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Advancing Engineering Geophysics through AI-Driven Field Data Acquisition: Developing Real-Time, High-Resolution Onsite Soil Assessment Methods to Prevent Telecommunications and Energy Tower Foundation Failure

Adeoye Makinde *, Robert Quainoo, Abayomi Alabi and Olatayo Joshua Awolola

Arcade Integrated Services Limited, Technical Department, Ikeja, Lagos State Nigeria.

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Abstract

Introduction: Structural and geotechnical engineering are rapidly evolving fields driven by the integration of Artificial Intelligence (AI) and advanced digital technologies. In structural engineering, AI enhances multiple domains including design optimization, structural analysis, material selection, seismic design, smart structure monitoring, project management, and education. The rapid expansion of telecommunication and energy infrastructure across diverse geological environments has heightened the need for reliable and sustainable foundation systems. Despite technological progress in geotechnical engineering, foundation failures in tower installations continue to occur, largely due to inadequate subsurface characterization and the limitations of conventional soil testing methods. Traditional techniques such as the Cone Penetration Test (CPT), Standard Penetration Test (SPT), and laboratory analyses are invasive, time-consuming, and restricted in spatial coverage, rendering them unsuitable for real-time decision-making during field operations.

Material and Method: To address these challenges, this study proposes the development of an AI-driven geophysical field data acquisition system designed for real-time, high-resolution onsite soil assessment. The system integrates Electrical Resistivity Tomography (ERT), Ground Penetrating Radar (GPR), and Seismic Refraction methods with advanced Artificial Intelligence (AI) and Machine Learning (ML) algorithms, such as Convolutional Neural Networks (CNNs) and Random Forests, to enhance data interpretation accuracy and reduce human subjectivity. The proposed framework operates across three functional layers data acquisition, AI analytics, and decision support enabling autonomous noise filtering, pattern recognition, and predictive modeling of soil stability parameters.

Result: This comprehensive bibliometric review examines global advancements, challenges, and trends in post-disaster building damage assessment and reconnaissance methods, emphasizing the growing role of Artificial Intelligence (AI) and emerging technologies. Analysis of publications from major databases highlights the increasing global collaboration and interdisciplinary integration that are driving innovation in disaster research. Such cooperation enhances knowledge sharing, strengthens regional resilience, and improves the global capacity to respond to and recover from disasters.

Discussion: The study underscores the transformative impact of remote sensing technologies including satellite imagery, UAVs, LiDAR, and Synthetic Aperture Radar (SAR) in delivering rapid, high-resolution damage assessments. However, challenges persist in data fusion, real-time processing, and the harmonization of diverse data sources. Machine learning and deep learning models, particularly Convolutional Neural Networks (CNNs) and transfer learning, have significantly improved the accuracy and speed of damage detection and prediction.

* Corresponding author: Adeoye Makinde

Conclusion: In parallel, AI's expanding role in structural and geotechnical engineering through design optimization, seismic assessment, and risk prediction demonstrates its potential to enhance infrastructure resilience. The findings also reveal emerging trends in earthen site protection, where digital and AI-assisted tools are increasingly applied for sustainable conservation.

Keywords: AI-Driven Field Data Acquisition; Real-time Geophysical Soil Assessment Methods

1. Introduction

Public engineering, with its array of sub-disciplines, holds a key role in shaping the physical environment we inhabit. Whether it involves designing sturdy structures, efficient transportation systems, managing water resources, or addressing environmental concerns, civil engineers navigate a broad and intricate set of responsibilities. Successful project outcomes hinge on effective communication, precise problem-solving (Hu, D.et al., 2019), and adaptability to evolving challenges. In recent times, Artificial Intelligence has emerged as a transformative force capable of enhancing these foundational aspects of civil engineering. Geotechnical engineering, crucial for understanding and managing soil-structure interaction, plays a pivotal role in ensuring the safety and stability of civil infrastructure (Xiao et al., 2018**)**.

As vital material carriers of human civilization, earthen sites have become a central topic in the implementation of the United Nations Sustainable Development Goals (SDGs) (Jokilehto, 1998) and the Convention Concerning the Protection of the World Cultural and Natural Heritage under the global sustainable

development agenda (Jokilehto, 1998, Deng and Wang 2014). Their conservation must strictly adhere to the principles of "authenticity, integrity, and minimal intervention" as established in the Venice Charter (EM-DAT: 2019), not only because the survival status of earthen sites is directly linked to the preservation of global cultural diversity but also because it directly affects the implementation effectiveness of SDG Target 11.4 (Gómez-Martín, et al., 2019): "Strengthen efforts to protect and safeguard the world's cultural and natural heritage". Earthquakes are among the most destructive occurrences in the natural world. Despite large-scale improvements in geophysical research, scientists have not yet been able to ensure proper or accurate prediction of earthquakes (Goodfellow, et al., 2016). Geological faults, seismic waves, and movements of tectonic movements that indicate about the possibility of occurring earthquakes have proved less successful. Indeed, in recent years, this cross-road opened up vast new possibilities in earthquake prediction since it provides data driven approaches which could analyze large amount of information with unprecedented speed and precision. The need for earthquake prediction cannot be overemphasized (Laohaviraphap, and Waroonkun, 2019). Historical instances of the major seismic events have led to catastrophes in loss of life and wide-scale destruction of infrastructure, causing overall economic loss. Early warning systems are important because it would help minimize the impact of such disasters by giving precious minutes to prepare and evacuate vulnerable areas. However, seismicity is an extremely complex process where many interacting variables behave in non-linear and partially unpredictable ways, leaving traditional seismology unable to develop reliable predictive models (Pal, 2005).

