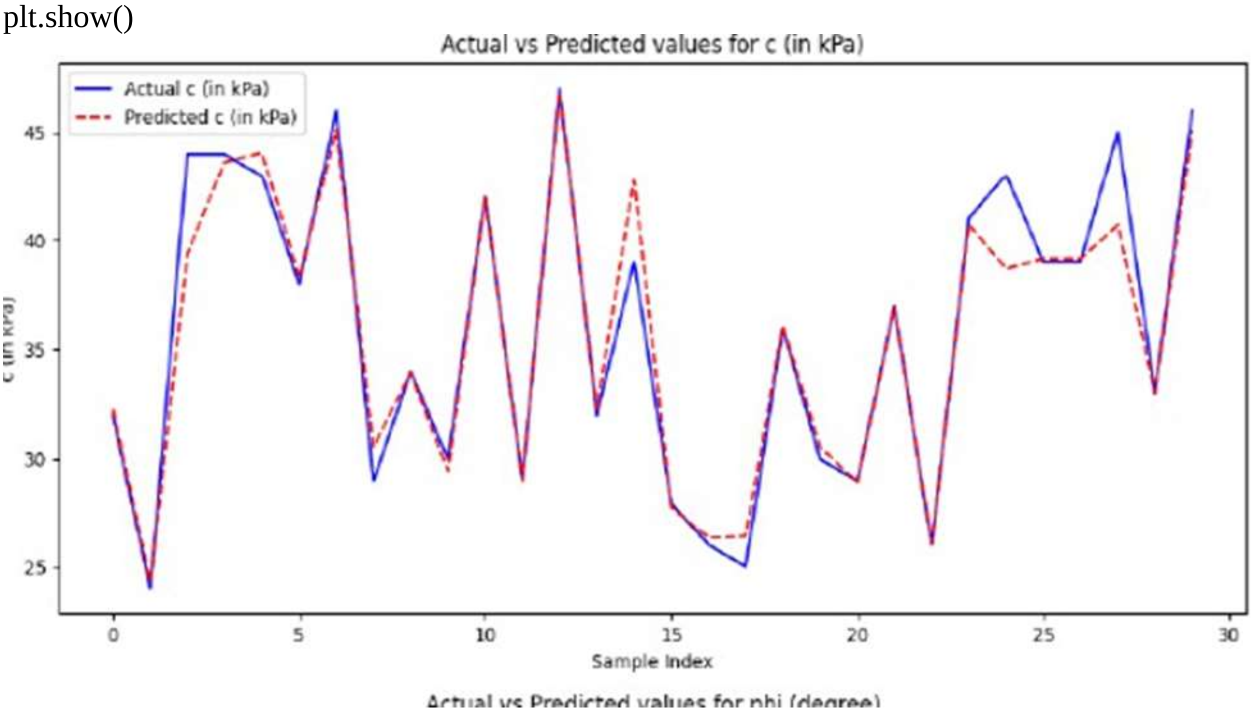
Sampl e. No.	**Flow index**	**Toughn e ss index**	**Activi t y**	**Maximu m dry density-LC* (kN/m3)**	**OMC-LC (%)**	**Unconfined Compressive Strength of remoulded soil @ OMC & MDD (kN/m2)**	**Direct shear test parameters@ OMC & MDD**		**Compressiv e index, Cc = 0.007(LL-10) for remoulded sample**
							c= 30 kPa	**ϕ= 25.07°**	
1	5	2.4	1.0909	17.4	16.67	419.87			0.175
2	6	2.3333	1.1667	16.18	19.95	381.45	26	22	0.21
3	7	3	1.5	15.12	20.32	351.53	25	21	0.231
4	6	3.3333	1.5385	16.24	21.54	346.51	24	23	0.238
5	6	3.3333	1.4286	18	22	383.42	28	24	0.245
6	5	4.2	1.75	13.49	24.88	373.77	29	22	0.259
7	6	3.1667	1.4615	13.01	30.01	328.11	30	22	0.252
8	7	2.1429	0.8333	13.04	28.64	364.56	31	21	0.28
9	8	2.625	1.05	13.16	32.37	335.21	32	20	0.287
10	8	2.25	0.9	12.85	35.13	375.21	33	19	0.315
11	4	5	1	12.56	33.07	351.53	34	18	0.322
12	5	4.8	1	16.65	33	346.51	35	18	0.336
13	6	2	0.4138	19.25	34.25	383.42	36	17	0.259
14	6	2.6667	0.8889	18.28	29	373.77	37	17	0.308
15	7	2.2857	0.4571	16.18	28.34	328.11	38	16	0.315
16	7	2.2857	0.4211	15.12	33.25	335.21	39	16	0.322
17	8	2.625	0.6176	16.24	37	375.21	40	15	0.336
18	9	2.5556	0.6389	18	36.14	351.53	41	15	0.35
19	5	4.2	0.5676	13.49	24.88	381.45	42	16	0.364
20	4	5.765	0.5765	13.01	30.01	351.53	43	16	0.378
21	5	6.724	0.8005	13.04	28.64	346.51	44	15	0.385
22	6	5.7267	0.9286	14.26	32.37	383.42	45	16	0.406
23	7	4.9586	0.8678	15.87	35.13	345.12	46	17	0.42
24	8	4.3775	0.9216	17	33.07	368.45	47	16	0.427
25	5	4.086	0.5238	18.96	34.27	333.4	48	16	0.434
26	5	2.4	1.0909	17.4	16.67	419.87	30	25.07	0.175
27	6	2.3333	1.0769	16.18	19.95	381.45	26	22	0.21
28	7	3	1.4	15.12	20.32	351.53	25	21	0.231
29	6	3.3333	1.6667	16.24	21.54	346.51	24	23	0.238
30	6	3.3333	1.4286	18	22	383.42	28	24	0.245
31	5	4.2	1.6154	13.49	24.88	373.77	29	22	0.259
32	6	3.1667	1.3571	13.01	30.01	328.11	30	22	0.252
33	7	2.1429	0.8333	13.04	28.64	364.56	31	21	0.28

