AFRIROCK 2025

PIONEERING PROGRESS :
THE FUTURE OF ROCK ENGINEERING

Machine learning as a catalyst to enhance collaboration across generations and disciplines in South African Rock Engineering

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Challenges in South African Rock Engineering

1. Geological Complexity

- Highly variable and unpredictable rock mass conditions.
- Deep-level mining increases stress and instability.

2. Generational Diversity

- Senior practitioners rely on traditional, experience-based methods, and younger ones push for tech-driven approaches.
- This leads to resistance, poor collaboration, and slow innovation and people working silos

3. Technical Limitations

- Difficulty in predicting ground behaviors and excavation conditions.

4. Design and Planning Gaps

- Lack of comprehensive geotechnical and design information.
- Decisions are often made reactively instead of proactively.

Multi-Generational, Trans-Disciplinary Workforce

- South African rock engineering involves professionals from multiple generations and different disciplines.
- Collaboration is essential between:

  - Rock engineering practitioners, Mining Engineers, Geo-Specialists, Geotechnical Engineers, Data Scientists, Computer Programmers, and safety experts.
- Senior professionals offer deep industry knowledge.
- Younger engineers contribute technological innovation and fresh perspectives.
- This combination creates valuable opportunities for **knowledge transfer** and **innovation**

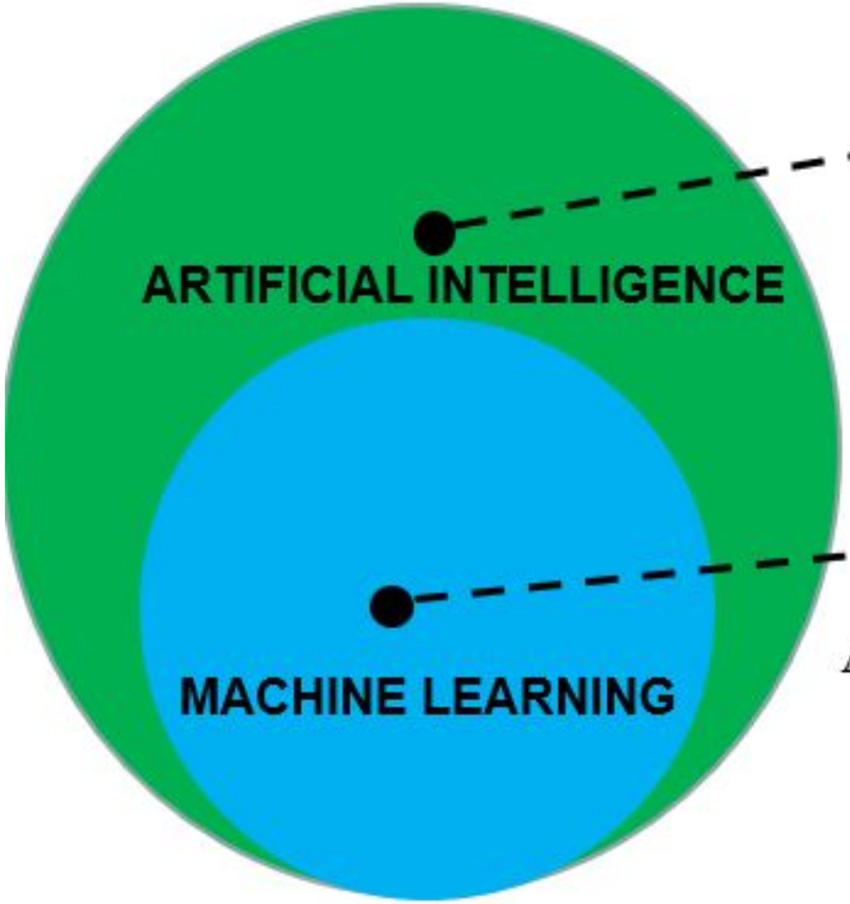
Collaboration and Communication Challenges

- Differences in technical proficiency and familiarity with digital tools can hinder collaboration.
- Workflow integration gaps often emerge between those using traditional methods and those adopting modern digital systems.
- The trans-disciplinary nature of the field adds complexity, requiring coordination across:
    - Rock Engineering, Geomechanics, civil engineering, geology, geophysics, and materials science.

