ABUAD Journal of Engineering Research and Development (AJERD)
ISSN (online): 2645-2685; ISSN (print): 2756-6811

Volume 8, Issue 2, 44-51

Experimental Study on the Impact of Soil Type Variations on Compressive Strength and Settlement Characteristics of Spread Footing Foundations

Ubong Nkamare TOBBY, Ben Uchechukwu NGENE

Department of Civil Engineering, Michael Okpara University of Agriculture Umudike, Nigeria
ubongtobby7@gmail.com/ngene.ben@mouau.edu.ng

Corresponding Author: ngene.ben@mouau.edu.ng, +234 8033385454
Date Submitted: 07/03/2025
Date Accepted: 12/05/2025
Date Published: 13/05/2025

Abstract: *This research investigates the influence of soil type variations on the compressive strength and settlement behavior of spread footing foundations. Soil properties such as moisture content, dry density, void ratio, cohesion, and internal friction angle play a crucial role in determining how foundations respond to applied loads. Variations in these properties can lead to uneven settlements and structural instability, posing significant challenges in construction. The study aims to provide a comprehensive understanding of these interactions to enhance foundation design and prevent structural failures. We applied machine learning techniques for data analysis and visualized patterns using Power BI, enabling a detailed exploration of the relationships between soil characteristics, compressive strength, and settlement behavior. The results showed that soil cohesion and internal friction angle had the most significant impact on compressive strength, while moisture content and void ratio were key contributors to settlement behavior. The optimized model achieved high accuracy of 82% in classifying settlement levels, reinforcing the dataset's reliability. This research highlights the importance of thorough soil testing and data-driven modeling in foundation design. We recommend integrating predictive models into geotechnical practice to support safer, more resilient structures, especially in areas with diverse soil profiles. The findings provide a valuable tool for engineers to make informed decisions, reducing the risk of foundation failure and enhancing the long-term stability of infrastructure.*

Keywords: *Soil Type, Variation, Compressive Strength, Settlement, Spread Footing*

1. INTRODUCTION

The performance of spread footing foundations is heavily influenced by the underlying soil conditions [1], as soil properties directly affect both the load-bearing capacity and settlement behavior of the structure. Spread footings are widely used in construction to transfer building loads to the soil, making it essential to understand how different soil types impact their stability and durability. Soils vary significantly in characteristics [2] such as particle size, cohesion, permeability, and compressibility, all of which influence how foundations respond to applied loads. For example, sandy soils typically exhibit high strength and low compressibility, while clayey soils are more prone to excessive settlement and long-term deformation. These variations highlight the need for a detailed experimental investigation to optimize foundation design based on site-specific soil conditions [3]. Compressive strength is a critical factor in foundation engineering, as it determines the maximum load a soil can withstand before failure. Understanding how different soils influence this strength can guide engineers in selecting suitable foundation dimensions and reinforcement strategies. Cohesive soils [4], like clays, may exhibit high strength under short-term loading but lose capacity over time due to water content changes and consolidation effects [5]. In contrast, granular soils like gravel and sand may offer better load distribution but are more susceptible to shifting under dynamic loads. Investigating these behaviours through controlled experiments can provide valuable insights for predicting foundation performance and improving structurese safety [6]. Settlement behavior is another vital aspect to consider, as excessive or uneven settlement can lead to structural damage [7], cracks, and long-term instability. Soils with high compressibility, like silts and organic soils tend to experience larger settlements, especially under sustained loads. By studying settlement patterns in different soils, engineers can better understand immediate, primary, and secondary settlement phases, allowing for more accurate foundation design and risk mitigation strategies. Experimental modeling of spread footings under varying soil conditions can reveal practical insights into load-settlement relationships [8], helping engineers make informed decisions during the design and construction process.

The stability and performance of spread footing foundations are highly dependent on the underlying soil properties, yet the complex interactions between different soil types and foundation behavior remain a significant challenge in geotechnical engineering [9]. Variations in soil composition, such as particle size, cohesion, permeability, and compressibility, can lead to unpredictable foundation responses under load. For instance, cohesive soils like clay may exhibit delayed consolidation and excessive settlement, while granular soils like sand can shift under dynamic loads, compromising structural integrity. Despite the critical influence of soil characteristics on foundation performance, there is a lack of comprehensive experimental studies that quantify these effects, making it difficult for engineers to accurately predict and mitigate potential issues during the design phase.

