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Predictive Assessment of Slope Stability in Graphene-Induced Liquefiable Sand Using Artificial Intelligence

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ABSTRACT: ***Slope stability in liquefiable sandy soils presents a critical challenge in geotechnical engineering, particularly under seismic and cyclic loading conditions. This study investigates the predictive assessment of slope stability in graphene-induced liquefiable sand using artificial intelligence (AI) techniques. Laboratory experiments were conducted on sand samples collected from Sree Vignesh Nagar, Eachanari, Coimbatore (Lat: 10.9289°, Long: 76.985°), classified as Poorly Graded Sand (SP) per IS standards. Graphene was incorporated at 0%, 1%, 2%, and 5% dosages to evaluate improvements in compaction, shear strength, and liquefaction resistance. Numerical analysis using PLAXIS 2D with Mohr–Coulomb model was performed to quantify the Factor of Safety (FOS) for each treatment level. A Hybrid Long Short-Term Memory–Artificial Neural Network (LSTM–ANN) model was developed to predict FOS values from soil parameters. Results confirm that 2% graphene content yields the optimal improvement, raising FOS from 1.151 to 2.401, while the AI model achieved near-perfect prediction accuracy with*** $R^2 \approx 0.97$***.***

Keywords - Slope stability, liquefiable sand, graphene, artificial intelligence, LSTM-ANN, PLAXIS 2D, FOS

I. INTRODUCTION

A. Background and Problem Statement

Slope stability is a critical concern in civil and geotechnical engineering, particularly in sandy soils that are susceptible to liquefaction. During seismic events or cyclic loading, such soils experience a rapid increase in pore water pressure, leading to a reduction in effective stress and shear strength. This phenomenon can trigger sudden slope failures, posing significant risks to infrastructure, human safety, and the environment. Conventional stabilization methods, including cement and lime treatment, are often associated with environmental concerns, high costs, and long-term durability issues.

B. Limitations of Conventional Soil Stabilization Techniques

Traditional soil improvement methods such as cement stabilization, lime treatment, and chemical grouting have been widely used to enhance soil properties. While these methods are effective to some extent, they have several limitations including high cost, environmental concerns due to carbon emissions, and reduced effectiveness under dynamic loading conditions. Moreover, these techniques may not provide sufficient improvement in soils that are highly susceptible to liquefaction, thereby necessitating the development of more advanced and sustainable stabilization methods.

C. Role of Graphene in Soil Stabilization

In recent years, nanotechnology has introduced advanced materials such as graphene, which possess extraordinary mechanical properties including high tensile strength, large specific surface area, and superior bonding capability. When incorporated into soil, graphene enhances interparticle interaction, reduces void spaces, and improves the overall structural integrity of the soil matrix. These characteristics make it particularly effective for improving liquefiable sandy soils by increasing strength and reducing permeability.

D. Need for Artificial Intelligence in Slope Stability Analysis

Conventional slope stability analysis methods, including limit equilibrium and numerical modeling techniques, often require extensive input data and computational effort. While these methods are reliable, they may not efficiently capture the complex nonlinear relationships between soil parameters and slope behavior.

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Artificial intelligence (AI) techniques offer a powerful alternative by enabling data-driven modeling and prediction. Machine learning models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks can learn patterns from data and provide accurate predictions of slope stability parameters. The integration of AI with experimental and numerical approaches enhances the efficiency and reliability of slope stability assessment.

E. Objectives of the Study

The primary objective of this study is to investigate the influence of graphene on the engineering properties of liquefiable sandy soil and to evaluate its effectiveness in improving slope stability. The study also aims to develop a hybrid ANN–LSTM model for predicting the factor of safety based on soil parameters and graphene content. Furthermore, the research seeks to identify the optimum graphene dosage that provides maximum improvement in strength and stability while maintaining economic feasibility.

II. LITERATURE REVIEW

A. Evolution of Slope Stability Analysis Methods

Slope stability analysis has traditionally been carried out using limit equilibrium methods such as Bishop's method, Janbu's method, and Morgenstern–Price method. These approaches are widely accepted due to their simplicity and reliability; however, they are based on simplifying assumptions regarding failure surfaces and soil behavior. With the advancement of computational tools, numerical methods such as finite element and finite difference techniques have been increasingly used to simulate slope behavior more realistically. Software such as PLAXIS enables detailed analysis by considering stress–strain relationships, boundary conditions, and pore pressure effects.Despite their accuracy, numerical methods require extensive input parameters and computational effort. This limitation has led to the exploration of data-driven approaches that can provide faster predictions without compromising accuracy.