In the wake of natural disasters, researchers are increasingly leveraging advanced technologies to meticulously gather information about buildings affected by such calamities. This critical task of identifying damaged structures is essential for ensuring public safety, as it informs residents about the condition of their homes and supports decisions on whether they can safely reoccupy their living spaces (Hu et al., 2019). Given the fundamental role of a home as a place of safety, accurately determining whether a building remains structurally sound after a disaster is paramount. To achieve this, researchers utilize a suite of state-of-the-art techniques, including remote sensing and aerial drone surveillance, to deliver precise and comprehensive assessments (Abbaspour et al., 2007). These technologies enable rapid evaluation of damage extent and critical structural weaknesses, providing residents with the information needed to feel secure and confident about the safety of their environments (Acharyya, et al., 2018). Furthermore, the application of these advanced technologies extends beyond immediate post-disaster assessments. They are instrumental in shaping long-term urban planning and improving disaster response strategies. By integrating data-driven insights from current and past events, urban planners can design more resilient infrastructures, and disaster response teams can refine their strategies to enhance efficacy and safety (Gopalakrishnan, 2018).

Jones and colleagues (2019) states that AI earthquake prediction relies mainly on massive datasets containing both historical and real-time information regarding seismic events. These datasets are often collected through large sensor networks located around boundaries for tectonic plates, providing valuable insight into the subsurface movements on Earth. Traditional ways of analysis are hindered by the interpretive skills required from the human mind and the ability to process only a small fraction of available information (Zhang and Wang, 2020).

Consequently, no singular optimal solution exists that fulfils all Decision Maker (DM) observations. MCDM assists adults in making decisions aligned with their preferences when confronted with variances (Bhatt et al., 2024) and application forms. Individuals seek to select the optimal solution when making decisions. It may be most advantageous to select only one. In most real-world decision- making processes, it is not enough to make a decision based on a single measure. Instead, many conflicting and contradictory goals must be considered. Therefore, the best solution that meets all DM requirements has not yet been developed. MCDM can help people make decisions based on their preferences when faced with conflicts (Boggia et al., 2018).

System integration analysis technology and energy management, encompassing climate change, environmental assessment, construction, and environmental management. (Antunes, 2020). Preliminary integration employing hybrid multi-criteria decision- making and fuzzy multi-criteria decision- making. Energy management issues related to rapid economic, political, technological, ecological, social and economic expansion have long been a concern for governments in countries and regions around the world (Boggia et al., 2018).;

Ultimately, environmental assessment was chosen as the initial domain to implement the decision-making process. Individuals endeavor to select the optimal solution when making decisions. In fact, analyzing just one measure can actually yield a good decision. In most real- world decision- making processes, it is not enough to derive a conclusion based on a single measure. Instead, multiple competing and inconsistent objectives must be evaluated (Phoon, 2008).

The rapid expansion of telecommunication and energy infrastructure across diverse geological terrains has increased the demand for reliable foundation systems. Despite advances in geotechnical engineering (Shen, et al. 2018)., foundation failures of telecommunication and energy towers remain a recurring challenge, often resulting from inadequate soil characterization and delayed or inaccurate subsurface assessment. Traditional soil testing methods such as cone penetration tests (CPT), standard penetration tests (SPT), and laboratory analyses are often time-consuming, site-limited, and invasive, making them unsuitable for real-time decision-making during field operation (Ojo et al., 2023).

Engineering geophysics provides non-invasive techniques for subsurface characterization, yet its effectiveness is constrained by data interpretation complexity, field noise, and human subjectivity. Recent developments in Artificial Intelligence (AI) and machine learning (ML) have opened opportunities to enhance geophysical data acquisition and interpretation, offering real-time, high-resolution insights into subsurface properties (Jordan and Mitchell. 2015). By integrating AI algorithms with geophysical sensors, it becomes possible to develop smart field systems capable of autonomous data analysis and immediate soil stability evaluation (Hu et al., 2012).

This research proposes the development of an AI-driven geophysical field data acquisition system for real-time, high-resolution soil assessment, specifically targeting the prevention of foundation failures in telecommunication and energy tower installations (Das and Basudhar, 2008).

1.1. Problem Statement

Telecommunication and energy towers are highly susceptible to structural failures resulting from inadequate understanding of subsurface conditions. Factors such as soil heterogeneity, high moisture content, collapsible soils, and shallow groundwater fluctuations contribute to instability and uneven settlement. Existing geophysical surveys, while effective, rely heavily on post-processing and expert interpretation, which introduce time delays and uncertainty in field decision-making.

Aim and Objectives

Aim

To develop and validate an AI-driven engineering geophysics framework for real-time, high-resolution onsite soil assessment to prevent telecommunication and energy tower foundation failures.

Specific Objectives

To integrate Artificial Intelligence algorithms with selected geophysical sensors (ERT, GPR, and seismic refraction) for enhanced soil property characterization.

- To design and implement a real-time field data acquisition and processing platform using edge-AI technology.
- To train and validate predictive models that correlate geophysical signatures with soil mechanical parameters.

- To evaluate the system's performance through controlled laboratory and field trials.
- To establish a risk-based assessment model linking soil stability indicators to foundation failure probabilities.

1.2. Research Questions

- How can AI improve the accuracy and speed of geophysical data interpretation in field conditions?
- What geophysical parameters are most predictive of soil strength and foundation stability?
- Can real-time AI analytics reliably classify subsurface materials and detect weak soil zones?
- What is the comparative accuracy of AI-based assessments versus traditional geotechnical tests?
- How can AI-driven geophysics be adopted as a standard for foundation risk assessment in infrastructure development?