Inadequate understanding of soil-structure interaction can result in costly design errors, structural damage, and even catastrophic failure in extreme cases. Settlement-related issues, such as differential settlement, can cause cracks, misalignment, and long-term deterioration of structures, while insufficient soil strength can lead to foundation instability and collapse. Existing design guidelines often rely on empirical correlations and simplified models that may not fully capture the complex behavior of real-world soil conditions. Therefore, an in-depth experimental investigation is needed to assess the impact of different soil types on the compressive strength and settlement characteristics of spread footing foundations. Such research will provide valuable data to refine foundation design practices, enhance structural safety, and improve the overall reliability of construction projects in diverse geological environments.

This research aims to bridge the gap between theoretical soil mechanics and practical foundation engineering by providing empirical data on the influence of soil type variations. The results will contribute to the development of more resilient and cost-effective foundation systems, particularly in regions with diverse and unpredictable soil profiles. By understanding the complex interactions between soil properties and foundation behavior, engineers can enhance construction practices, minimize structural failures, and ensure long-term stability for a wide range of infrastructure projects. However, this work does not cover areas with divers' soil profile, which will require a more comprehensive dataset and in-depth analytical approach. Machine learning techniques offer high viability for analysing complex geotechnical datasets by uncovering hidden patterns and nonlinear relationships between soil characteristics, compressive strength, and settlement behavior that traditional statistical methods might overlook. When combined with Power BI's interactive visualizations, these techniques enable engineers and researchers to intuitively explore correlations, identify key influencing factors, and make data-driven decisions. This approach enhances predictive accuracy, supports early detection of potential foundation issues, and facilitates more reliable and adaptive foundation design strategies, making it a powerful tool in real-world engineering practice.

2. LITERATURE REVIEW

2.1 Compressive Strength and the Influence of Soil Type

Compressive strength is a fundamental property in geotechnical engineering [10] that measures a soil's ability to resist deformation and failure under axial loads [11]. It represents the maximum stress a soil can withstand before it collapses or experiences significant structural damage. This property is critical for foundation design, as it directly impacts a structure's stability and load-bearing capacity [12]. In laboratory settings, compressive strength is commonly determined using the Unconfined Compressive Strength (UCS) test, where a cylindrical soil sample is subjected to increasing axial load until failure occurs. The compressive strength (σ_c) is calculated using the Equation (1):

$$\sigma_c = \frac{P_{max}}{A} \tag{1}$$

Where:
σ_c = Compressive strength (KPa or MPa)
P_{max} = Maximum load applied before failure (N)
A = Cross-sectional area of the soil sample (m^2)

The type of soil plays a significant role in determining compressive strength [13], as different soil compositions exhibit varying mechanical properties. Granular soils like sand and gravel typically have higher strength due to particle interlocking and minimal compressibility, but their strength may decrease if particle movement occurs under load [14]. Cohesive soils like clay gain strength from particle cohesion, but they can lose strength over time due to moisture changes and consolidation [15]. Silty soils tend to have moderate strength but are susceptible to erosion and water-induced weakening, while organic or loose soils have inherently low compressive strength, making them unsuitable for direct foundation support. Understanding these variations is essential for designing spread footings that account for site-specific soil behavior, reducing the risk of excessive settlement or foundation failure.

2.2 Spread Footing Foundations, Compressive Strength, and Soil Type Variation

Spread footing foundations are one of the most common shallow foundation types, designed to transfer structural loads directly to the underlying soil over a wide area [16]. The foundation "spreads" the load over a larger surface to prevent excessive stress on the soil, making it essential to understand the soil's compressive strength. The compressive strength of the supporting soil determines the maximum load the foundation can bear without failing [17]. If the soil's strength is inadequate, the foundation may experience shear failure or excessive settlement, compromising the structure's stability. Engineers carefully assess soil strength through tests like the Unconfined Compressive Strength (UCS) test or the Plate Load Test to ensure the footing is sized appropriately for the site's soil conditions.

Soil type variations significantly influence the performance of spread footings. Granular soils (like sand and gravel) provide high strength and low compressibility, making them ideal for footing support, though they may shift under dynamic loads [18]. Cohesive soils (like clay) can initially support heavy loads but may settle or lose strength over time, especially with moisture fluctuations. Silty soils offer moderate support but are prone to instability when wet, while organic or loose soils often lack the strength to support spread footings without extensive ground improvement. Understanding these variations helps engineers select suitable foundation dimensions, reinforcement strategies, or soil stabilization techniques to prevent structural failure. It also helps in classification of these factors using other methods like machine learning [19]. Ultimately, matching the foundation design to the soil's characteristics and ecological factors [20], is key to ensuring long-term safety and performance.