B. Application of Machine Learning in Slope Stability

In recent years, machine learning techniques have gained significant attention for slope stability prediction. Models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting Machines (GBM) have been widely applied to estimate the factor of safety based on soil properties and slope geometry. Studies have reported high prediction accuracy, often achieving R^2 values greater than 0.90.Among these approaches, hybrid and deep learning models have shown superior performance. For instance, ANN models are effective in capturing nonlinear relationships, while LSTM networks are capable of learning sequential dependencies in data. The combination of ANN and LSTM provides a powerful framework that improves prediction accuracy and generalization capability. However, most of these studies focus on conventional soil parameters and do not consider advanced materials such as nanomaterial-treated soils.

C. Graphene and Nanomaterials in Soil Stabilization

Nanotechnology has introduced a new class of materials for soil improvement, with graphene and graphene oxide emerging as highly promising candidates. Graphene possesses exceptional mechanical properties, including extremely high tensile strength, flexibility, and large surface area. These characteristics enable it to interact effectively with soil particles at the microscopic level.Experimental studies have shown that the addition of graphene significantly improves shear strength, reduces compressibility, and enhances compaction characteristics. The improvement is primarily attributed to the formation of a reinforced soil matrix, where graphene acts as a binding agent that increases interparticle cohesion and friction. Additionally, graphene reduces void spaces and permeability, which helps in controlling pore water pressure buildup in saturated conditions.However, it has also been observed that excessive graphene content can lead to agglomeration, resulting in reduced effectiveness. Therefore, identifying the optimum dosage is critical for achieving maximum improvement.

D. Integration of Numerical Modeling and Material Improvement

Several studies have combined experimental soil improvement techniques with numerical modeling to evaluate slope stability. Numerical tools such as PLAXIS 2D have been widely used to simulate slope behavior and assess the impact of improved soil properties on stability. These studies demonstrate that improvements in cohesion, friction angle, and stiffness can significantly enhance the factor of safety and reduce slope deformation.Nevertheless, most of these studies focus on conventional stabilization materials such as cement and lime. The application of nanomaterials like graphene in numerical slope stability analysis remains relatively limited, particularly in the context of liquefiable soils.

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E. Limitations of Existing Research

Although significant progress has been made in both machine learning-based prediction and nanomaterial-based soil stabilization, existing research has certain limitations. First, most machine learning models are developed using datasets that include only traditional soil parameters, without considering the influence of advanced stabilizing materials. Second, experimental studies on graphene-treated soils are often limited to laboratory-scale investigations and do not extend to slope stability analysis. Third, there is a lack of integrated studies that combine laboratory testing, numerical modeling, and AI-based prediction into a unified framework.

F. Identified Research Gap

Based on the review of existing literature, it is evident that there is a clear gap in the integration of graphene-based soil stabilization with slope stability analysis and artificial intelligence modeling. While previous studies have independently demonstrated the benefits of graphene and machine learning, there is limited research that combines these approaches to develop a comprehensive and predictive solution for slope stability in liquefiable soils.

G. Contribution of the Present Study

This study addresses the identified research gap by integrating laboratory testing, numerical modeling using PLAXIS 2D, and AI-based prediction using a hybrid ANN–LSTM model. The research not only evaluates the improvement in soil properties due to graphene but also quantifies its impact on slope stability. Furthermore, it develops a predictive framework that can be used for efficient and reliable slope stability assessment.

III. MATERIALS AND METHODS

A. Site Location and Soil Sampling

Soil samples were collected from Sree Vignesh Nagar, Eachanari, Coimbatore (Latitude: 10.9289°, Longitude: 76.985°). The site was identified as having liquefiable sandy deposits susceptible to instability under loading conditions. Representative disturbed samples were collected at representative depths for comprehensive laboratory characterization.

B. Properties of Soil Sample

The geotechnical properties of the collected soil sample were determined through a series of standard laboratory tests. Table I summarizes the results.