1.3. Justification

Natural disasters are characterized by their sudden onset, immense destructive power, and inherent unpredictability, posing significant threats to human life and the security of property. These catastrophic events can strike with little to no warning, leading to substantial loss of life, extensive damage to infrastructure, and profound economic disruptions. Between 2000 and 2019, there were 510,837 deaths and 3.9 billion people affected by 6681 climate-related disasters (Alexander, 2002). In 2020 alone, disaster events attributed to natural hazards affected approximately 100 million people, accounted for an estimated USD 190 billion in global economic losses, and resulted in 15,082 deaths. These staggering figures underscore the critical importance of effective disaster management and mitigation strategies Hu et al., 2019). The increasing frequency and severity of natural disasters, exacerbated by climate change and urbanization, necessitates robust methodologies for assessing and responding to building damage post-disaster. Identifying critically affected areas and delivering essential aid to disaster-impacted regions is a pivotal component of effective disaster management.

Significance of the Study

This study holds considerable significance for both academic research and practical applications in engineering geophysics, Artificial Intelligence, and infrastructure development. It seeks to bridge the existing gap between conventional geophysical methods and advanced computational intelligence by introducing a real-time, AI-assisted framework for subsurface soil assessment. The significance of this research can be viewed from several dimensions technological, engineering, economic, and societal.

Firstly, the study will provide a novel approach to integrating Artificial Intelligence (AI) into geophysical field operations. Traditional geophysical investigations often rely on manual interpretation, which can be time-consuming and prone to human error. By embedding AI-driven analytics directly into the field data acquisition process, this research will establish a smart, adaptive, and automated system capable of improving the accuracy and efficiency of soil characterization.

Secondly, the research is expected to enhance the speed, precision, and reliability of onsite soil characterization. Through real-time processing of data obtained from electrical resistivity tomography, ground-penetrating radar, and seismic surveys, the AI system will generate immediate feedback on subsurface conditions. This advancement will enable engineers to make timely and well-informed decisions during site investigations, minimizing uncertainties and reducing the time between data collection and interpretation.

Thirdly, the study aims to reduce the incidence of foundation failures in telecommunication and energy tower infrastructure. By developing predictive models that assess soil stability and detect weak zones, the system will help identify high-risk areas before construction. This proactive approach will prevent costly structural failures, improve public safety, and extend the service life of critical infrastructure.

Furthermore, the research will contribute to the ongoing digital transformation of geotechnical and geophysical engineering. The integration of AI, real-time data analytics, and intelligent sensors aligns with global trends toward Industry 4.0 and Smart Infrastructure technologies. The study's outcomes will therefore promote innovation, data-driven practices, and sustainable engineering solutions.

Lastly, the study will support national development goals by improving the resilience and sustainability of telecommunication and energy networks. Reliable infrastructure is essential for economic growth, security, and connectivity. By enhancing foundation stability through AI-assisted soil assessment, this research contributes to building a more robust and sustainable technological infrastructure capable of supporting national and regional development agendas. This study will not only advance the frontiers of engineering geophysics but will also provide practical tools for enhancing safety, reducing costs, and promoting innovation in infrastructure development.

Scope and Delimitation of the Study

This study is designed to focus on the application of Artificial Intelligence (AI) in enhancing geophysical field operations for real-time soil assessment and foundation stability analysis. The scope defines the specific areas covered by the research, while the delimitations clarify the boundaries and limitations within which the investigation will be conducted. And will primarily concentrate on shallow subsurface soil characterization, extending to a maximum depth of 30 meters. This depth range is selected because most telecommunication and energy tower foundations are typically embedded within this zone, where soil behavior critically influences structural stability. The research will therefore emphasize the identification of weak or unstable soil layers, moisture variations, and other subsurface anomalies that could contribute to differential settlement or foundation failure.

To achieve these objectives, the research will integrate three complementary geophysical methods; Electrical Resistivity Tomography (ERT), Ground Penetrating Radar (GPR), and Seismic Refraction. These techniques were chosen for their ability to provide distinct yet interrelated information about the subsurface. Cortes and Vapnik (1995) exert that ERT will be used to determine soil resistivity and moisture distribution; GPR will offer high-resolution imaging of shallow subsurface structures; and seismic refraction will provide information on soil stiffness and stratification. The integration of these methods will ensure a comprehensive and multidimensional assessment of soil conditions. Analytical aspect of the study will employ AI modeling techniques, particularly Convolutional Neural Networks (CNNs) and Random Forest algorithms, for pattern recognition and parameter estimation (ASTM D5778–20. 2020). CNNs will be utilized to analyze spatially distributed geophysical data and detect complex subsurface patterns, while Random Forest models will be applied for predictive analysis and feature importance ranking. These AI tools will facilitate the transformation of raw geophysical data into meaningful geotechnical indicators such as bearing capacity, compaction, and stability indice (Catbas and Malekzadeh, 2016).

Furthermore, the developed AI–geophysics framework will undergo field validation at selected telecommunication and energy tower sites located in varied geologic terrains. This ensures that the system's performance and reliability are tested under different soil conditions, ranging from lateritic soils to sandy, clayey, and weathered rock formations. The validation phase will compare AI-based predictions with conventional geotechnical test results to assess the system's accuracy and practical applicability (Chen et al., 1996).

In terms of delimitation, the study will not cover deep foundation systems, marine or offshore installations, or non-tower infrastructure such as bridges or buildings. The focus will remain strictly on shallow foundations associated with telecommunication and energy towers. Additionally, the research will be limited to the use of the selected geophysical methods and AI algorithms specified above; other advanced sensing technologies or alternative machine learning models fall outside the scope of this investigation.

1.4. Conceptual Model of the Study

The conceptual model developed for this study illustrates the interaction between Artificial Intelligence, geophysical data acquisition, and engineering decision-making in the context of soil assessment and foundation stability analysis. It is designed to translate theoretical principles into a structured operational framework capable of delivering real-time, high-resolution insights into subsurface conditions (Das and Sivakugan, 2018).

