Digging Deeper: The Role of Big Data Analytics in Geotechnical Investigations

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Abstract. This review paper explores the transformative role of big data analytics in geotechnical engineering, transferring past conventional methods to a data-driven paradigm that complements decision-making and precision in subsurface investigations. By integrating large statistics analytics with geotechnical engineering, this study demonstrates big improvements in website characterization, danger assessment, and production methodologies. The research underscores the capability of big data to revolutionize geotechnical investigations through improved prediction models, threat management, and sustainable engineering practices, highlighting the critical role of big data in addressing international warming and ozone depletion. Through the examination of numerous case studies and AI-driven methodologies, this paper sheds light at the efficiency gains and environmental benefits attainable in geotechnical engineering.

Keyword-: Big-data, geotechnical engineering, artificial intelligence, machine learning.

1 Introduction

The building and the field of geotechnical engineering sectors greatly benefit from the vast amounts of data generated by geotechnical studies. To transmit data in a meaningful way, data analysis and visualization are required. They are also necessary to comprehend the difficulties faced by institutions that gather and/or utilize geotechnical data. Power BI is the name of Microsoft's interactive data visualization and analysis product for business intelligence (BI). For evaluating geo-data that varies both geographically and temporally, statistical analysis is essential in geotechnical and geological engineering. Data analysis techniques have been developed in order to effectively handle the enormous number of

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ambiguous and partial data that has resulted from the fast development of sensing and digitalization technology. Within the fields of digital intelligence as well as the digital marketplace, there is a continuous change in paradigms away from conventional models based on physics to data-driven frameworks. This is because models powered by data are more flexible and useful in situations where physical insights or mechanisms are not well understood or are too complicated to accurately model [1]. The work in [2] attempts to use the biological notion of "Gene" to characterize the genetic properties of geo-materials. The study suggests a novel strategy based on the common characteristics of particular rock types in a particular area or zone. The technique looks for genetic traits by analyzing geo-material parametric data using big data theory. A software platform is created to handle and evaluate large amounts of data. In order to provide advice for defining geo-material characteristics, data support for engineering construction, and potential use in natural disaster prevention, the research examines approximately 80,000 sets of geo-material physio-mechanical data from a typical region. One well-known aspect of the field of geotechnical engineering is site individuality. Information from one site's study are unable to be simply applied to another site. Nonetheless, it happens frequently that specific to the site making decisions is aided by non-site-specific (generic) information. To calculate design soil characteristics, for example, engineers frequently use transformation models; most transformation models are calibrated using generic data. Preventing the usage of these models would be quite impractical and excessive [3]. On the other hand, the effectiveness of these transformation models suggests that site-specific decision-making may benefit from the use of generic data. It is appropriate for geotechnical engineers to consider the usefulness of generic databases in this BIG DATA era. The significance of dependability calculations in geotechnical design is covered in [4], with an emphasis on quality control throughout the life cycle of the structure. It emphasizes that although uncertainties may be handled probabilistically, they are usually "known unknowns" that ask for historical data and measurable information. When dealing with complicated real-world data, imprecise data, and geographic variability that is difficult to handle with deterministic methods, reliability is helpful. Because geographic uncertainties affect seismic site impacts, a geospatial database is essential for describing geotechnical information particular to a site and enhancing geospatial zonation techniques. A big data platform, geostatistical density estimation, and optimization of the geostatistical interpolation approach are some of the components of the multi-source geospatial information system that [5] built. In order to provide geospatial zonation of site-specific seismic site impacts, the framework was applied to the Seoul metropolitan region in South Korea. For every administrative region, the zonal conditions comprised multi-source geospatial maps, geo-layers, and site impact factors. Geotechnical engineering studies need the use of geotechnical tests, but irregular findings may arise from complex techniques, imprecise data management, or unique characteristics of the soil. In geotechnical engineering studies, the BP neural network geographic information system is employed to guarantee smooth progress and accurate data. This method guarantees proper data processing and offers a strong framework for the research, guaranteeing the dependability and accuracy of the findings [6]. A major priority for trade and scientific researchers together is the establishment of a geotechnical database for Kazakhstan's Nur-Sultan University. A fixed dataset comprising a city map and user-generated information collected from more than 2000 boreholes were used to construct the database. Depending on their stratigraphic intervention and geological origin, the city was reorganized into eight zones, with six primary engineering-geological components (EGE) identified [7]. The soils' engineering characteristics were taken into account; distribution borders separating eluvial and alluvial types, as well as plasticity limitations, were precisely associated with elasticity modulus E. For driven piles, a geotechnical map was constructed to identify the ideal changes in pile length for every zone.

