Machine Learning and Underground Geomechanics:

data needs, algorithm development, uncertainty, and engineering verification

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INTRODUCTION

Decision making in the fields of geomechanics and rock engineering is challenging due to the inherent uncertainty associated with the behaviour of natural earth materials. Thanks to digitalized mapping and instrumentation techniques, geomechanical professionals have increasing access to large datasets containing a wealth of information. The rock engineering industry is now shifting its collective focus on finding new ways to interpret the vast amounts of "big data" being collected.

A promising new field of research is emerging where machine learning algorithms (MLAs) are being applied to rock engineering problems to assist with the tedium of manual data processing and extracting useful correlations. Two MLAs are compared that were developed for end member rock mass behaviours (squeezing ground and spalling ground) in terms of their data needs, complexity, generalizability, performance evaluation, verification, and practical applications.

MACHINE LEARNING AND GEOMECHANICS

MLAs have emerged as powerful techniques for examining geomechanical data and extracting nuanced rock mass deformation phenomena (Elmo et al., 2020; Morgenroth et al., 2019).

Artificial Neural Networks (ANNs) are a type of MLA that can identify relationships between input variables and the output using a framework that mimics the interconnected neurons in the brain, thus being able to find correlations that can be used to reproduce the actual observed ground behaviour. Applying ANNs to geomechanical datasets allows rock engineering professionals to extract relationships between inputs and nuances on the rock mass deformation mechanisms. This research compares two types of ANNs: a Convolutional Neural Network (CNN) and a Long-Short Term (LSTM) network. The former algorithm type was developed image processing, and the latter for time series data processing. Both were adapted to take geomechanical inputs to forecast underground excavation behaviour.

CASE STUDIES

SQUEEZING GROUND CONVOLUTIONAL NEURAL NETWORK (CNN)

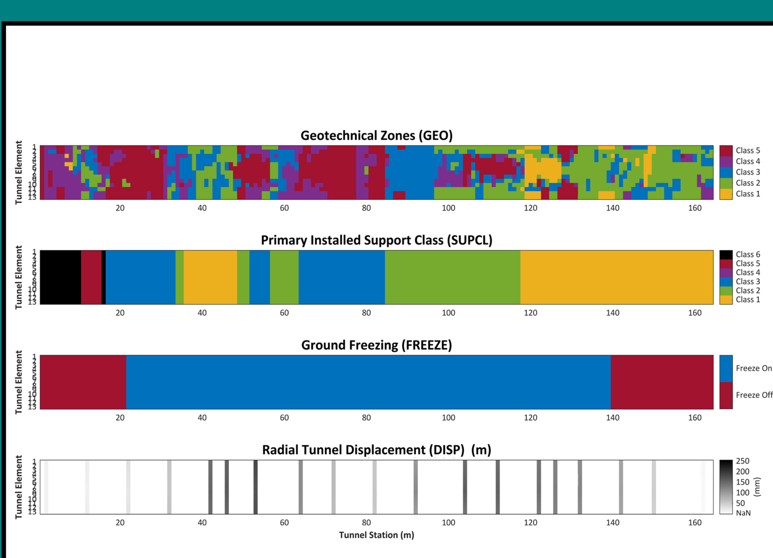

Fig 1. CNN input data – GEO, SUPCL, FREEZE, and DISP

- A CNN was developed to predict yield to the tunnel liner elements, prioritizing accuracy for areas of high liner yield (Morgenroth et al. 2021a).
- The input was formatted as an image with four channels (Fig. 1):
  1. GEO – geotechnical zone
  2. SUPCL – primary installed support class
  3. FREEZE – ground freezing on or off
  4. DISP – radial tunnel convergence at specific locations
- The targets are the yield of the tunnel liner elements:
  - Class 0 – no yield
  - Class 1 – minor yield
  - Class 2 – major yield
  - Class 3 – total tunnel reprofiling required
- Forecasting of tunnel lining yield will allow for timelier rehabilitation and more accurate operations budgeting.