The model is composed of three main functional layers; the Data Acquisition Layer, the AI Analytics Layer, and the Decision-Support Layer. Each layer performs a distinct but interdependent role, ensuring that data collection, processing, and application are seamlessly integrated to achieve accurate and timely soil characterization (Das and Sivakugan, 2018).

1.5. Data Acquisition Layer

The first layer involves the collection of geophysical data from the field using advanced, non-invasive instruments. Specifically, Electrical Resistivity Tomography (ERT), Ground Penetrating Radar (GPR), and Seismic Refraction methods are employed to obtain complementary information about the subsurface (LeCun et al., 2015).

The ERT technique measures the electrical resistivity of soil materials to identify variations related to moisture content, porosity, and clay content. GPR provides high-resolution imaging of shallow subsurface structures, enabling the detection of voids, fractures, and buried objects. Seismic refraction, on the other hand, determines the velocity of seismic waves through soil layers, which correlates with density and stiffness (Das, and Sivakugan, 2018).

Together, these methods generate a rich dataset that captures the electrical, mechanical, and structural properties of the soil. The layer is designed to operate in real-time, feeding continuous data streams to the next analytical phase. This setup represents the foundation of the model, as the quality of the collected data directly influences the accuracy of the AI-driven analysis.

1.6. AI Analytics Layer

The second layer forms the core of the intelligent system, where Artificial Intelligence (AI) and Machine Learning (ML) algorithms process and interpret the data collected from the field. Guided by systems theory and information theory, this layer ensures that the flow of information is efficient, adaptive, and self-correcting (Das, and Sivakugan, 2018).

The analytical process begins with data preprocessing, which includes noise filtering, normalization, and feature extraction to enhance signal quality. Thereafter, machine learning models, such as Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs), are applied to detect complex patterns and relationships within the geophysical datasets (LeCun et al., 2015).

These models learn from training data to identify correlations between geophysical signals (e.g., resistivity or seismic velocity) and soil mechanical properties (e.g., shear strength, bearing capacity, and moisture level). Through continuous learning, the AI system can generate predictive models that assess soil stability and highlight potential failure zones. The real-time analytical capability of this layer allows for immediate interpretation and feedback during field operations (Malmgren-Hansen et al., 2020).

1.7. Decision-Support Layer

The third and final layer focuses on transforming the AI-generated analytical results into practical, engineering-relevant insights. This stage integrates AI outputs with geotechnical and soil behavior theories such as the Terzaghi Effective Stress Principle and the Mohr–Coulomb Failure Criterion to produce interpretable indicators of soil stability and bearing capacity (Malmgren-Hansen, et al., 2020).

The outputs are presented in the form of soil stability maps, risk classifications, and foundation suitability scores, which provide engineers with clear, actionable information. The layer serves as a decision-support system, guiding site engineers and project managers in selecting appropriate foundation types, determining safe load capacities, and identifying zones that require additional soil treatment or reinforcement (Das, and Sivakugan, 2018).

By linking AI analysis with established geotechnical frameworks, this layer ensures that technological innovation is firmly grounded in engineering science, enhancing both accuracy and reliability in field decision-making.

2. Theoretical framework

This study is grounded on several interrelated theories that explain how Artificial Intelligence (AI) can enhance engineering geophysics in achieving real-time, high-resolution soil assessments for preventing telecommunication and energy tower foundation failures. The framework draws upon principles from systems theory, information theory, machine learning and pattern recognition, artificial neural networks, geotechnical failure theories, and decision-support theory. Each theory provides a conceptual basis for the integration of AI and geophysical methods into a unified, intelligent field system capable of adaptive data acquisition and predictive interpretation.

The theoretical framework provides the intellectual foundation for developing an AI-driven geophysical field system that is adaptive (Malmgren-Hansen, et al., 2020), data-efficient, and decision-oriented. By combining scientific soil behavior theories with modern AI and systems concepts, this study contributes to a new paradigm in engineering geophysics where subsurface investigations are no longer static or retrospective, but intelligent, real-time, and predictive (Mitchell, 1997).

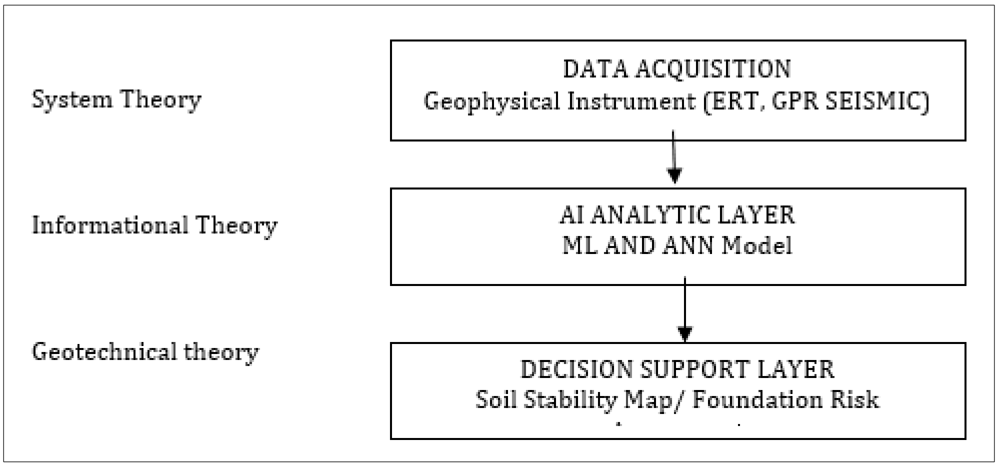

Figure 1 AI driven geophysical field system

2.1. Geotechnical Failure and Soil Behavior Theories

Core Theories includes the the following; Terzaghi's Effective Stress Principle (1943), Mohr–Coulomb Failure Criterion, Elastic–Plastic Soil Models.