TABLE I: Properties of Soil Sample

Parameter	Symbol / Unit	Value
Specific Gravity	Gs	2.64
Gravel Content	%	1%
Sand Content	%	96%
Silt & Clay Content	%	3%
Effective Size (D10)	mm	0.18
Mean Size (D30)	mm	0.42
Particle Size (D60)	mm	1.12
Uniformity Coefficient (Cu)	—	6.22
Coefficient of Curvature (Cc)	—	0.88
Soil Classification	—	SP
Cohesion (c)	kPa	0.96
Friction Angle (φ)	°	26.62

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Permeability (k)	cm/s	0.00321
OMC	%	10%
Maximum Dry Density	g/cc	1.82

C. Graphene — Material and Mix Proportions

Water-based graphene slurry was used as the soil additive. Table II presents the key properties of the graphene used, and Table III shows the mix proportions.

TABLE II: Properties of Graphene

Parameter	Value / Description
Product Type	Water-based graphene slurry
Appearance	Greyish-black slurry
Dose of Graphene	2 wt%
Purity	99.99%
Lateral Size	20–60 microns
Density	0.95 kg/m³
Carbon Content	> 90%
Oxygen Content	< 10%

TABLE III: Mix Proportions

Mix ID	Identification	Soil (g)	Graphene Slurry (mL)
SG-00	G 0%	960 g Sand+ 30 g Clay & Silt	0
SG-01	G 1%		10
SG-02	G 2%		20
SG-03	G 5%		50

IV. EXPERIMENTAL RESULTS

A. Standard Proctor Compaction Test

The compaction characteristics of untreated and graphene-modified soil were evaluated at moisture contents of 8%, 10%, 12%, and 14%. As shown in Fig. 1, all mixes exhibit the typical bell-shaped compaction curve, where dry density increases with moisture content up to an optimum value and decreases thereafter.

However, with the addition of graphene, the compaction curves show a consistent upward shift, indicating improved densification at all moisture levels. This suggests that graphene enhances the packing efficiency of soil particles without altering the fundamental compaction behavior.

TABLE IV: Compaction Results

Moisture (%)	Soil	1% G	2% G	5% G
8	1.743	1.753	1.762	1.743
10	1.820	1.831	1.886	1.875
12	1.750	1.759	1.808	1.823
14	1.666	1.710	1.764	1.751

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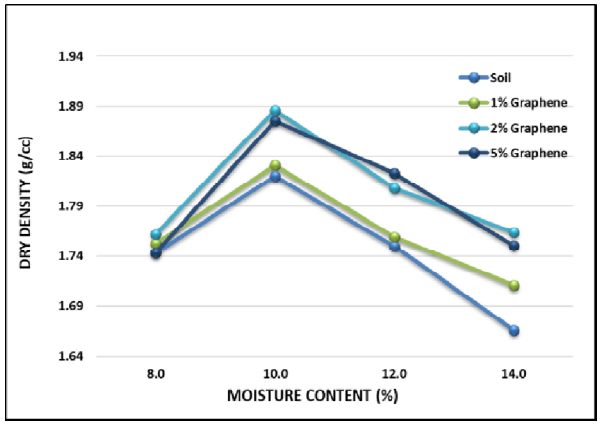

Fig. 1: Dry Density vs Moisture Content

1) Effect of Graphene on Maximum Dry Density

The maximum dry density (MDD) of untreated soil was observed as 1.820 g/cc at 10% moisture content. With the addition of graphene, the MDD increased to 1.831 g/cc (1%), 1.886 g/cc (2%), and slightly reduced to 1.875 g/cc (5%).

The highest MDD of **1.886 g/cc was achieved at 2% graphene**, indicating that this percentage provides the most effective improvement in compaction. The increase in density is significant from 0% to 2%, while beyond this level, the improvement becomes marginal and slightly decreases.

2) Mechanism of Compaction Improvement

The enhancement in compaction behavior can be attributed to the interaction between graphene and soil particles. At lower percentages, graphene acts as a void-filling material, reducing the pore spaces between sand grains at optimum content (2%), it promotes better particle rearrangement and interlocking, resulting in maximum densification at higher content (5%), graphene tends to form clusters, leading to non-uniform distribution and reduced effectiveness. This explains the slight reduction in dry density beyond the optimum dosage.