Path Forward – Skills and Safety

- To ensure safe and sustainable practices, the industry must:
  - Foster **interdisciplinary teamwork**.
  - Invest in **upskilling** for emerging technologies and digital tools.
- Aligns with the vision of the Mine Health and Safety Council:
  - *"Every mine worker returning from work unharmed every day, striving for zero harm in our lifetime."*

Understanding ML in Rock Engineering



ARTIFICIAL INTELLIGENCE

Any techniques that allow a machine to mimic human intelligence using logic, if then rules, decision trees, and machine learning

MACHINE LEARNING

A subset of **AI** that uses statistical techniques to learn patterns in data enabling them to learn with experience ("training")

Understanding ML in Rock Engineering

- The integration of ML in rock engineering builds upon
  - existing empirical and numerical methodologies, offering predictive capabilities that enhance decision-making processes.
- However, these conventional methods rely heavily on expert judgment to integrate categorical and numerical data, leaving room for uncertainty and subjectivity.
- ML can bridge this gap by identifying complex patterns in rock engineering datasets, improving the accuracy and reliability of predictions.

Machine Learning Applications In Rock Engineering

Application	ML Models Used	Applications
Rock Mass Properties Prediction	Artificial Neural Networks (ANNs)	- Predict rock mass properties based on observed site conditions.
		- Estimate large-scale rock mass behaviour using laboratory-scale properties and geological mapping.
		- Enhance rock mass classification (e.g., Q-system, RMR) by integrating multisource geotechnical data (Jing & Hudson, 2002).
Predicting Rock Failure and Stability	Decision Trees, Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), Ensemble Learning	- Classify rock stability levels, based on historical failure data and stress conditions (Jing & Hudson, 2002).
		- Detect early instability signs through image recognition of rock surfaces using CNNs.
		- Ensemble learning improves the reliability of seismicity analysis and correlates well with actual induced rockburst events (Masethe *et al.*, 2024).
Laboratory Testing & Constitutive Behaviour	ANNs, SVMs	- Predict crack initiation and damage thresholds using geology and peak unconfined compressive strength (UCS).
		- Estimate constitutive behaviour based on laboratory tests and field observations.
Slope Stability Assessment	ANNs, SVMs, Random Forests (RFs), Clustering	- Predict slope movements using geometric and sensor data (e.g., piezometers, inclinometers).

Application	ML Models Used	Applications
Automated Geological Mapping & Point Cloud Analysis for Tunnel Deformations		- Estimate volumes of structurally controlled failures based on mapped discontinuities.
	RF, k-Nearest Neighbours (kNN), CNNs	- ML-powered image recognition automates geological mapping, improving accuracy in rock classification and fracture detection (Bieniawski, 1973).
		- Process LiDAR and hyperspectral imaging data to estimate rock quality designation (RQD) values.
		- Use successive tunnel scans to detect volume changes and predict time-dependent deformations.
Tunnel Performance Prediction & Mine Support Design	ANNs, SVMs, RFs, Reinforcement Learning	- Predict stress/strain fields for numerical models to refine mine support design.
		- Optimise tunnel support class based on geological conditions, excavation methods, and environmental factors (Barton *et al.*, 1974).
		- Use microseismic data to assess rock mass deformation as excavation progresses.
Rock Burst Prediction	ANNs, Naïve Bayes, kNN, RFs, SVMs, Decision Tree	- Predict the magnitude and location of rockburst events using 3D excavation geometry and seismic event data.
		- Estimate failed material volume and rock support performance, based on past rockburst events.
		- Assess rockburst probability using mapped rock classification data (Jing & Hudson, 2002).
Numerical Model Enhancement	ANNs, Reinforcement Learning	- Calculate numerical models (e.g., finite element, discrete element methods) using past simulation results and observed site conditions to improve predictive accuracy.
Blasting Optimisation	ANNs, SVMs	- Predict blast damage and optimise blasting parameters for enhanced safety and efficiency.
		- Estimate blast parameters based on mapped rock classification data, improving precision in rock fragmentation.

Bridging Generational Gaps through ML in the South African Rock Engineering Context