The classical soil mechanics theories explain how soils respond to applied loads, moisture variations, and environmental stresses. Terzaghi's principle emphasizes that effective stress (the difference between total stress and pore-water pressure) controls soil strength and compressibility. The Mohr–Coulomb criterion provides a mathematical model for predicting shear failure based on internal friction and cohesion. These geotechnical theories provide the physical foundation for translating AI-derived geophysical parameters into meaningful engineering indicators. For example, changes in resistivity or seismic velocity may correspond to changes in effective stress or pore-water pressure. By linking AI interpretations to these theoretical principles, the model can produce quantitative predictions of soil stability and bearing capacity. This integration bridges the gap between data-driven AI approaches and physics-based soil behavior models, ensuring that the proposed system remains scientifically valid and practically applicable to tower foundation engineering.

2.2. Machine Learning and Pattern Recognition Theory

Machine Learning (ML) theory was formally established by Vladimir Vapnik and Alexey Chervonenkis in the 1970s, and later popularized by Tom Mitchell in 1997. It posits that a system can automatically learn from data and improve its performance without explicit programming. Pattern recognition, a subset of ML, focuses on identifying relationships, correlations, or structures within complex datasets. In this exploration, ML theory provides the foundation for designing algorithms that can recognize patterns between geophysical signatures (resistivity, seismic velocity, radar reflections) and soil mechanical properties (shear strength, bearing capacity, cohesion). Through supervised and unsupervised learning, AI models can classify soil types and predict subsurface stability conditions. For instance, during field acquisition, the ML model can instantly classify regions of the subsurface as "stable," "moderately stable," or "unstable," based on learned relationships from prior datasets. Pattern recognition enables the model to detect early warning signals of potential foundation failure, even when such anomalies are subtle or buried under noise. This makes ML theory central to the automation of geophysical interpretation and real-time decision-making (Pregnolato, et al., 2012).

2.3. Artificial Neural Network (ANN) Theory

The theory of Artificial Neural Networks (ANNs) was introduced by McCulloch and Pitts in 1943 and further advanced by Rumelhart, Hinton, and Williams (1986) through the backpropagation algorithm. ANNs are computational models inspired by the structure of the human brain, consisting of interconnected "neurons" that process input data through layers of weighted connections. ANN theory underpins the development of the AI model used for interpreting geophysical data. By training the network on a large dataset of soil-geophysical correlations, the ANN can generalize learned patterns and make nonlinear predictions about subsurface properties from new input data. For example, the ANN can predict soil bearing capacity, moisture content, or the likelihood of differential settlement directly from field measurements. Its ability to adapt and self-correct through iterative learning allows it to continuously improve accuracy over time. This makes ANN theory ideal for dynamic field environments where soil conditions vary rapidly and unpredictably. In addition, deep learning architectures (e.g., Convolutional Neural Networks, CNNs) extend the ANN concept by performing spatial feature extraction, enabling the generation of high-resolution 2D and 3D subsurface models in real time.

2.4. Systems Theory

Systems theory was first introduced by Ludwig von Bertalanffy in the 1950s. It postulates that every system is composed of interrelated and interdependent components that interact to achieve a specific objective. A system's behavior cannot be fully understood by analyzing its parts in isolation; rather, the interconnections and feedback mechanisms between the components determine overall performance. In the context of AI-driven engineering geophysics, the soil environment, geophysical sensors, AI algorithms, and human operators form an integrated system. The sensors act as input components that collect subsurface data; the AI algorithms serve as the processing component that interprets and analyzes the data; and engineers represent the control and feedback element that acts based on system output. Applying systems theory ensures that the design of the AI-geophysics framework incorporates feedback loops, where real-time data influence subsequent acquisition parameters. For example, if AI detects anomalies in resistivity data indicating potential weak zones, the system can automatically adjust its scanning resolution or depth of investigation. This promotes efficiency, adaptability, and continuous system optimization key attributes for real-time soil assessment.

2.5. Information Theory

Developed by Claude Shannon in 1948, information theory explains how information is transmitted, encoded, and decoded through a communication system with minimal loss or distortion. It deals with the quantification of information and focuses on minimizing uncertainty (entropy) in data processing (Pregnolato, et al. 2012).

Geophysical data, such as signals from Electrical Resistivity Tomography (ERT), Ground Penetrating Radar (GPR), or seismic refraction, are inherently noisy and complex. Applying information theory principles allows the AI model to function as an information optimizer, separating meaningful patterns (signals) from background noise. By minimizing entropy, AI algorithms can enhance signal-to-noise ratios (SNR) and improve the accuracy and clarity of subsurface images (Raghavesh et al., 2018). In practical terms, this means that soil anomalies such as voids, weak zones, or moisture variations can be detected more precisely. The theory thus supports the development of efficient algorithms for data compression, transmission, and real-time interpretation in field conditions (Seyed Hakim et al., 2011).

2.6. Decision Support Theory

Herbert Simon (1960) introduced the decision support theory, which focuses on how technology and computational tools can assist human decision-making processes. Decision Support Systems (DSS) are designed to analyze data and provide actionable insights that enhance the quality, speed, and reliability of decisions. In this research, the AI-driven geophysical system serves as a decision-support tool for engineers. It processes large volumes of geophysical data, interprets them through AI models, and outputs easy-to-understand indicators such as soil stability maps, risk indices, and foundation suitability scores. By providing these insights in real time, the system assists engineers in making informed decisions about tower placement, foundation type, and depth of anchorage. The decision-support theory ensures that human expertise remains integral to the system, with AI functioning as a complement rather than a replacement (Pregnolato et al., 2012).