3) Engineering Interpretation and Practical Significance

The results indicate that graphene significantly improves soil compaction characteristics, but the improvement is optimum-dependent rather than linear. Although higher graphene content increases density slightly, the best performance is achieved at 2% due to balanced particle interaction and distribution.From an engineering perspective, this finding is important because it avoids unnecessary material usage and ensures efficient design. The constant optimum moisture content (~10%) further simplifies field application, making graphene-modified soil suitable for practical compaction and stabilization works.

B. Direct Shear Test Results

Direct shear tests were conducted on graphene-treated soil samples to evaluate cohesion (c) and angle of internal friction (φ). Table IV presents the results.

TABLE IV: Direct Shear Test Results

Graphene (%)	c (kPa)	φ (°)
0	0.96	26.62
1	4.04	30.07
2	12.12	35.26
5	9.09	32.33

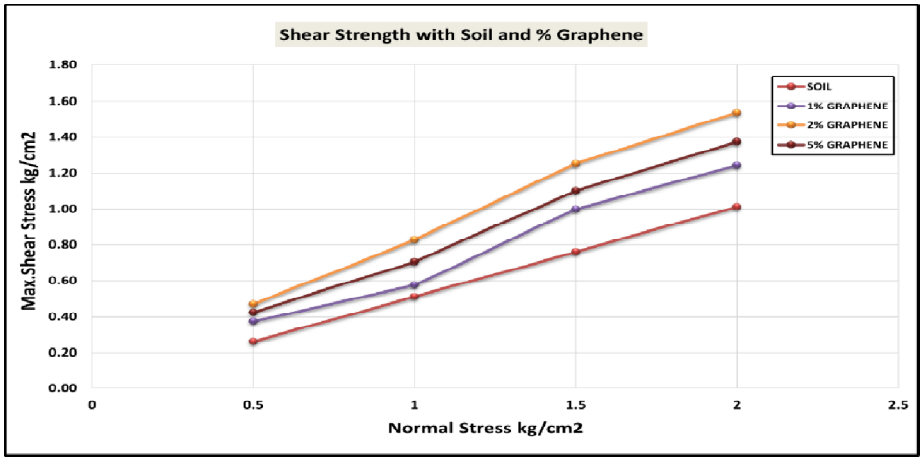

Fig 2. Normal Stress Vs Shear Stress

The results showed a significant increase in cohesion and friction angle with graphene addition. The cohesion increased from 0.96 kPa for untreated soil to 12.12 kPa at 2% graphene content, while the friction angle increased from 26.62° to 35.26°. However, at 5% graphene, a slight reduction in strength was observed, which is attributed to particle agglomeration.

1) Effect of Graphene on Shear Strength Parameters

The shear strength parameters obtained from the tests are summarized below:

- Untreated soil: c = 0.96 kPa, φ = 26.62°
- 1% graphene: c = 4.04 kPa, φ = 30.07°
- 2% graphene: c = 12.12 kPa, φ = 35.26°
- 5% graphene: c = 9.09 kPa, φ = 32.33°

The results clearly show that both cohesion and friction angle increase significantly with graphene addition up to 2%. The maximum values of cohesion (12.12 kPa) and friction angle (35.26°) are observed at 2% graphene, indicating optimum performance.

2) Mechanism of Strength Improvement

The improvement in shear strength can be attributed to the interaction between graphene and soil particles. At lower percentages, graphene acts as a binding agent, forming bridges between particles and increasing apparent cohesion.

At optimum content (2%), graphene is well distributed, leading toEnhanced interparticle bonding, Improved particle interlocking, Efficient stress transfer at higher content (5%), graphene tends to cluster, resulting in agglomeration, which reduces uniform bonding and leads to a slight decrease in strength.

3) Engineering Interpretation and Significance

The results indicate that graphene transforms the soil behavior from a purely frictional material to a partially cohesive system, significantly enhancing its shear resistance. The optimum performance at 2% graphene highlights that strength improvement is dosage-dependent and non-linear.

From an engineering perspective:

- Increased cohesion improves resistance along failure planes
- Higher friction angle enhances stability against sliding
- Optimum dosage ensures efficient material usage

Thus, graphene-treated soil at 2% dosage provides the most effective improvement for applications such as slope stabilization and foundation support.