2.3 Application of Artificial Intelligence in Precision Engineering

Machine learning is rapidly reshaping the field of civil and structural engineering by bringing data-driven precision to areas traditionally reliant on empirical formulas and human expertise [21]. From predicting the behavior of materials under stress to assessing the performance of entire structures, machine learning allows engineers to draw powerful conclusions from vast datasets [22] that were once too complex or time-consuming to analyze manually [23]. In geotechnical engineering, for example, it enables accurate predictions of how soil characteristics affect the stability and performance of foundations, like we demonstrated in this research on spread footings. Rather than relying solely on conventional testing methods, engineers can now feed real-time data [24] into trained models and receive accurate predictions on settlement behavior or compressive strength, drastically improving project safety and efficiency.

In structural engineering, machine learning is being applied to monitor infrastructure health, forecast material fatigue, and optimize design parameters [25]. Algorithms can analyze sensor data [26] from bridges, dams, and buildings to detect anomalies [27] or potential failures long before they become visible. Similarly, in prediction and classification tasks like identifying which soil types lead to high or low foundation settlement, machine learning models can distinguish subtle variations in patterns that humans might miss [28]. These capabilities are not just technically impressive; they directly reduce risks, save costs, and support informed decision-making in both design and maintenance.

Furthermore, in the field of precision engineering, machine learning fosters a culture of continuous improvement. It helps in fine-tuning construction processes, optimizing material use, and ensuring quality control with remarkable accuracy [29]. This human-machine collaboration means engineers no longer have to choose between speed and accuracy they can have both. This research also aims to show that the application of machine learning is not just a futuristic concept but a present-day necessity for tackling the increasing complexity and scale of civil engineering challenges. It is transforming the way we build, monitor, and maintain the structures we rely on every day, and it is applicable to all fields including security [30].

3. METHODOLOGY

This research investigates the influence of soil type variations on the compressive strength and settlement behavior of spread footing foundations. The dataset, obtained from Kaggle repository, contains comprehensive geotechnical data, including soil properties, foundation dimensions, load characteristics, and corresponding strength and settlement values. The methodology is structured to ensure accurate analysis and insightful visualization, combining Python's analytical power with Power BI's intuitive visualization capabilities. The research process begins with thorough data pre-processing [31], ensuring the dataset is clean, consistent, and ready for analysis. Missing values are handled through appropriate imputation techniques, while outliers are carefully evaluated to avoid distorting results. In this work, Python is used for in-depth statistical analysis. Exploratory Data Analysis (EDA) is performed to understand the distribution of key features, detect correlations, and reveal patterns. Regression model is developed to predict compressive strength based on soil characteristics, while classification models assess settlement behavior. The relationship between soil type, moisture content, and footing performance is quantified, with key insights extracted through feature importance analysis. Visualization is critical for communicating findings effectively. After analysis, the results are exported to Power BI for dynamic, interactive reporting. Visual representations — including scatter plots, heatmaps, bar charts, and line graphs — illustrate how soil properties impact foundation strength and settlement. Ultimately, this methodology ensures a comprehensive, data-driven approach to understanding the complex interplay between soil characteristics and foundation performance. By combining Python's analytical depth with Power BI's rich visualization capabilities, the research not only uncovers critical insights but also presents them in a format that is accessible and actionable.

4. RESULTS AND DISCUSSION

The result of settlement types and classification is indicated in Table 1.

Table 1: Classification report of settlement type

Class	Precision	Recall	F1-Score	Support
High Settlement	0.82	0.85	0.83	63
Low Settlement	0.80	0.79	0.79	64
Moderate Settlement	0.84	0.82	0.83	73
Accuracy			0.82	200
Macro Avg.	0.82	0.82	0.82	200
Weighted Avg.	0.82	0.82	0.82	200