34	8	2.625	1.05	13.16	32.37	335.21	32	20	0.287
35	8	2.25	1	12.85	35.13	375.21	33	19	0.315
36	4	5	1.1111	12.56	33.07	351.53	34	18	0.322
37	5	4.8	1	16.65	33	346.51	35	18	0.336
38	6	2	0.4138	19.25	34.25	383.42	36	17	0.259
39	6	2.6667	0.8889	18.28	29	373.77	37	17	0.308
40	7	2.2857	0.5	16.18	28.34	328.11	38	16	0.315
41	7	2.2857	0.4211	15.12	33.25	335.21	39	16	0.322
42	8	2.625	0.6563	16.24	37	375.21	40	15	0.336
43	9	2.5556	0.6389	18	36.14	351.53	41	15	0.35
44	5	4.2	0.5676	13.49	24.88	381.45	42	16	0.364
45	4	5.765	0.6068	13.01	30.01	351.53	43	16	0.378
46	5	6.724	0.9339	13.04	28.64	346.51	44	15	0.385
47	6	5.7267	0.881	14.26	32.37	383.42	45	16	0.406
48	7	4.9086	0.9286	15.87	35.13	345.12	46	17	0.406
49	8	4.3388	0.9134	17	33.07	368.45	47	16	0.42
50	5	7.004	0.8979	18.96	34.27	333.4	48	16	0.427

5.2 Testing of Soil Sample Data by Software Analysis:

Python code

import matplotlib.pyplot as plt # Plot the results fig, axs = plt.subplots(2, 1, figsize=(10, 10)) # Plot for 'c (in kPa)' axs[0].plot(target_c.values, label='Actual c (in kPa)', color='blue') axs[0].plot(predictions_c, label='Predicted c (in kPa)', color='red', linestyle='dashed') axs[0].set_title('Actual vs Predicted values for c (in kPa)') axs[0].set_xlabel('Sample Index') axs[0].set_ylabel('c (in kPa)') axs[0].legend() # Plot for 'phi (degree)' axs[1].plot(target_phi.values, label='Actual phi (degree)', color='blue') axs[1].plot(predictions_phi, label='Predicted phi (degree)', color='red', linestyle='dashed') axs[1].set_title('Actual vs Predicted values for phi (degree)') axs[1].set_xlabel('Sample Index') axs[1].set_ylabel('phi (degree)') axs[1].legend() plt.tight_layout() plt.show()