SPALLING GROUND LSTM (LSTM) NETWORK

- This case study investigates the use of an LSTM network to predict stresses in a previously calibrated FLAC3D model as new microseismic events occur, thereby automating the FLAC3D calibration process (Morgenroth et al. 2021b).
- Two sources of input data (Fig 2):
  1. The microseismic database, including the location and timing of the events, and microseismic parameters (e.g., moment magnitude, energy, apparent stress).
  2. The geology and geomechanical parameters from the FLAC3D model (Kalenchuk, 2018).
- The targets are the 3 principal stresses at each FLAC3D zone.
- The automated calibration the FLAC3D model will allow for more frequent model recalibration and updating of excavation sequencing based on ongoing seismicity.

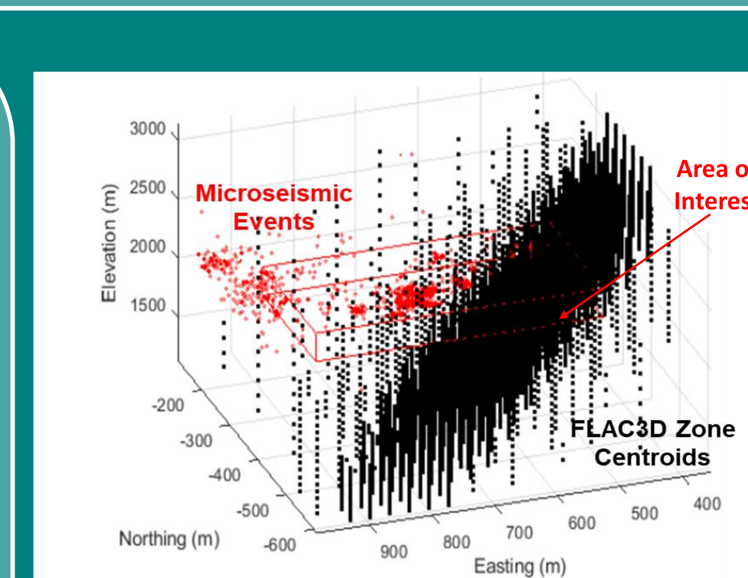

Fig 2. LSTM input data – time series of microseismic events and geomechanical parameters

ALGORITHM DEVELOPMENT

- The CNN was developed to maximize the use of the tunnel mapping data and surveying of tunnel convergence. Training data was formatted into images, where each successive image represented a snapshot in time.
- CNN hyperparameters optimized: amount of training data, convolution filter size, input error weighting, network layer architecture (Fig 3)
- Model performance criterion: Corrected Akaike Information Criterion (AIC_c), accuracy (%)

Final architecture:

- Categorical input encoding: ordinal
- Amount of data: all time steps preceding prediction timestep
- Filter size: 30 x 30 pixels
- Error weighting: sigmoid (Targeted Class 2/3 model) & inverse frequency (Global Balanced Model)

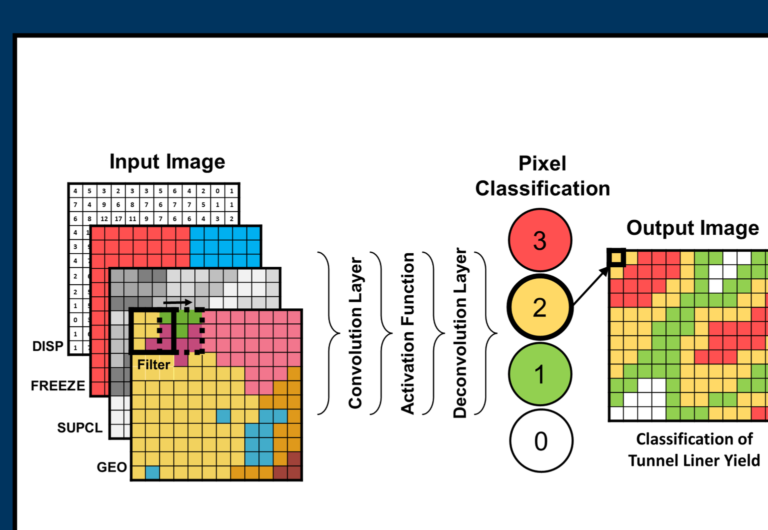

Fig 3. Squeezing ground CNN schematic, showing input and output images and CNN layer architecture