2 The Emergence of Big Data in Geotechnical Engineering

Prescriptive measures have given way to more precise approximations based on scant information from site inspections in this sector. Decision-making techniques should be more data-responsive in the data-driven age we live in, particularly when handling zettabytes of data, there are multiple steps involved in geo data pipeline as depicted in Fig. 1. In spite of their quality or ability to fit into a physical model, every data is valuable, according to [8]. Finding this value via hearing the reality of the data using probabilistic, machine learning, or other data-driven methodologies is a challenge for academics. This will reimagine the geotechnical engineer's job in an immersive setting where machine intelligence is probably already present. There are several obstacles in the way of the geotechnical engineering profession's efforts to advance gender equality, which prevents women from being recruited and represented in academic positions. While women make about 15%–17% of structural engineering faculty nationwide, only 11% of geotechnical engineering professors are female at the moment. Just one in ten US research institutions have two or more female faculty members, and over one-third do not. Because of their underrepresentation, fewer women are finishing their bachelor's, master's, and doctorate degrees, which is a pipeline issue [9]. Maintaining a strong female faculty is essential to the development and sustainability of the field. With an emphasis on data-centricity, fit for practice, and geotechnical context, [10] promotes a data-centric geotechnics agenda. It promotes innovative algorithms for geotechnical data, taking use of new technology, meeting practical demands, and utilizing existing knowledge. Research on data-driven site characterisation (DDSC), which addresses issues including explainable site recognition and unattractive data, is ongoing. Developing ML into a vital tool, knowing how to learn, and becoming intelligent—like digital twins—are among the challenges. The goal of this agenda is to revolutionize machine learning in geotechnics going forward. With an emphasis on the Three Gorges Reservoir region, [11] examines the application of big data and artificial intelligence (AI) in geohazard studies. It attempts to be a resource for upcoming researchers and offers up-to-date information on AI's possibilities in geohazard studies. In order to improve our knowledge of geological terrains and related risks, recommendations for strengthening AI and big data application in geotechnical research have to be developed.

Fig. 1. The digital geo-data pipeline comprises five steps.

Characterizing the geotechnical site is essential for civil engineering projects. This procedure is now more accurate and efficient because to the combination of AI and IoT technology [12].

Geospatial and geological data are analyzed using AI, while on-site real-time monitoring and data collection are made possible by IoT technology. Geophysical data is gathered via ground-embedded sensor networks, which offer a dynamic picture of subsurface conditions. By feeding this data into AI models, predictions are improved and site characterization accuracy is increased. Geotechnical engineering may more easily integrate AI and IoT because to frameworks and tools like Building Information Modeling (BIM) and Geographic Information Systems (GIS). The growth of contemporary infrastructure and guaranteeing the durability and sustainability of civil engineering projects in the future depend on this synergy. Industry 4.0 and new technologies like machine learning are causing a movement in geotechnical engineering toward digital transformation and intelligence. However, because of the sparse and unattractive data, machine learning research and applications in geotechnical practice are moving slowly. A project-specific training database reflecting project-specific data and domain knowledge in geotechnical procedures, such as soil mechanics and numerical analytical principles, is suggested to be developed by [13]. The swift advancement of novel technologies has substantially augmented our knowledge and competence in artificial intelligence. The proliferation of geographical data, strong computational capabilities, and advances in artificial intelligence have led to an increase in geographic analysis for environmental applications. AI is changing the research landscape and making high-resolution geospatial analytics possible [14]. Large datasets need the use of traditional data-processing tools; however, artificial intelligence (AI) has emerged as a substitute for these applications, providing greater comprehension and the ability to extract information from the massive volumes of data produced [15].