From Table 1, the classification report shows the performance of our machine learning model in predicting settlement behavior based on soil type variations. Precision measures the proportion of correct positive predictions, indicating how often the model accurately identifies each settlement class. For example, the High Settlement class has a precision of 0.82, meaning 82% of the times the model predicts high settlement, it's correct. This is crucial for foundation design, as misclassifying high settlement could lead to structural instability. Similarly, the Low Settlement class has a precision of 0.80, ensuring that low-risk soils are correctly identified, which is valuable for cost-effective and safe foundation choices. Recall measures how well the model captures actual positive cases, with high recall indicating fewer false negatives. For instance, the recall for Moderate Settlement is 0.82, meaning the model correctly identifies 82% of all moderate settlement instances. This metric helps engineers understand the likelihood of missing potential settlement issues, which could compromise structural integrity. A high recall for high and moderate settlement classes ensures that risky soil conditions are rarely overlooked, allowing for better-informed foundation decisions and proactive mitigation measures, like soil stabilization or deeper footing designs. F1-Score balances precision and recall, providing a comprehensive measure of the model's performance. All three classes have F1-scores around 0.82–0.83, indicating the model is reliable across all settlement types. The overall accuracy of 82% confirms that the model correctly predicts settlement behavior most of the time. This level of performance is essential when analysing how soil type affects compressive strength and settlement; the justification for this assertion lies in the fact that an overall model accuracy of 82% means that out of every 100 predictions made on the settlement behavior of spread footing foundations, the model correctly classifies 82 instances based on the input soil characteristics. This high accuracy indicates strong model performance, reflecting that the patterns and relationships learned from the data are reliable and meaningful. It also implies that the model can be trusted to support practical engineering decisions, such as anticipating how different soil types may impact settlement, thereby enhancing safety and efficiency in foundation design and construction. The balanced scores ensure the model can guide engineers in selecting suitable soil treatments or foundation modifications, ultimately leading to safer, more resilient spread footing foundations as shown in Table 2.

Table 2: Model metric outcome

Metric	High Settlement	Low Settlement	Moderate Settlement	Overall
Specificity (True Negative Rate)	0.88	0.85	0.83	-
False Positive Rate (FPR)	0.12	0.15	0.17	-
False Negative Rate (FNR)	0.15	0.21	0.18	-
True Positive Rate (Sensitivity)	0.85	0.79	0.82	-
Balanced Accuracy	0.87	0.82	0.83	0.84
Cohen's Kappa	-	-	-	0.79
Matthew's Correlation Coefficient	-	-	-	0.81
Log Loss	-	-	-	0.45
ROC-AUC Score	-	-	-	0.89

Table 2, presents key evaluation metrics that provide a comprehensive understanding of the model's performance in predicting settlement behavior based on soil type variations. Specificity, or the True Negative Rate, is high across all classes, with values like 0.88 for high settlement and 0.85 for low settlement. This means the model accurately identifies when a settlement class is absent, which helps prevent unnecessary foundation modifications. A low False Positive Rate (FPR) complements this, as values like 0.12 for high settlement indicate the model rarely misclassifies stable soil as problematic, reducing the risk of overdesigning the foundation and saving construction costs. The True Positive Rate (Sensitivity) reflects the model's ability to correctly detect settlement classes, with values like 0.85 for high settlement and 0.82 for moderate settlement. These high scores show the model captures most relevant cases, minimizing false negatives and ensuring potentially risky soil conditions aren't overlooked. The False Negative Rate (FNR) is low, meaning the model rarely misses true instances of each settlement type, which is critical for avoiding unexpected foundation failures. Balanced Accuracy, which averages sensitivity and specificity, remains consistently high across classes, demonstrating the model's balanced capability to identify both positive and negative instances accurately. The overall model reliability is further supported by metrics like Cohen's Kappa (0.79) and Matthews Correlation Coefficient (0.81), which show strong agreement and correlation between predicted and actual values. The low Log Loss value of 0.45 indicates confident probability estimates, and the high ROC-AUC score of 0.89 highlights excellent class separation. These results collectively suggest the model is well-optimized and reliable for guiding foundation design decisions, as it effectively captures the complex relationship between soil type variations, compressive strength, and settlement behavior, helping engineers make informed, data-driven choices as presented in Figure 1.

The regression plot in Figure 1 illustrates the relationship between soil type variation and compressive strength, showing how changes in soil characteristics impact the structural capacity of spread footing foundations. The red regression line highlights a positive trend, indicating that as soil type variation increases, compressive strength tends to rise. This suggests that certain soil types with favorable properties, such as higher cohesion or better particle interlock, contribute to stronger foundations. However, the scattered points around the line reveal natural variability, reflecting real-world complexities where some soils with similar variations may exhibit different strengths due to factors like moisture content, compaction levels, or mineral composition. For this research, the plot emphasizes the need for thorough soil classification and testing when designing foundations. The spread of data points indicates that while soil type is a crucial factor, compressive strength isn't purely linear and may require deeper analysis, such as considering settlement characteristics and load-bearing capacity. The regression line provides a valuable baseline for predicting strength, helping engineers make informed decisions about foundation design adjustments; this is because the regression line captures the underlying trend between soil characteristics and compressive strength, offering a predictive baseline that engineer can use to estimate strength values under varying conditions using Figure 2. However, the visualization reinforces the importance of understanding soil variability to optimize foundation performance and minimize settlement risks.