2.7. Methodology of the Research

Disaster reconnaissance is a vital and complex field that utilizes a range of advanced technologies to perform its functions. To ensure the inclusion of the most relevant research works in this area, it is essential to follow a clear and systematic methodology. This research adopts a structured approach beginning with the collection of data by retrieving relevant publications from a selected database. The research paper employs a methodology centered around two primary components: an extensive literature review and a bibliometric analysis. This initial step is followed by a meticulous data-sorting process to identify additional pertinent research articles for comprehensive analysis. The final stage involves conducting a bibliometric analysis to construct a detailed science map of the existing literature. This plan provides an in-depth understanding of the current research landscape, highlighting significant trends and gaps, and ultimately offering suggestions for future research directions.

For this study, the Scopus database has been chosen due to its extensive range of high-quality publications, particularly those related to interdisciplinary and technologically advanced aspects of disaster reconnaissance. Leveraging Scopus ensures a robust foundation for our bibliometric analysis. The following subsections describe the methodology in detail.

2.8. Article Collection from Sources

This study conducts a multifaceted analysis of academic research related to the earthen site surface conservation using the core collections of the Web of Science and Scopus databases as the primary data sources. These two databases were selected because they offer broad disciplinary coverage, large-scale data repositories, high-quality literature, and comprehensive citation information. Additionally, both platforms provide robust technical support and user-friendly retrieval experiences, coupled with powerful analytical functions. Their authoritative status in the field and high level of academic recognition make them particularly well suited for bibliometric research. These characteristics ensure that the data extracted for this study are both comprehensive and reliable, thereby laying a solid foundation for the analysis. To more accurately capture cutting-edge developments in the field of earthen site surface conservation, this study focuses on the literature published before 2020. The quality of input data is crucial for any literature review, necessitating a comprehensive database and a rigorous search strategy before proceeding to bibliometric analysis and discussion. For this research, the literature has been derived from the Scopus database, as it has a wider range of disaster reconnaissance-related research articles and provides a broader scope for interdisciplinary research topics. Articles featured in the Scopus database have undergone peer review, ensuring they meet established criteria for research quality. The related publications were chosen with certain keywords. However, at first, some research questions were developed and then keywords were selected.

- What are the comparative strengths and limitations of remote sensing (satellite, UAV) versus ground-based sensing technologies in the detection and assessment of building damage following various types of disasters (e.g., earthquakes, floods, hurricanes)?
- How can Artificial Intelligence and deep learning techniques (e.g., CNNs) improve the accuracy and efficiency of building damage assessment from diverse data sources?
- Considering the challenges in real-time data collection and analysis in post-disaster scenarios, what are the most effective AI-driven strategies for rapidly assessing building damage to support immediate response and recovery efforts?
- How do machine learning models compare in their ability to detect, segment, and classify different types of building damage in disaster-affected areas?

Based on the above research questions, the following keywords were chosen for final data collection:

Publications that include the specified keywords in their titles, abstracts, or designated keyword sections are identified using the Scopus database keyword search tool. The search criteria involve selecting the title/abstract/keywords option within the database. This comprehensive search covers a decade, specifically from 2014 to 2020, ensuring a robust collection of the relevant literature over this period. The goal is to capture a wide array of studies and articles that align with the research focus, providing a solid foundation for analysis and review within the chosen timeframe

3. Result

Structural engineering, a convergence of science and art, holds a crucial role in shaping the built environment through design, analysis, and construction. The field is rapidly advancing with the integration of advanced technologies, and Artificial Intelligence (AI) is progressively becoming an integral aspect of structural engineering research.

3.1. Design Optimization and Generative Design

In the pursuit of efficient and cost-effective structures, design optimization is paramount in structural engineering. AI can enrich generative design processes by assisting engineers in exploring diverse design possibilities. By inputting constraints, material properties, and relevant parameters, AI generates creative and varied design suggestions (Huang and Li, 2020). Such iterative process allows for the discovery of novel and optimized designs not immediately apparent through traditional methods. Additionally, AI aids in creating design

3.2. Structural Analysis and Simulation

Ensuring the safety and reliability of structures relies heavily on accurate structural analysis. AI enhances structural analysis software by providing natural language interfaces, making interactions more intuitive and accessible for engineers. Moreover, it assists in interpreting simulation results, analyzing complex output data, and presenting insights comprehensibly. This empowers engineers to make informed decisions based on simulation outcomes, even without expertise in data analysis.

3.3. Material Selection and Research Material selection is pivotal for the longevity and performance of structures.

AI aids in material research by processing vast amounts of data, including properties, environmental factors, and sustainability considerations. It assists in identifying new materials or combinations that offer improved performance or reduced environmental impact. Furthermore, it facilitates communication between structural engineers and materials scientists, translating technical information and fostering collaboration.

3.4. Seismic Design and Retrofitting

AI contributes to seismic design by simulating earthquake scenarios, analyzing vulnerabilities, and

proposing retrofitting strategies. Through conversation, engineers explore different retrofitting options and evaluate their impact on structural integrity. In post-earthquake scenarios, AI aids in rapid damage assessment, analyzing data and providing insights into structural conditions, recommending immediate actions for safety and recovery.

3.5. Smart Structures and Sensor Integration

In smart structures, AI interprets sensor data and aids decision-making based on real-time information. Engineers engage in conversations to discuss sensor readings, analyze trends, and make informed decisions regarding structural health. Additionally, it contributes to predictive maintenance strategies, processing historical data to predict potential issues and allowing proactive maintenance to minimize downtime.

3.6. Collaborative Project Management

For large-scale projects, AI serves as a virtual assistant, aiding in scheduling, documentation, and

information retrieval. It facilitates communication and collaboration by providing a centralized platform for team discussions. AI organizes and summarizes conversations, ensuring important decisions and insights are easily accessible to all team members.

3.7. Education and Knowledge Transfer

AI plays a significant role in educating and training engineers, serving as a virtual tutor for explanations and interactive learning experiences. It aids in knowledge transfer within organizations by capturing and storing institutional knowledge, making it easily accessible to new team members (Deng and Wang, 2014). Through conversations, it simulates interactions with professionals, providing valuable insights and practical wisdom.