3 Applications of Big Data Analytics in Geotechnical Investigations

Faced with global warming and ozone depletion, there is a need for technology that can replace detrimental engineering methods [16]. Artificial intelligence approaches can reduce reliance on laboratory operations, decreasing carbon dioxide emissions and improving precision in earthwork construction and design. The study conducted in [17] investigates the applications of intelligent learning algorithms such as artificial neural networks, Fuzzy Logic, GEP, ANFIS, and ANOVA in the fields of geotechnical engineering. These algorithms aid in the prediction of geotechnical and environmental issues, hence lowering global effect. Experimental approaches throughout earthworks are located infrastructures development and construction can be complicated, resulting in mistakes or human error that cause unanticipated emissions. The majority of these challenges have been handled using evolutionary learning approaches. The study conducted in [18] focuses on utilizing artificial neural networks (ANNs) to forecast the eventual axial capacity of drilled shafts, which are often utilized for roads, bridges, and high-rise structures. The study employs stress testing from the Nevada Deep Foundation Stress Test Database to address foundation engineering challenges such as soil variability and building techniques. On unknown data, the ANN model performed well in terms of generalization and prediction accuracy, with a RMSE of 2807.08 Kilopounds force, a MAE of 2380.6 kips, and an R-squared of 87%. The study employed in [19] a multivariate dataset of J-CLAY/5/124 Jiangsu clays from China to develop an artificial neural network (ANN) model for predicting subgrade resilience modulus (Mr). The ANN model become trained and optimized with the Tabu-search technique. The version confirmed remarkable accuracy, with modified R2 values of 0.87560629 and 0.892192118. The forecasts had low inaccuracies, with a mean absolute error (MAE) of 0.217086317 and a mean squared error (MSE) of 0.071266013. Tabu-search optimization advanced the model's overall performance, resulting in increased recall, precision, F1 score, accuracy, and loss reduction. The ANN model produced encouraging results while estimating

 https://doi.org/10.1051/e3sconf/202452904012

the subgrade resilience modulus of J-CLAY/five/124 Jiangsu clays, presenting useful insights for geotechnical engineering applications. The investigation performed in [20] seeks to combine previous advances in Bayesian studies in site recognition and to provide a Bayesian inverse evaluation framework for direct assessment of actual variability. The framework connects the incidence and spread of intrinsic fluctuation, statistically unpredictability, measurement inaccuracies, and conversion uncertainty in the course of geotechnical web page characterization to numerous stages of site research. This mapping simplifies the derivation of chance features for soil and rock parameters, resulting in a more effective method for use in various web page characterization demanding situations. The have a look at carried out in [21] describes a hybrid adaptive sequential sampling (ASS) approach that consists of ANN, Monte Carlo dropout (ANN_MCD), and random forests. The ANN is suitable for many output issues, however the MCD effectively predicts uncertainty at unsampled sites. The RF evaluates input feature sensitivity, weights the sample space, and avoids interference. The approach has proved effective in geotechnical engineering, with decreased computational costs and the possibilities for geotechnical sampling. The cone penetration test (CPT) is a popular method for soil assessment and evaluating physical properties. The study compared in [22] the effectiveness of two machine learning algorithms, random forest and deep learning, on CPT test data to predict tip and sleeve resistance [22]. The random forest regression technique outperformed deep neural networks for prediction, with coefficients of determination ranging from 0.65 to 0.68 for tip resistance and 0.14 to 0.75 for sleeve resistance. Practical consequences include collecting design parameters from simpler tests, lowering project costs, increasing CPT quality and efficiency, and assisting with geotechnical project choices. Table 1 compares the different techniques used in geotechnical engineering.

Table 1. Different artificial intelligence and machine learning techniques utilized in geotechnical engineering.

Study	AI/ML Technique Used	Application Focus	Key Metrics (RMSE, MAE, R-squared, etc.)	Outcomes and Benefits
[17]	ANN, Fuzzy Logic, GEP, ANFIS, ANOVA	Prediction in geotechnical and environmental issues	-	Reduced global impact, improved prediction in geotechnical issues
[18]	ANN	Axial capacity of drilled shafts	RMSE: 2807.08 kip, MAE: 2380.6 kip, R-squared: 87%	Improved prediction accuracy for foundation engineering
[19]	ANN with Tabu-Search optimization	Subgrade resilience modulus prediction	R2: 0.875-0.892, MAE: 0.217, MSE: 0.071	High accuracy in predicting subgrade resilience, enhanced model performance
[20]	Bayesian inverse analysis	Site characterization	-	Efficient approach for deriving probability functions for soil/rock parameters
[21]	ANN, Monte Carlo dropout, Random Forests	Geotechnical sampling	-	Reduced computational costs, effective in geotechnical engineering sampling
[22]	Random Forest, Deep Learning	Soil assessment (CPT data)	R-squared: 0.65-0.75 (Tip resistance), 0.14-	Superior performance of Random Forest in soil assessment