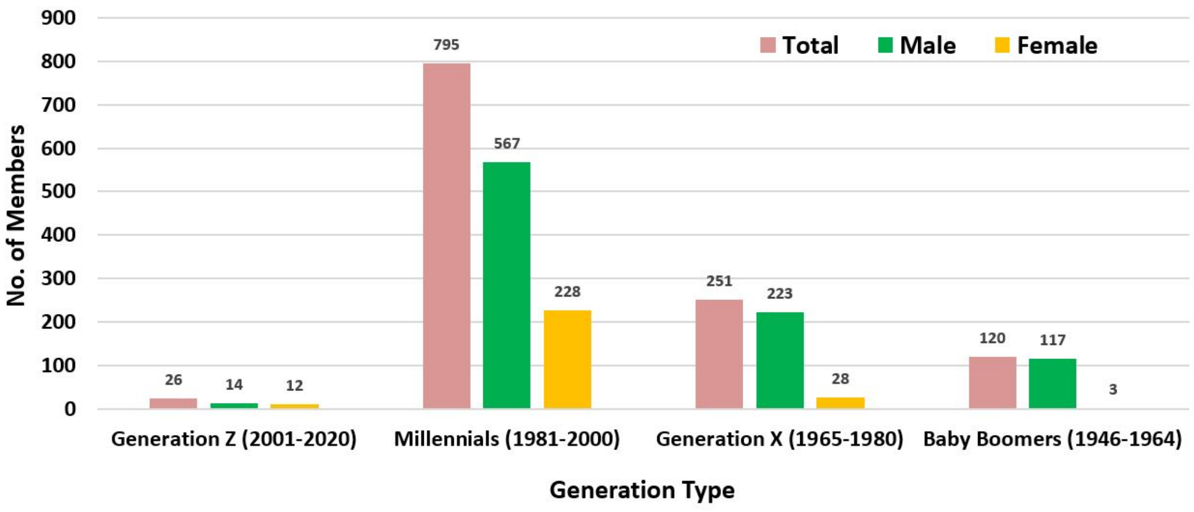
- ML integration in South African rock engineering connects experienced professionals and younger, tech-savvy engineers.
- Veterans(old generation) rely on traditional methods, while newer entrants bring computational proficiency and innovation.
- ML fosters collaboration and knowledge transfer, merging experiential insight with data-driven approaches.

Benefits and Impacts of ML in Rock Engineering

- **Predictive modelling** enables the anticipation of project challenges using past data, boosting junior engineer confidence.
- ML reduces **bias in decision-making**, shifting reliance from anecdotal evidence to empirical data.
- Enhances **inclusivity and retention** by creating a learning-driven, adaptive, and multi-generational work culture.

Different generations in the rock engineering fraternity (South Africa)

Generation	Characterised	Motivated	Communication Style	Worldview
Baby Boomers	Optimistic, Competitive, Workaholic, and Team-Oriented	Company loyalty, teamwork, and duty	Efficient methods, including phone calls and face-to-face	Achievement comes after paying one's dues, sacrificing for success
Generation X	Flexible, Informal, Sceptical and Independent	Diversity, work-life balance, and personal-professional interests	Efficient methods, including phone calls and face-to-face	Favouring diversity, quick to leave if the employer fails to meet their needs
Millennials	Competitive, Civic- and Open-minded, Achievement-oriented	Responsibility, the quality of a manager, and unique work experiences	IMs, texts, and emails	Seeking challenge, growth, and work-life balance; likely to leave if dissatisfied
Generation Z	Global, Entrepreneurial, Progressive, and Less focused	Diversity, personalisation, individuality, creativity	Social media, texts, IMs	Digital device addicts value independence and individuality, and prefer innovative environments



Leveraging Generational Strengths in Rock Engineering

- Each generation offers **unique strengths** that can accelerate ML adoption.
  - **Baby Boomers**: Provide deep industry experience and mentorship.
  - **Generation X**: Adaptable; bridge practical applications with new tech.
  - **Millennials**: Tech-savvy and innovation-driven; key to implementing AI tools.
  - **Generation Z**: Digitally native; leads creative applications of emerging technologies.
- Together, these generations push the **boundaries of ML in rock engineering**.