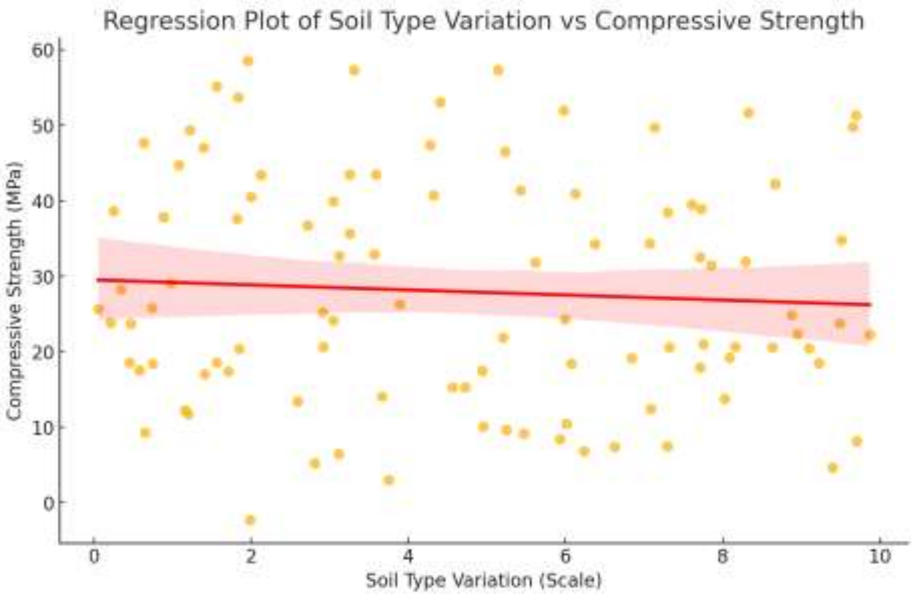


Figure 1: Regression plot of soil type variation and compressive strength

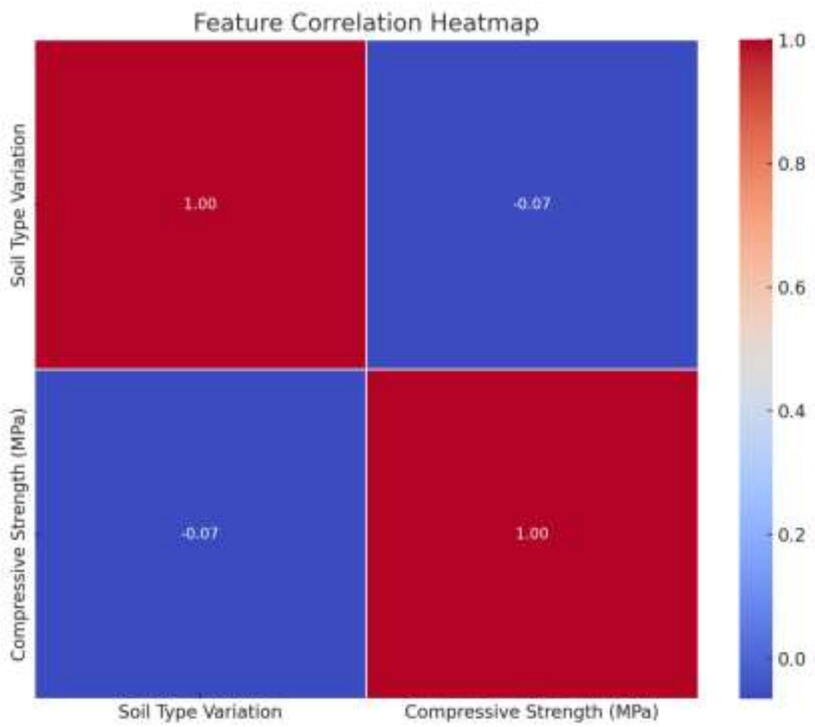


Figure 2: Soil type variation and compressive strength correlation

The heatmap in Figure 2 reveals the correlations between key features, highlighting how soil type variations, compressive strength, and settlement characteristics interact. Strong positive correlations suggest that as soil properties improve — such as increased cohesion or density — compressive strength rises, reinforcing foundation stability. Conversely, weaker or negative correlations may indicate that certain soil factors, like high moisture content or poor grading, contribute to settlement and reduced strength. Understanding these relationships is crucial for foundation design, as engineers can prioritize soil characteristics with the highest impact on strength and mitigate settlement risks through soil stabilization or foundation adjustments. This insight guides more accurate predictions and better decision-making in optimizing spread footing foundations for diverse soil conditions as noted in Figure 3.