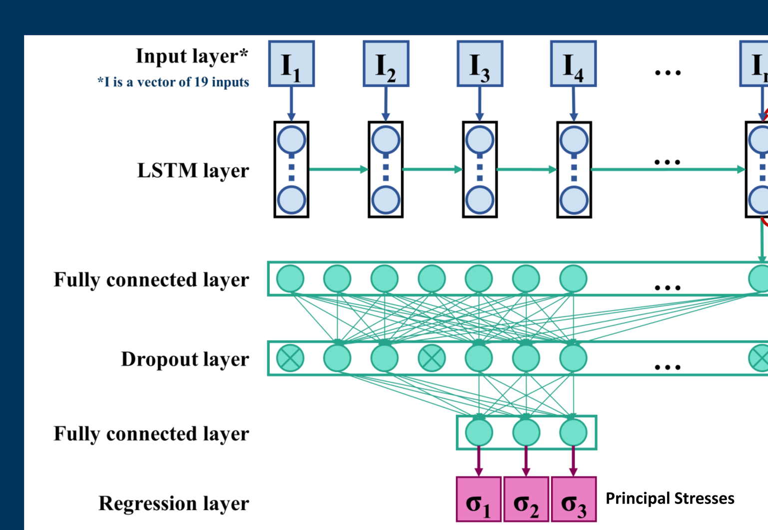

Fig 4. Spalling ground LSTM schematic, showing time series input layer and LSTM layer architecture

- The LSTM was developed using an iterative process where each parameter was optimized while holding all others constant. Training data was formatted by matching each microseismic event to the nearest zone centroid in the FLAC3D model.
- LSTM hyperparameters optimized: input pre-processing, categorical input encoding (ordinal versus numerical), training solver, network layer architecture (Fig 4), cost function
- Model performance criteria: AIC_c, regression coefficient (R^2), and percent capture (% capt.)

Final architecture:

- Input pre-processing: z-score normalization
- Categorical input encoding: numerical (max and min GSI)
- Solver: SGD
- Cost function: Mean Squared Error

ENSEMBLE MODELLING AND UNCERTAINTY

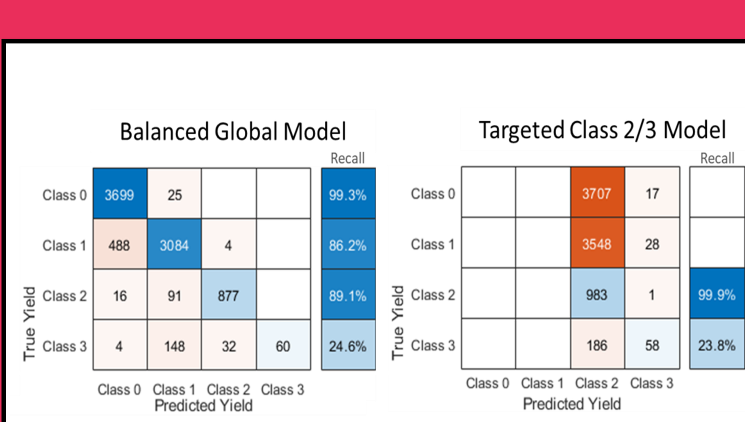

Fig 5. CNN performance for ensemble of 30 models

Ensemble modelling is a powerful way to quantify uncertainty in data driven modelling, such as MLAs. Each member of an ensemble is trained independently, and the predictions are combined to form a statistical distribution of possible outputs. An ensemble of models will generalize well to a dataset, as compared to a single, finite model that represents only one random initialization of weights and biases. This approach allows the developer of the algorithm to gain an understanding of how well the model is converging to the global optimum, as well as to determine the variance of the model output. In general, a minimum of 30 models should be trained as part of an ensemble.