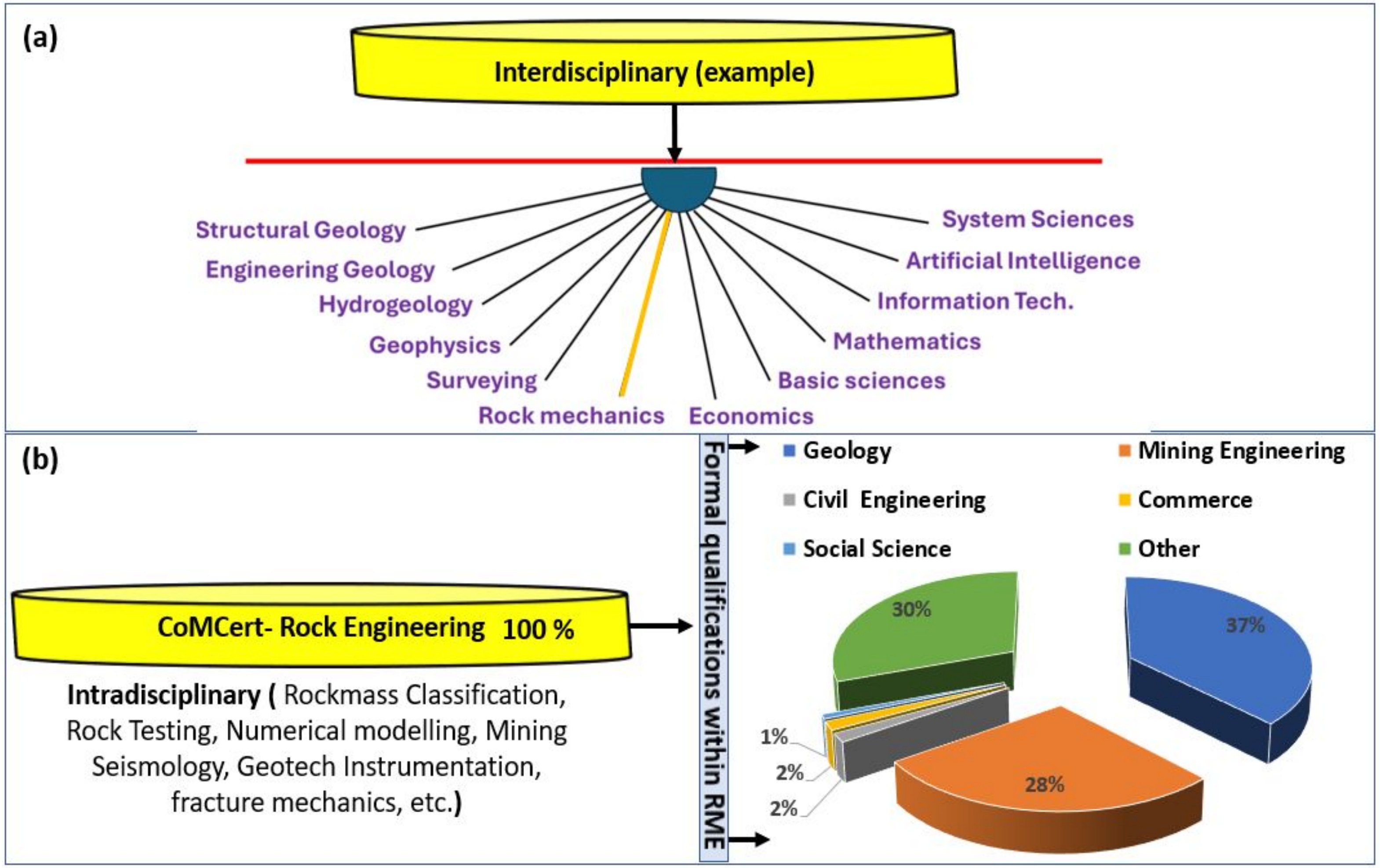
Enhancing Intra-Disciplinary Collaboration through ML

- **Enhancing Intra-Disciplinary Collaboration through ML**
  - ML enriches intradisciplinary synergy within rock engineering.

- **Empowering Research and Decision-Making**
  - ML enables data-driven, evidence-based decisions.

- **Cultivating a Culture of Continuous Improvement**
  - As ML models are retrained, prediction accuracy improves.

Intradisciplinary vs interdisciplinary composition in the rock engineering discipline within the South African context.



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Reasons for the Reluctance to Adopt Machine Learning

1. Lack of Trust in Black-Box Models
- Engineers prefer transparent, explainable methods.
- ML often seen as opaque and difficult to interpret.

2. Cultural and Behavioural Resistance
- Experienced professionals may distrust or undervalue AI/ML tools.
- Perceived threat to traditional expertise and decision-making authority.

3. Skill Gaps and Training Deficits
- Limited exposure to data science and AI in traditional rock engineering education.
- Shortage of interdisciplinary teams combining geotechnical and ML expertise.

4. Data Limitations
- Inadequate historical and real-time geotechnical datasets.
- Poor data quality undermines ML model reliability.

5. Lack of Institutional Support
- Minimal investment in innovation and digital infrastructure.
- No clear industry guidelines or frameworks for ML integration.

6. Perceived Cost and Complexity
- Implementation of ML systems is seen as expensive and resource-intensive.
- Fear of overhauling existing workflows and systems.

Conclusions

- ML offers transformative potential by improving accuracy, predictive capabilities, and operational efficiency, but generational gaps and resistance to change often slow its integration.
- Fostering cross-generational collaboration is essential for facilitating the transfer of knowledge and expertise
- The use of ML can potentially revolutionise rock engineering practices by leveraging the strengths of experienced professionals and digitally proficient younger rock engineering practitioners
- Through the amalgamation of traditional expertise and modern technology, South Africa's mining industry can transition toward a more data-driven and resilient future, better equipped to navigate the complexities of deep-level mining

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THANK YOU