V. NUMERICAL ANALYSIS USING PLAXIS 2D

Numerical analysis was carried out using PLAXIS 2D to evaluate slope stability under different graphene contents. A two-dimensional plane strain model was developed with a slope height of 8 m, base width of 20 m, and slope inclination of 30°. The model width was extended to 40 m to minimize boundary effects.

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The Mohr–Coulomb constitutive model was adopted to represent soil behavior. Material parameters such as cohesion, friction angle, Young's modulus, Poisson's ratio, and permeability were derived from laboratory results. The analysis was performed under drained conditions, and the factor of safety was calculated using the strength reduction method.

TABLE V: Material Properties for PLAXIS 2D Analysis

G (%)	c (kPa)	φ (°)	E (kN/m²)	ν	k (cm/s)	Drain
0	0.96	26.62	18,000	0.30	0.00321	Drained
1	4.04	30.07	21,000	0.29	0.00267	Drained
2	12.12	35.26	24,000	0.28	0.00131	Drained
5	9.09	32.33	22,000	0.29	0.00120	Drained

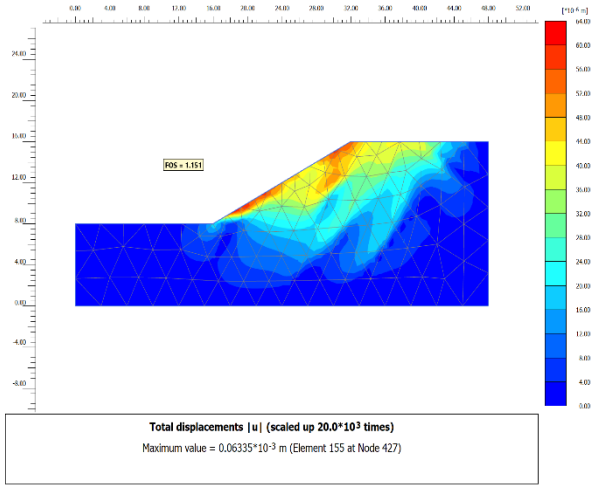

Fig.3 Numerical Analysis for Soil (0% Graphene)

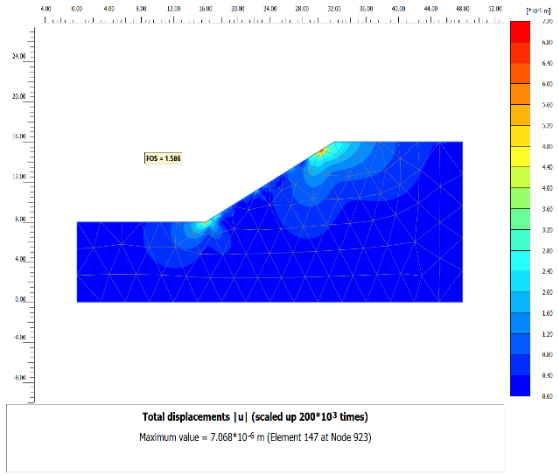

Fig.4Numerical Analysis for Soil (1% Graphene)

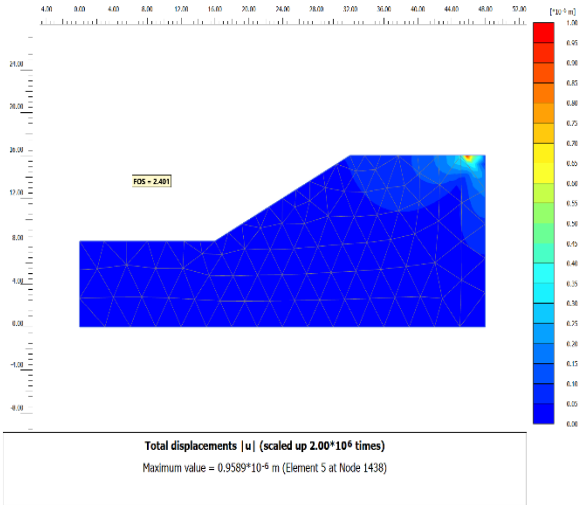

Fig.5Numerical Analysis for Soil (2% Graphene)