5.3 Comparison of Data using Experimental Method & Python Method:

INPUT						OUTPUT (C= Cohesion & ϕ= Angle of Internal Friction)			
Sampl e No.	**Silt size (%) <75micr on**	**Clay size (%) <2micr on**	**%age finer 75micr on**	**Maximum dry density- LC* (kN/m3)**	**OMC- LC (%)**	**Analytical (Lab Method)**		**Programme**	
1	87	11	98	17.4	16.67	**c= 30 kPa**	**ϕ= 25.07°**	**c= 30.5 kPa**	**ϕ= 25.17°**
2	83	12	95	16.18	19.95	26	22	25	21.5
3	80	14	94	15.12	20.32	25	21	24	21
4	81	13	94	16.24	21.54	24	23	24	23
5	79	14	93	18	22	28	24	27	23
6	83	12	95	13.49	24.88	29	22	28	22
7	81	13	94	13.01	30.01	30	22	29.5	21
8	78	18	96	13.04	28.64	31	21	30	20
9	75	20	95	13.16	32.37	32	20	31	20
10	74	20	94	12.85	35.13	33	19	33	18
11	72	20	92	12.56	33.07	34	18	33	17
12	69	24	93	16.65	33	35	18	35	18
13	65	29	94	19.25	34.25	36	17	36	17
14	78	18	96	18.28	29	37	17	36	16
15	62	35	97	16.18	28.34	38	16	39	17
16	60	38	98	15.12	33.25	39	16	38	16
17	62	34	96	16.24	37	40	15	39	14
18	59	36	95	18	36.14	41	15	41	15
19	57	37	94	13.49	24.88	42	16	43	16
20	56	40	96	13.01	30.01	43	16	42	16
21	55	42	97	13.04	28.64	44	15	44	15
22	58	37	95	14.26	32.37	45	16	44	15
23	54	40	94	15.87	35.13	46	17	45	16
24	52	38	90	17	33.07	47	16	45	15
25	50	39	89	18.96	34.27	48	16	46	17
26	86	11	97	17.4	16.67	30	25.07	31	26
27	82	13	95	16.18	19.95	26	22	25	21
28	81	15	96	15.12	20.32	25	21	24	20
29	82	12	94	16.24	21.54	24	23	23	23
30	79	14	93	18	22	28	24	27	24
31	82	13	95	13.49	24.88	29	22	30	21
32	80	14	94	13.01	30.01	30	22	29	22
33	78	18	96	13.04	28.64	31	21	31	21
34	75	20	95	13.16	32.37	32	20	32	20
35	76	18	94	12.85	35.13	33	19	32	18
36	74	18	92	12.56	33.07	34	18	33	18
37	69	24	93	16.65	33	35	18	36	18
38	65	29	94	19.25	34.25	36	17	36	17
39	78	18	96	18.28	29	37	17	37	18
40	65	32	97	16.18	28.34	38	16	38	16
41	60	38	98	15.12	33.25	39	16	39	17
42	64	32	96	16.24	37	40	15	40	15

6.0 CONCLUSION

Artificial Intelligence (AI) tools are presented as a viable substitute for conventional approaches in evaluating the geotechnical characteristics of fine-graded soils. Geotechnical engineers may make

more precise and effective forecasts by using AI, which will eventually improve the stability and safety of engineering projects. To properly use AI in geotechnical engineering, further study and development in this field are required. The many soil qualities, including ILLITE, KAOLINITE, and MONTMORILLONITE, are examined and validated using artificial intelligence approaches. These calculations include Liquid Limit, Plastic Limit, Maximum Dry Density, Specific Gravity, Toughness Index, Flow Index, Direct Shear Test, and others.
The code makes use of the capabilities of many essential Python packages to carry out extensive data analysis and machine learning operations. Pandas makes it easier to prepare and manipulate data, while Matplotlib gives you a way to display the findings and a set of tools to help you create and assess machine learning models. Standard regression metrics and cross-validation are used to thoroughly assess the performance. This collection of tools and approaches demonstrates modern data science processes and shows how machine learning, visualization, and data manipulation interact together. The model demonstrates strong performance in predicting c with high R2 values in both training and cross-validation. The model does, however, indicate less consistent performance for phi.

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