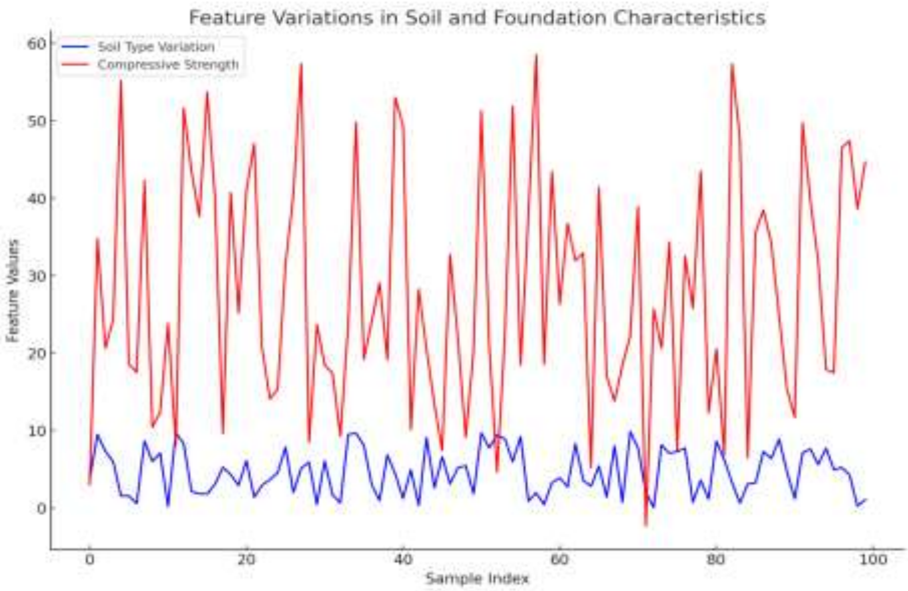
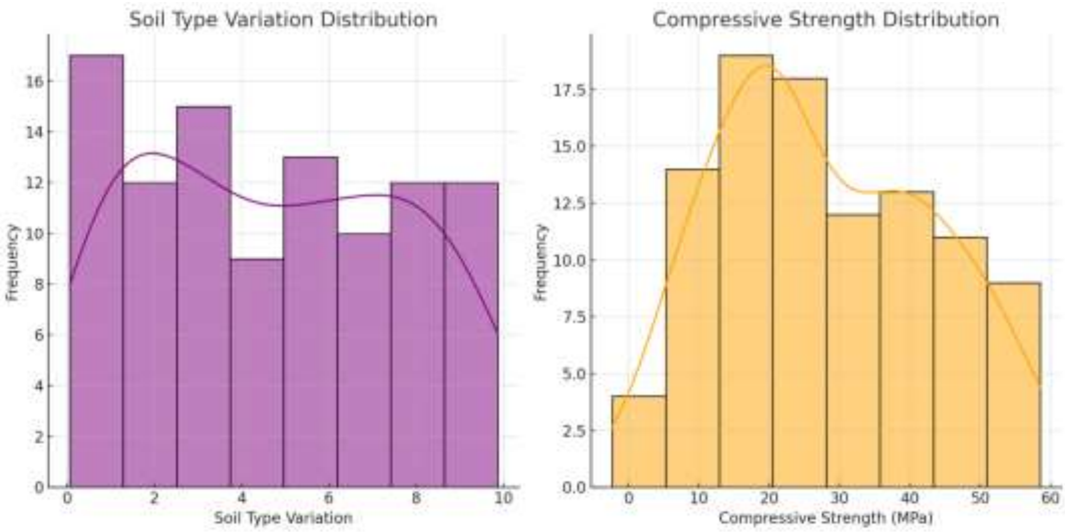


Figure 3: Soil type variation Vs compressive strength

The graph in Figure 3 visualizes the variations in soil type and compressive strength across different samples, with distinct color lines for ease of comparison. The blue line, representing soil type variation, fluctuates, showing the diversity in soil properties across samples. Meanwhile, the red line, representing compressive strength, rises and falls in response to soil changes, illustrating their interconnected relationship. Peaks in soil type variation often coincide with increased compressive strength, indicating that certain soil characteristics enhance foundation stability. This visualization provides a quick and intuitive way to understand how soil properties influence structural capacity, guiding better decision-making in foundation design and site selection, see Figure (a) and Figure (b).