3.7.1. Basic Protection Stage (2000–2010)

Due to severe natural disasters and human-induced damage, earthen sites were in urgent need of protection during this period. Archaeologists began to explore the fundamental scientific issues related to earthen sites. The main focus was on the architecture and material mechanics of earthen sites, using simulation experiments to identify weak points in site walls and earthen structures. A pioneering “risk factor” quantitative assessment framework was proposed, and univariate analyses on material mechanical properties were conducted (Deng and Wang, 2014). However, a comprehensive protection system had yet to be established, and policy interventions were largely absent.

3.7.2. Policy Foundation Stage (2011–2015)

This stage followed China’s endorsement of The Nara Document on Authenticity (Asia–Pacific region). During this time, the principle of authenticity was officially established, and earthen sites were incorporated into the legal framework of “cultural heritage” protection. The research focus shifted from individual surface restoration to systematic protection (Jones, et al., 2019). Emphasis was placed on minimal intervention techniques based on the theoretical principles of authenticity and reversibility. Efforts were made to build international standard protection procedures and cooperation models, although the field was still in the early stage of multidisciplinary integration.

3.7.3. Transformation and Response Stage (2016–2017)

With increasingly extreme global weather, earthen sites faced intensified damage from water erosion, salt corrosion, and thermal expansion and contraction. “Climate change,” “water,” and “temperature” became key research topics in surface protection. Disaster modeling was introduced, and weather-resistant reinforcement materials were developed alongside on-site emergency response plans (Gómez-Martín et al., 2019). The research emphasis shifted from static protection to dynamic prevention, following a multidisciplinary research path.

3.7.4. Conceptual Expansion Stage (2017–2018)

The Paris Agreement emphasized synergizing carbon reduction with local development. The keyword "resilience" surged in 2018 and became a central topic. This stage marked a shift beyond traditional protection concepts, incorporating approaches such as vegetation-based protection and microclimate regulation to enhance system robustness (Bishop, 2006).

3.7.5. Innovation and Cooperation Stage (2018–2019)

Advanced digital technologies rapidly developed during this period, with 3D laser scanning and BIM technology being widely applied in the surface protection of earthen sites. At the same time, the Belt and Road Initiative facilitated international cooperation in the protection of earthen site surfaces, promoting a shift from traditional material improvement to intelligent monitoring enabled by digital technology (Bonaccorso, 2017).

3.7.6. Integrated Protection Stage (2019–2020)

Following advances in frontier technologies and updates in conservation philosophy, earthen site surface protection has centered on "sustainable strategies," "living conservation," and "dynamic monitoring" (Deng and Wang, 2014). The focus has turned to integrated approaches combining conservation, heritage transmission, and development, with tools such as VR virtual displays enabling the continuation of living heritage and transformation of its value. Generally, the current research trend in earthen site surface protection is evolving from qualitative to quantitative approaches and from single-method studies to multi-method interdisciplinary collaboration (Lin et al., 1997). With the continuous development of frontier digital technologies, significant progress has been made in the scientific understanding and practical implementation of earthen site surface protection.

3.8. Role of AI in Geotechnical Engineering

Geotechnical engineering, a subset of civil engineering, concentrates on comprehending the behavior of earth materials and leveraging this understanding in the formulation and execution of infrastructure projects. In recent times, Artificial Intelligence (AI) has made notable advancements across various disciplines (Xiao et al. 2018), with geotechnical engineering being no exception. The state-of-the-art language model, AI, developed by AI, has been instrumental in cutting-edge geotechnical research, transforming the approach to intricate problems.

3.9. Data Analysis and Interpretation

A primary application of AI in geotechnical research lies in data analysis and interpretation. Geotechnical data involves intricate soil properties, site conditions, and environmental factors. AI proves valuable in processing extensive datasets, extracting meaningful insights, and discerning patterns that conventional methods might find challenging. Its natural language processing capabilities empower researchers to engage in dialogues with the model, posing questions and receiving detailed responses that aid in deciphering complex geotechnical data. For instance, researchers can employ AI to scrutinize soil composition data, geophysical survey findings, or laboratory test results (Solanki Pattanayak et al. 2014). Through interactive sessions with the model, they can gain insights into the correlations between different parameters, assisting in making well-informed decisions during the design and construction phases of geotechnical projects.

3.10. Decision Support Systems

AI plays a pivotal role in crafting decision support systems for geotechnical engineering applications. These systems guide engineers in making informed decisions by delivering pertinent information and insights. Integrating AI into these systems enhances their ability to comprehend and respond to user queries, ultimately refining decision-making processes. For instance, engineers can interact with AI to receive real- time recommendations for foundation design based on site-specific conditions (Jiang et al., 2020). The model's grasp of complex engineering concepts and contextual information makes it a valuable asset in developing decision support systems tailored to the distinctive challenges of geotechnical projects.

3.11. Risk Assessment and Prediction

Geotechnical projects inherently harbor uncertainties and risks associated with ground conditions. AI contributes to risk assessment and prediction by assimilating historical project data, factoring in various risk elements, and offering insights into potential challenges. Researchers leverage the model to simulate different scenarios and evaluate the likelihood of adverse events, facilitating proactive risk management. In areas prone to landslides, AI can analyze historical landslide data, weather patterns, and soil characteristics to predict potential landslide risks (Guo et al., 2017).

Through dialogues with the model, engineers can explore diverse mitigation strategies and assess their effectiveness, ultimately enhancing the resilience of infrastructure in vulnerable regions.