In both these case studies, each member of an ensemble represents a re-initialized model with the same hyperparameters and architecture. The training data is also shuffled randomly with replacement for each ensemble member to prevent overfitting and to ensure a well generalized model.

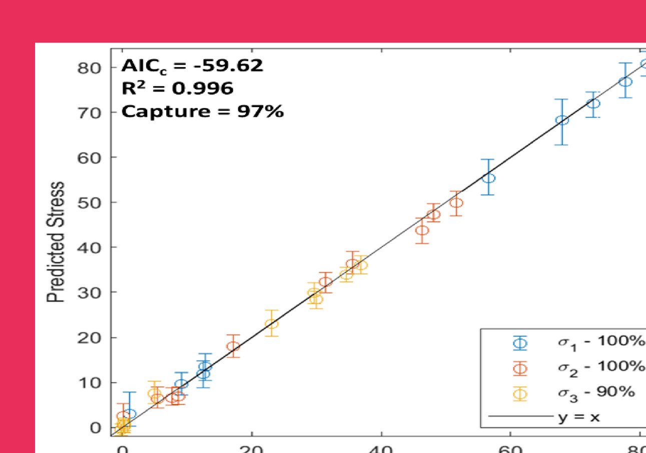

Fig 6. LSTM performance for ensemble of 100 models

An ensemble of 30 models was computed for two CNN architectures – a Global Balanced model and a Targeted Class 2/3 model. An ensemble size of 30 was chosen due to the computational expense of the CNN.

Ensemble performance (Fig 5): Global Balance accuracy = 52%, Targeted Class 2/3 accuracy = 62%

An ensemble of 100 LSTM networks were computed for each combination of model parameters to quantify model performance and make selections regarding hyperparameters and CNN architecture.

Ensemble performance (Fig 6): AIC_c = -59.62, R^2 = 0.996, % capt. = 97 %

CONCLUSIONS AND RECOMMENDATIONS

At the onset of model development, it is crucial that data formatting and pre-processing approaches are selected and applied with caution. It is easy to accidentally overprint the nuanced relationships between inputs and the output, and therefore a data analysis should be completed to understand their distributions and correlations. Only then should data be manipulated to preserve its original form as much as possible. For example, for the Cigar Lake Mine case study, the input image format was selected to preserve the format of the original tunnel mapping. For the Garson Mine dataset, normalization of the inputs was applied using the z-score once it was determined that they had a normal distribution.

During algorithm development, algorithm architecture selection and hyperparameter tuning are sensitive and must be validated in the context of the physical system for which the model is built. For example, the CNN architecture was appropriate for performing spatial and temporal predictions using the Cigar Lake Mine dataset, however an earlier ANN was not as successful. For the Garson Mine LSTM, the length of the time series of microseismic events used to train the model was investigated prior to its selection.

It is prudent to quantify ML model uncertainty with ensemble techniques that capture the range of predictions. This allows the model developer to determine if the observed targets far within the range of possible ML predictions, and serves as a breaker mechanism if adjustments need to be made to improve performance. For these two case studies, at least 30 models were needed to adequately capture the uncertainty of the developed algorithms.

Finally, engineering verification metrics should ideally be selected prior to algorithm development. In other words, it is not sufficient to target good model performance in the ML sense, but also to ensure that what is being predicted makes sense in the context of the engineering problem being addressed. For example, for Cigar Lake Mine targeting good Class 2, not global, prediction was key to ensuring excavation stability.

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