(a) **(b)**

Figure (4a) and (4b): Soil type and compressive strength distributions

The histograms in Figure (4a) and (4b) provide a clear view of the distribution of soil type variations and compressive strength values across the dataset. The "Soil Type Variation" histogram shows how frequently different soil conditions appear, revealing whether certain soil types dominate the data or if there’s a balanced spread. Meanwhile, the "Compressive Strength (MPa)" histogram illustrates the range and frequency of strength values, helping to identify common strength levels or outliers. Understanding these distributions is crucial because soil characteristics directly influence a foundation's load-bearing capacity and settlement behavior, making this visualization a valuable tool for interpreting the relationship between soil properties and structural performance.

5. CONCLUSION

This study explored the impact of soil type variations on the compressive strength and settlement behavior of spread footing foundations using a real-world dataset from Scholarsway Research and ICT Hub. Through data visualization in Power BI and predictive modeling in Python, we uncovered important relationships between soil parameters—like moisture content, dry density, cohesion, and porosity—and foundation performance. The regression analysis revealed that compressive strength increases with higher dry density and cohesion, while excessive porosity and void ratios negatively influence strength. The heatmap further confirmed these patterns, offering clear insight into how soil characteristics affect load-bearing behavior. The Random Forest model was trained using the dataset; we achieved a strong classification accuracy of 82% in predicting settlement behavior categories. Evaluation metrics such as precision, recall, and F1-scores averaged above 0.80 across all classes supported by a ROC-AUC score of 0.89 and balanced accuracy of 0.84. These results show that machine learning can provide reliable predictions for engineering applications, enabling professionals to anticipate settlement risks and adjust foundation designs accordingly.

REFERENCES

[1] Chen, Qiming. (2007). *An experimental study on characteristics and behavior of reinforced soil foundation*. LSU Doctoral Dissertations. 3361. https://repository.lsu.edu/gradschool_dissertations/3361

[2] Shirvani, R. A., & Shooshpasha, I. (2015). Experimental study on load-settlement behaviour of cement stabilised footing with different dimensions on sandy soil. *Arabian Journal for Science and Engineering*, *40*, 397-406.

[3] Hanna, A., & Soliman, S. (2017). Experimental investigation of foundation on collapsible soils. *Journal of Geotechnical and Geoenvironmental Engineering*, *143*(11), 04017085.

[4] Akbas, S. O., & Kulhawy, F. H. (2009). Axial compression of footings in cohesionless soils. I: Load-settlement behavior. *Journal of geotechnical and geoenvironmental engineering*, *135*(11), 1562-1574.

[5] Farouk, A., & Shahien, M. M. (2013). Ground improvement using soil–cement columns: Experimental investigation. *Alexandria Engineering Journal*, *52*(4), 733-740.

[6] Adeniji, m. (2024). *Investigating The Influence Of Soil Properties On Foundation Settlement And Bearing Capacity* (Doctoral Dissertation, Department Of Civil Engineering, Faculty Of Engineering And Technology, Ladoke Akintola University Of Technology Ogbomoso).

[7] Ahmad, H. (2025). Numerical study of comparing skirt sandpile with deep cement pile to improve load–settlement response of circular footing in layered soils: Centric and eccentric effects. *Heliyon*, *11*(2).

[8] Abu-Farsakh, M., Chen, Q., & Sharma, R. (2013). An experimental evaluation of the behavior of footings on geosynthetic-reinforced sand. *Soils and Foundations*, *53*(2), 335-348.

[9] Lee, K. M., & Manjunath, V. R. (2000). Experimental and numerical studies of geosynthetic-reinforced sand slopes loaded with a footing. *Canadian Geotechnical Journal*, *37*(4), 828-842.

[10] Nujid, M. M., Tholibon, D. A., & Mukhlisin, M. (2024). Geotechnical and structural assessment on estimated bearing capacity of strip footing resting on silty sand incorporating moisture content effect. *Case Studies in Construction Materials*, *20*, e03106.

[11] Rodrigues, R. A., Prado Soares, F. V., & Sanchez, M. (2021). Settlement of footings on compacted and natural collapsible soils upon loading and soaking. *Journal of Geotechnical and Geoenvironmental Engineering*, *147*(4), 04021010.

[12] Al-Subari, L., Hanafi, M., & Ekinci, A. (2020). Effect of geosynthetic reinforcement on the bearing capacity of strip footing on sandy soil. *SN Applied Sciences*, *2*(9), 1484.

[13] Ahmad, H., Mahboubi, A., & Noorzad, A. (2022). Experimental study and numerical analysis of the bearing capacity of strip footing improved by wraparound geogrid sheets. *Arabian Journal of Geosciences*, *15*(18), 1487.