3.12. Geotechnical Design Optimization

Optimizing geotechnical designs is a critical facet of engineering projects. AI aids in this optimization process by generating design suggestions, considering diverse constraints and objectives. The model's capacity to comprehend and generate human-like text facilitates communication of complex design concepts, fostering collaboration between engineers and the AI system (Jiang et al., 2020). For example, researchers can collaborate with AI to explore innovative foundation designs for tall structures in seismic regions. The model suggests design modifications based on seismic data, soil conditions, and structural requirements, leading to more efficient and resilient designs.

3.13. Natural Language Interface for Geotechnical Software

Traditionally, engineers interact with geotechnical software through graphical user interfaces or command-line inputs. Introducing a natural language interface powered by AI simplifies the interaction process, making geotechnical software more accessible to a broader audience, including those without extensive technical expertise (Jiang et al., 2020). Engineers can instruct AI to perform specific analyses, generate reports, or provide educational insights on geotechnical principles. This user-friendly interface streamlines workflows, reduces the learning curve for new software, and enhances collaboration among interdisciplinary teams working on geotechnical projects

4. Conclusion

This comprehensive bibliometric review of post-disaster building damage assessment and reconnaissance methods highlights the significant advancements and challenges within this critical field. The findings on global collaboration and scholarly impact in the field of disaster reconnaissance highlight several key benefits. Firstly, the comprehensive analysis of the global citation network and the geographical distribution of publications underscores the interconnectedness of research efforts worldwide. This interconnectedness facilitates the sharing of knowledge, technologies, and methodologies, thereby accelerating advancements in disaster reconnaissance. Moreover, the collaboration across different regions allows for a diverse range of perspectives and expertise, which enhances the robustness and applicability of research findings. In structural engineering, AI assumes a pivotal role.

Its aptitude for comprehending intricate structural designs, analyzing load-bearing capacities, and proposing optimized solutions positions it as a collaborative ally for engineers. The ability to generate design alternatives and conduct virtual simulations facilitates swift iteration and optimization, resulting in cost-effective and resilient structures. This not only accelerates the design phase but also ensures the safety and dependability of infrastructure projects. In geotechnical engineering, AI's proficiency in processing extensive geological data and providing insights into soil behavior is invaluable. By assisting in site selection, foundation design, and risk

assessment, AI empowers geotechnical engineers to make informed decisions, mitigating potential hazards and streamlining construction processes. Disaster is a global phenomenon, affecting millions of people each year and resulting in significant economic losses worldwide. Understanding the geographical distribution of publications helps researchers and policymakers identify regions with significant contributions and those that may require more attention and support. This awareness can guide targeted efforts to strengthen research capabilities and disaster response strategies globally. Additionally, such analyses help to understand different approaches around the world to fight disasters and improve preparedness. The global citation network will help identify critical papers, and the distribution of publications will help understand the study areas and affected regions. Ultimately, the enhanced global collaboration fosters a more resilient and prepared international community, better equipped to mitigate the impacts of natural disasters and improve recovery efforts.

At present, the surface protection of earthen sites is shifting toward a preventive paradigm, yet there remain significant gaps in data integration, the application of cutting-edge technologies, and the coordination between ecological and cultural dimensions. This study systematically analyzes the technological evolution of earthen site surface protection since the 21st century through bibliometric analysis and AI-assisted semantic mining.

The increasing frequency and severity of natural disasters necessitate robust and efficient methodologies for assessing building damage, which is pivotal for effective disaster management and mitigation strategies. This appraisal underscores the importance of leveraging advanced technologies such as satellite imagery, and UAVs in conjunction with machine learning and deep learning techniques. These technologies have revolutionized the way researchers collect and analyze data, providing high-resolution, accurate, and timely information crucial for disaster response.

Optical satellite imagery, despite its limitations under adverse weather conditions, remains a widely used tool due to its extensive coverage and frequent revisit times. Synthetic aperture radar (SAR), with its all-weather and night-time operational capabilities, offers a reliable alternative, especially in detecting structural deformations. LiDAR, known for its precise 3D mapping capabilities, proves invaluable for detailed structural analysis and damage assessment. The integration of these diverse data sources presents significant challenges, particularly in terms of data fusion and processing. Developing sophisticated algorithms that can effectively merge data from optical, infrared, LiDAR, radar, and ground-based observations is essential for creating comprehensive damage assessment models. Moreover, this review highlights the need for real-time data processing capabilities to provide immediate insights for emergency responders, thereby enhancing the effectiveness of disaster response efforts.

One of the standout insights from this review is the evolving role of machine learning and deep learning technologies in enhancing the accuracy and efficiency of building damage assessments. Innovative applications of convolutional neural networks (CNNs) and transfer learning have demonstrated significant potential in processing large datasets and rapidly adapting to unfamiliar disaster scenarios. These advancements facilitate more precise damage evaluations in real-time, which are critical for effective response and recovery operations. They also play a crucial role in long-term urban planning and resilience building, offering tools that can predict potential damage and optimize urban layouts to mitigate future disaster impacts. Future research directions should focus on overcoming the challenges identified through this review and exploring groundbreaking solutions. There is a particular need to enhance UAV capabilities, such as extending flight durations and increasing payload capacities, which would revolutionize data collection, especially in areas that are difficult to access following a disaster. Moreover, the development of user-friendly software tools and platforms for data fusion and real-time processing is essential. These tools would democratize the use of advanced technologies, making them accessible and practical for a broader range of stakeholders, including local governments, emergency responders, and community planners.

In conclusion, although significant strides have been made in the field of post-disaster building damage assessment, there remains a wealth of opportunities for further research and technological innovation. Addressing the highlighted challenges and leveraging the potential of emerging technologies will enable the development of more effective and efficient disaster management practices. Such progress is vital for enhancing the resilience and safety of communities worldwide, equipping them with the necessary tools and knowledge to better predict, respond to, and recover from disastrous events.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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