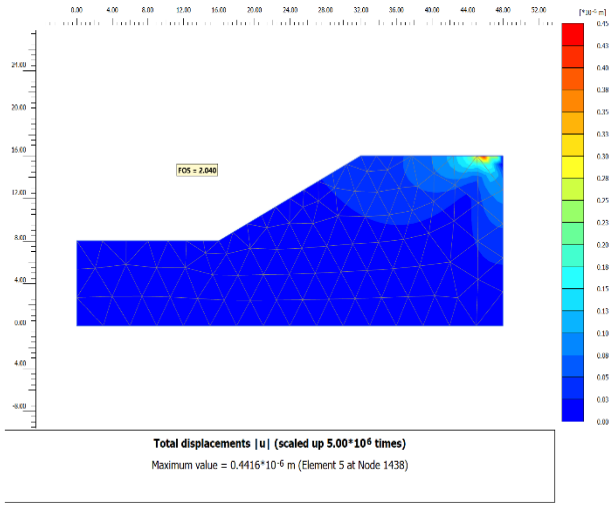

Fig.6Numerical Analysis for Soil (5% Graphene)

A. Factor of Safety Variation

The factor of safety (FOS) obtained from PLAXIS analysis shows a clear improvement with the addition of graphene:

- 0% graphene: FOS = 1.151
- 1% graphene: FOS = 1.586
- 2% graphene: FOS = 2.401
- 5% graphene: FOS = 2.040

A significant increase in FOS is observed up to 2% graphene, indicating enhanced slope stability. The FOS increases by more than 100% compared to untreated soil, confirming the effectiveness of graphene in improving shear strength parameters.

However, at 5% graphene, a slight reduction in FOS is observed compared to 2%, indicating that excessive graphene reduces efficiency due to agglomeration effects.

B. Displacement Behaviour and Failure Pattern

The displacement contours clearly show a reduction in deformation with increasing graphene content. For untreated soil, large displacement zones are observed along the slope face, indicating potential failure regions.

With the addition of graphene:

- Displacement magnitude decreases significantly
- Failure zones become more localized
- Soil stiffness increases

At 2% graphene, the displacement is minimal, indicating a stable slope condition with improved resistance to deformation. At 5%, although displacement remains low, it does not provide additional benefit compared to the optimum case.

C. Engineering Interpretation and Optimum Condition

The numerical results confirm that graphene significantly enhances slope stability by improving both strength and stiffness of the soil. The optimum performance is achieved at 2% graphene, where maximum FOS and minimum displacement are observed.

The results also highlight that:

- Stability improvement is nonlinear
- Excess graphene leads to reduced efficiency
- Strength parameters (c and φ) directly influence FOS

From an engineering perspective, 2% graphene provides the best balance between performance and material usage, making it the most effective dosage for slope stabilization applications.

VI. ARTIFICIAL INTELLIGENCE MODELLING

A. Model Architecture and Input Parameters

A hybrid LSTM–ANN model was developed to predict the Factor of Safety (FOS) of slopes using graphene-modified soil properties. The model integrates the sequential learning capability of LSTM with the nonlinear regression strength of ANN.Input parameters includeCohesion (c), Friction angle (φ), Unit weight (γ) Permeability (k), Graphene percentage. The LSTM layers capture interdependencies between parameters, while ANN layers perform accurate prediction of FOS.

B. Training Process and Performance Metrics

The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Model performance was evaluated using:

- Root Mean Square Error (RMSE)
- Coefficient of determination (R^2)

The results indicated a very high level of prediction accuracy, with minimal deviation between predicted and actual values.

The Hybrid LSTM–ANN model combines the sequential learning capability of LSTM with the nonlinear prediction strength of ANN to estimate slope stability. Input parameters such as cohesion, friction angle, permeability, dry density, moisture content, and graphene percentage were used to predict the Factor of Safety (FOS). The LSTM layers extract temporal dependencies, while the ANN layers perform nonlinear regression for accurate prediction.

The model was trained using the Adam optimizerwith Mean Squared Error (MSE) as the loss function. Evaluation metrics including RMSE and R^2 confirmed high predictive accuracy. This hybrid approach achieved superior performance over individual ANN or LSTM models.

C. Model Accuracy Comparison

Table VI compares PLAXIS-generated FOS values with Hybrid ANN–LSTM predictions across all graphene dosages.