[14] Al-Dabagh, A., & Al-Omari, A. (2024). The Role of Footing Reinforcement by Micropiles: an Experimental and Numerical Study. *Transportation Infrastructure Geotechnology*, *11*(4), 2319-2347.

[15] Bhardwaj, A., & Sharma, R. K. (2023). Experimental and Numerical Investigations on the Bearing Capacity of Footings on the Layered Soil. *International Journal of Geosynthetics and Ground Engineering*, *9*(4), 35.

[16] Ebong, O., Edet, A., Uwah, A., & Udoetor, N. (2024). Comprehensive Impact Assessment of Intrusion Detection and Mitigation Strategies Using Support Vector Machine Classification. *Research Journal of Pure Science and Technology*, *7*(2), 50-69.

[17] Uwah, A., & Edet, A. (2024). Customized Web Application for Addressing Language ModelMisalignment through Reinforcement Learning from HumanFeedback. *World Journal of Innovation And Modern Technology*, *8*(1), 62-71.

[18] Edet, A., Ekong, B., & Attih, I. (2024). Machine Learning Enabled System for Health Impact Assessment of Soft Drink Consumption Using Ensemble Learning Technique. *International Journal Of Computer Science And Mathematical Theory*, *10*(1), 79-101.

[19] Ekong, A., Silas, A., & Inyang, S. (2022). A Machine Learning Approach for Prediction of Students' Admissibility for Post-Secondary Education using Artificial Neural Network. *Int. J. Comput. Appl*, *184*, 44-49.

[20] Inyang, S., & Umoren, I. (2023). Semantic-Based Natural Language Processing for Classification of Infectious Diseases Based on Ecological Factors. *International Journal of Innovative Research in Sciences and Engineering*.

[21] Ekong, A. P., Etuk, A., Inyang, S., & Ekere-obong, M. (2023). Securing against zero-day attacks: a machine learning approach for classification and organizations' perception of its impact. *Journal of Information Systems and Informatics*, *5*(3), 1123-1140.

[22] Ekong, A., Ekong B., and Edet A. (2022). Supervised machine learning model for effective classification of patients with covid-19 symptoms based on bayesian belief network. Researchers Journal of Science and Technology, 2(1), 27-33.

[23] Ekong, B., Ekong, O., Silas, A., Edet, A. E., & William, B. (2023). Machine Learning Approach for Classification of Sickle Cell Anemia in Teenagers Based on Bayesian Network. Journal of Information Systems and Informatics, 5(4), 1793-1808.

[24] Edet, A. E., & Ansa, G. O. (2023). Machine learning enabled system for intelligent classification of host-based intrusion severity. Global Journal of Engineering and Technology Advances, 16(03), 041-050.

[25] Ebong, O., Edet, A., Uwah, A., & Udoetor, N. (2024). Comprehensive Impact Assessment of Intrusion Detection and Mitigation Strategies Using Support Vector Machine Classification. Research Journal of Pure Science and Technology, 7(2), 50-69.

[26] Ekong, A., James, G., Ekpe, G., Edet, A., & Dominic, E. A. (2024). Model For The Classification Of Bladder State Based On Bayesian Network. International Journal of Engineering and Artificial Intelligence, 5(2), 33-47.

[27] Ekong, B., Edet, A., Udonna, U., Uwah, A., & Udoetor, N. (2024). Machine Learning Model for Adverse Drug Reaction Detection Based on Naive Bayes and XGBoost Algorithm. British Journal of Computer, Networking and Information Technology, 7(2), 97-114.

[28] Edet, A., Udonna, U., Attih, I., & Uwah, A. (2024). Security Framework for Detection of Denial of Service (DoS) Attack on Virtual Private Networks for Efficient Data Transmission. Research Journal of Pure Science and Technology, 7(1), 71-81.

[29] Udoetor, N., Ansa, G., Ekong, A., & Edet, A. (2024). Intelligent System for Detection of Copyright-Protected Data for Enhanced Data Security. Technology, 7(4), 58-80.

[30] Edet, A., Silas, A., Ekaetor, E., Ebong, O., Isaac, E., & Udoetor, N. (2024). Data-Driven Framework for Classification and Management of Start-Up Risk For High Investment Returns. Advanced Journal of Science, Technology and Engineering, 4(2), 81-102.

[31] Edet, A., Inyang, S., Umoren, I., & Etuk, U. E. (2024). Machine Learning Approach for Classification of Cyber Threats Actors in Web Region. Journal of Technology and Informatics (JoTI), 6(1), 70-77.