			0.75 (Sleeve resistance)	

4 Improving Soil and Rock Characterization through Data Analytics

The conservation of water and the sustainability of the environment may be impacted by soil deterioration resulting from dryland farming, which mostly uses chemical fertilizers [23]. Utilizing geographic information system, field investigations, and laboratory soil sample evaluation, investigators tested the soil on agricultural land to ascertain the state of soil degradation. Three categories of soil degradation were distinguished by the study: mild, moderate, and high. Additionally, non-degraded and mild degradation states of the soil were found. Permeability, total porosity, and fractional composition are the causes of mild deterioration [24]. Researchers employed soil degradation potential maps for high-potential locations in an effort to stop soil deterioration. Conservation practices ought to be applied to locations where soil deterioration is present. Degraded soils can also benefit from the addition of organic matter to improve stability and water-carrying ability [25]. In order to manage groundwater resource availability in Morocco's Arghen basin, a multicriteria technique is being developed using in [26]. It creates thematic maps that depict the hydrodynamic functioning and geometry of the aquifer using a geographic information system. Eleven variables, such as hydrology, topography, and geology, are used in the study to map and categorize regions according to their hydrogeological potential. According to the research in [27], 17% of the basin is made up of positive potential sectors, 64% of medium potential sectors, and 18% of negative sections. 159 borehole data sets were used to validate the groundwater potential map [28]. Geological risks are serious concerns to the environment and human society because they are brought on by geodynamic activity or environmental changes. Geological hazard analysis has advanced as a result of the expansion of Earth observation data and the growth of deep learning. In order to better understand the use of deep learning to geological hazard assessments, [29] focuses on six typical data sources: in-situ monitoring systems, satellite platforms, and unmanned aerial vehicles. Convolutional and recurrent neural networks are two examples of deep learning models that are introduced as depicted in Fig.2.

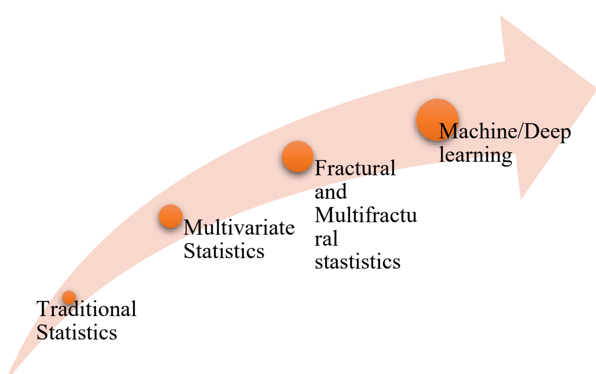

Fig.2. Different pre-processing methods of Geotechnical Data

Their applications for geological hazards are reviewed, and potential and obstacles for more study are highlighted in [30]. A hybrid stacking ensemble strategy is suggested in [31-34] to enhance the prediction of slope stability. Among 11 optimized machine learning (OML) approaches, the technique employs an artificial bee colony (ABC) algorithm to determine the optimal combination of basic classifiers and an appropriate meta-classifier. Training and testing were conducted using finite element analysis (FEA) [35-36]. Slope stability prediction was significantly improved by the hybrid stacking ensemble approach, which had an AUC of 90.4%, 7% better than the top 11 OML methods [37]. The hybrid stacking ensemble approach performed significantly better than the standard ensemble classifier when compared against it. The linear vector quantization (LVQ) approach was also used to investigate the significance of variables for slope stability [38-41].

5 Conclusion

This review based study effectively shows the significant effect of big data analytics on geotechnical engineering. Geotechnical investigations have become precise, effective and sustainable for the environment by shifting from old empirical approaches to revolutionary, data-driven procedures.

- Transition from traditional empirical methods to data-driven techniques improves accuracy, efficiency, and sustainability.
- AI and machine learning reduce uncertainties and enhance predictability of soil and rock characteristics.
- Integration of big data analytics fosters sustainable methods, aligning with international efforts to mitigate climate change impacts.

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