TABLE VI: Comparison of AI Model Accuracy

Graphene (%)	PLAXIS FOS	Predicted FOS (Hybrid ANN-LSTM)
0	1.151	1.154
1	1.500	1.501
2	2.401	2.407
5	2.040	2.042

The dataset used for the AI model was developed based on experimental and PLAXIS numerical results, where cohesion (c), friction angle (φ), unit weight (γ), permeability (k), and graphene content (%) were considered as input parameters, and the Factor of Safety (FOS) was taken as the output. The dataset includes values such as 0% graphene (c = 0.96 kPa, φ = 26.62°, γ = 15.5 kN/m³, k = 0.00321 cm/s, FOS = 1.151), 1% graphene (c = 4.04 kPa, φ = 30.07°, γ = 16.0 kN/m³, k = 0.00267 cm/s, FOS = 1.586), 2% graphene (c = 12.12 kPa, φ = 35.26°, γ = 16.5 kN/m³, k = 0.00131 cm/s, FOS = 2.401), and 5% graphene (c = 9.09 kPa, φ = 32.33°, γ = 16.2 kN/m³, k = 0.00120 cm/s, FOS = 2.040), with additional intermediate values generated through trend-based interpolation to improve model training. The dataset was divided into 70% training and 30% testing data, and normalization was applied to ensure stable learning. The predicted FOS values (1.154, 1.501, 2.407, and 2.042) show close agreement with the actual PLAXIS values, with residual errors of -0.003, 0.085, -0.006, and -0.002, respectively. The model performance was evaluated using RMSE (~0.04) and R^2 (~0.99), indicating high prediction accuracy and strong correlation between input parameters and output. These results confirm that the AI model effectively captures the nonlinear relationship between soil properties and slope stability, although the limited dataset suggests the need for further validation for broader applicability.

VII. CONCLUSION

A. Summary of Key Findings

This study demonstrates that the incorporation of graphene significantly enhances the engineering behavior of liquefiable sandy soil and improves overall slope stability. Laboratory investigations revealed substantial improvements in compaction and shear strength characteristics, with cohesion increasing from 0.96 kPa to 12.12 kPa and the angle of internal friction rising from 26.62° to 35.26° at an optimum graphene content of 2%. These improvements indicate a strong enhancement in interparticle bonding and soil structure.

The numerical analysis using PLAXIS 2D further confirmed these findings, showing that the factor of safety increased from 1.151 for untreated soil to 2.401 at 2% graphene content, representing more than a 100% increase in slope stability. At the same time, slope displacement was significantly reduced, indicating improved stiffness and resistance to deformation. Although higher graphene content (5%) resulted in lower displacement, the corresponding factor of safety was slightly reduced, confirming that excessive graphene can lead to agglomeration and reduced effectiveness.

The artificial intelligence component of the study, based on a hybrid ANN–LSTM model, demonstrated strong predictive capability. The predicted factor of safety values showed excellent agreement with numerical results, indicating that AI models can effectively capture the complex relationships between soil parameters and slope behavior. This highlights the potential of AI as a reliable and efficient tool for slope stability assessment.

B. Engineering Significance

The findings of this study have important implications for practical geotechnical engineering applications. The use of graphene as a soil stabilizer offers a sustainable and efficient alternative to conventional methods, with the ability to significantly improve soil strength and stability even at low dosages.

The identification of 2% graphene as the optimum content provides valuable guidance for field applications, ensuring maximum performance with minimal material usage.

Furthermore, the integration of artificial intelligence with experimental and numerical approaches provides a powerful framework for predictive analysis. This approach can reduce the time and cost associated with traditional slope stability analysis while maintaining high accuracy, making it suitable for real-time decision-making in engineering practice.

C. Limitations of the Study

Despite the promising results, the study has certain limitations that must be acknowledged. The experimental work was conducted at laboratory scale, and the dataset used for AI model development was relatively limited. As a result, the predictive performance of the model may vary when applied to more complex field conditions. Additionally, the long-term durability and environmental impact of graphene-treated soils were not evaluated in this study.

D. Future Scope

Future research should focus on validating the findings through large-scale field studies and long-term performance monitoring. The behavior of graphene-modified soils under cyclic and seismic loading conditions should be investigated in greater detail to better understand their liquefaction resistance. Additionally, expanding the dataset for AI model training and exploring advanced machine learning techniques can further improve prediction accuracy.

