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Applications of Artificial Intelligence and Machine Learning in Geotechnical Engineering

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- 1. Overview of Artificial intelligence (AI) and Machine Learning (ML)
- 2. Al in Geotechnical engineering Examples of applications :
 - Scale of Construction sites
 - Laboratory scale
 - Micro scale
- 3. Benefits and Limitations of AI

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What exactly is AI?



Al is a computational technique that attempts to mimic, in a very simplistic way, the human cognition ability (e.g. brain, genes, nerve system) to think and learn on its own.

It is a simulation of human intelligence into machines to do tasks that we would normally rely on humans to perform.



What exactly is AI?



Al models are data-driven models which means that they rely on the data alone to determine the structure of a phenomenon (or system) without the need for assumptions or simplifications about that system, which is in contrast to most physically-based modelling techniques.



AI and ML





Al refers to the capability of a machine to perform a certain behavior; while ML is the algorithm that learns patterns from datasets to predict future outcomes, recognize patterns, or suggest different classes to the data.

Major AI Techniques











The use of different AI techniques in some applications in geotechnical engineering



Beghbani, A., Choudhury, T., Costa, S., Reiner, J. (2022). "Application of artificial intelligence in geotechnical engineering: A state-of-the-art review" *Earth-Science Reviews 228*, https://doi.org/10.1016/j.earscirev.2022.103991.

Artificial Neural Networks





Artificial Neural Networks (ANN)



Concept



©book: Memristor and Memristive Neural Networks









Examples of Applications: Scale of Construction Sites

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Examples of Applications



Dam Safety



https://www.hdrinc.com/insights/digital-twin-diablo-dam-comes-life

The Diablo Dam was built in 1936 along the Skagit River in northwestern Washington.

To ensure the dam's safety, a digital twin (virtual replica of the dam) was created merging real data obtained with embedded sensor network and incorporating machine learning and artificial intelligence to perform predictive analysis and determine how asset and geotechnical conditions would change with time (such as natural shifting, erosion of the surrounding soil, automatically identify cracks and spalls) allowing operators to take corrective actions to immediately improve their targeted maintenance scheduling and help ensure safe operations.

Examples of Applications



Slope Stability



Safety on Construction Sites



- Real time monitoring of the site
- Plan ahead for optimum slopes
- Identify any misuse of personal protective equipment (e.g. safety helmet or vest)
- When a dangerous act is predicted, the system will alert the safety officer and inspector to avoid injuries

Examples of Applications



Prediction of the load-settlement curve of Driven Piles



Several in-situ full-scale pile load tests, as well as cone penetration test (CPT) data were used to develop AI model.

The tests were conducted on sites of different soil types and geotechnical conditions, ranging from cohesive clays to cohesionless sands including layered soils

Shahin, M. A. (2014). "Load-settlement modelling of axially loaded drilled shafts using CPT-based recurrent neural networks." International Journal of Geomechanics, ASCE, 14(6), 06014012(1-7).

Shahin, M. A. (2014). "Load-settlement modelling of axially loaded steel driven piles using CPT-based recurrent neural networks." Soils and Foundations, 54(3), 515-522.

Examples of Applications

Prediction of the load-settlement curve of Driven Piles

Input parameters at current state:

D: equivalent diameter(mm) L: pile embedment length (m) \overline{q}_{c-tip} : weighted average cone point resistance over the pile tip failure zone \overline{f}_{R-tip} : weighted average friction ratio over the pile tip failure zone $\overline{q}_{c-shaft}$: weighted average cone point resistance over the pile embedmeent length \overline{f}_{R-tip} : weighted average friction

 $\overline{f}_{R-shaft}$: weighted average friction ratio over the pile embedment length ε_i : normalized axial settlement (%) $\Delta \varepsilon_i$: increment in axial settlement (%) Q_i : pile load (kN)





Examples of Applications



Prediction of the load-settlement curve of Driven Piles



Performance measure	Training	Validation
Coefficient of correlation, r	0.997	0.994
Coefficient of Determination, R ²	0.993	0.974

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Examples of Applications



Prediction of the load-settlement curve of Driven Piles

How engineers can use the developed AI model?

AI models can be used to establish a relationship between inputs and outputs which can be implemented in a simple user-friendly application.

Enter pile diameter (mm):	
Enter pile embedment length (m):	
Enter weighted average cone point resistance over pile tip failure zone (MPa):	
Enter weighted average friction ratio over pile tip failure zone:	
Enter weighted average cone point resistance over pile embedment length (MPa)	y:
Enter weighted average friction ratio over over pile embedment length:	
······	oad-Settlement curve —
ANN Model for Load-Settlement Res	
By : Mohamed SHAH	Bearing Capacity of Drilled Shafts (Bored Piles)
Place refer to the journal paper of model developer	1200
Prease refer to the journal paper of model developer	1.00
	1000 -
Run	
	800 -
	E 600 -
	400 -
	200 -



Examples of Applications: Laboratory Scale

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Examples of Applications

Prediction of the Mechanical behavior of Railway Ballast





Diameter = 300 mm

Height = 600 mm



AI Model Features:

 D_{50} : diameter at which 50% of the specimens pass through the sieve *C*_{*u*} : *coefficient of uniformity C_c* : coefficient of curvature e: void ratio Υ : bulk unit weight (kN/m³) σ_3 : confining pressure ε_i : axial strain (%) $\Delta \varepsilon_i$: axial strain increment (%) q_i: deviator stress (kPa) ε_{v_i} : volumetric strain (%)



Examples of Applications



Prediction of the Mechanical behavior of Railway Ballast



Shahin, M. A., Indraratna, B. (2006). "Modeling the mechanical behaviour of railway ballast using artificial neural networks", *Canadian Geotechnical Journal*, 43: 1144-1152.



Examples of Applications: Micro - Scale

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Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils





The collapse of Teton dam (Wikipedia)

Illustration of the suffusion process (Sibille (2016)).

Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils



Fines do not participate in stress transfer



Understressed fines provide lateral support to coarse matrix

Coarse and fine transfer approximately equal stress

Case (iv)

Skempton and Brogan (1994) proposed that a stressreduction factor, α , can be defined as the proportion of the overburden acting on the loose fraction in the no flow condition:

$$\sigma'_{fine} = \alpha \ \sigma'$$

where σ'_{fine} is the effective stress transferred by the finer fraction; σ' overburden effective stress; and α is stress-reduction factor.

Different fabric cases (Shire et al. (2014))

Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils

Discrete element modeling







Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils



Performance measures	Training	Validation
Coefficient of correlation, r	0.924	0.917
Coefficient of Determination, R ²	0.853	0.852

Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils



 $\alpha = 5.46 + 4.48tanh H_1 + 3.82tanh H_2$

$$H_1 = -0.08 - 9.6 \frac{D'_{15}}{d'_{85}} + 0.71FC - 1.07e + 6.16G$$
$$H_2 = -1.81 - 3.62 \frac{D'_{15}}{d'_{85}} + 7.73FC - 8.36e + 2.05G$$

Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils

Sensitivity analysis





Examples of Applications



Fabric and Effective Stress Distribution in Internally Unstable Soils

Sensitivity analysis



The sensitivity analysis shows that the model is robust and able to reflect the role of important parameters compared to the available geotechnical knowledge



Benefits and Limitations of AI

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Benefits and Limitations of AI

Benefits of AI





Benefits and Challenges of AI

Limitations and Challenges







Prof. Mohamed Shahin (Curtin University, Australia)

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