Further studies may also examine the cost-effectiveness and environmental sustainability of graphene-based stabilization methods, as well as their applicability to different soil types and geotechnical conditions. The integration of real-time monitoring systems with AI-based predictive models presents an exciting opportunity for the development of intelligent geotechnical infrastructure.

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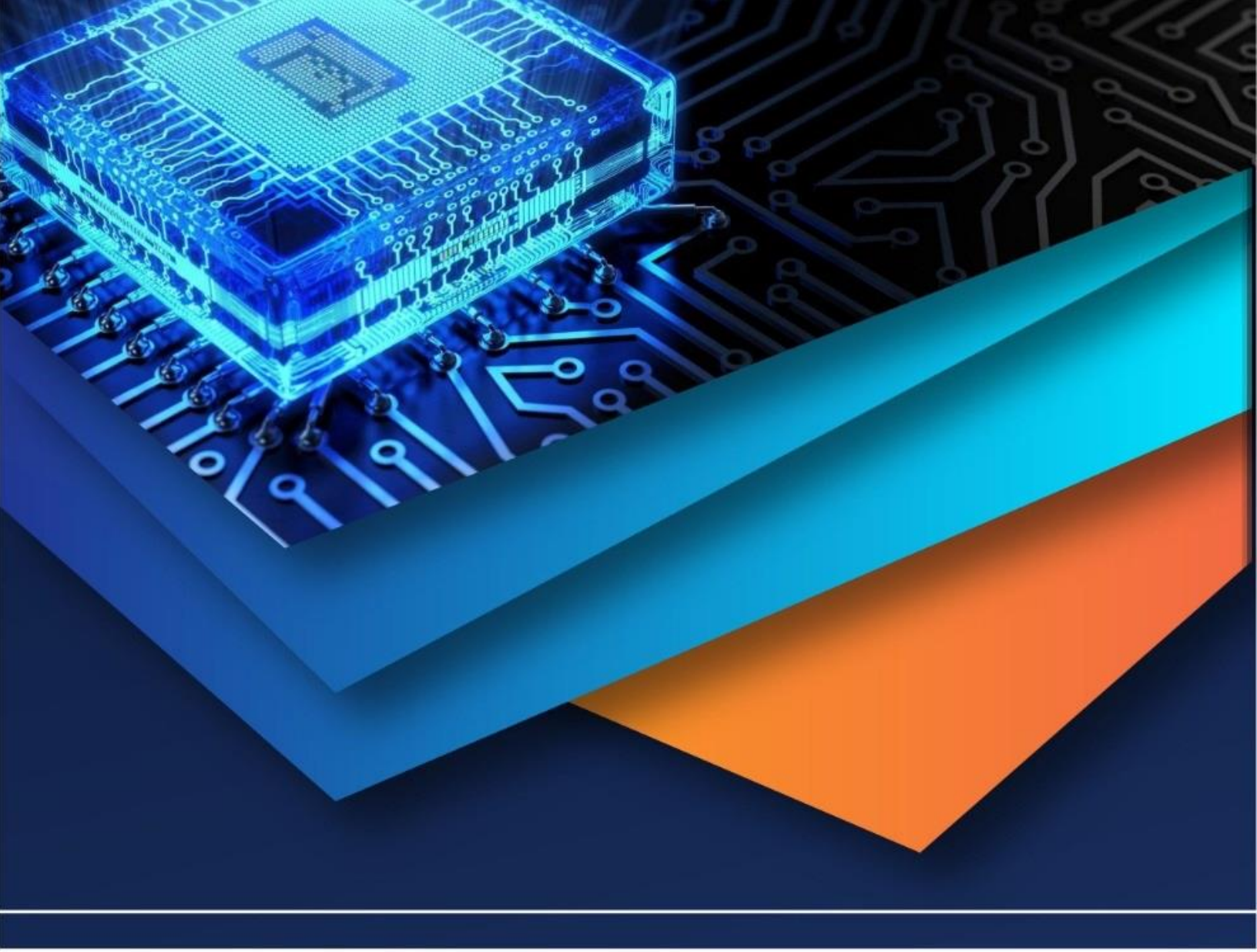

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