AFRIROCK 2025

PIONEERING PROGRESS :
THE FUTURE OF ROCK ENGINEERING

Comparison of Machine Learning Classification for Rockbursts Prediction: A Case Study of South African Gold and Platinum Mines

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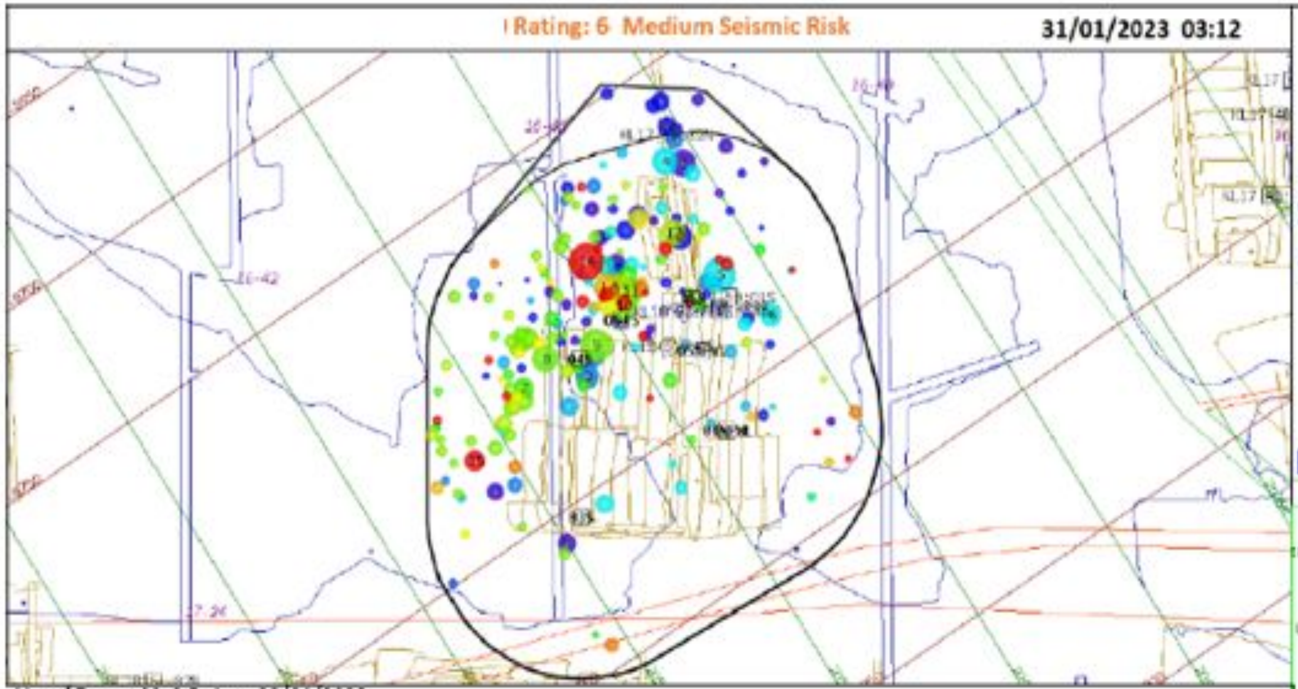
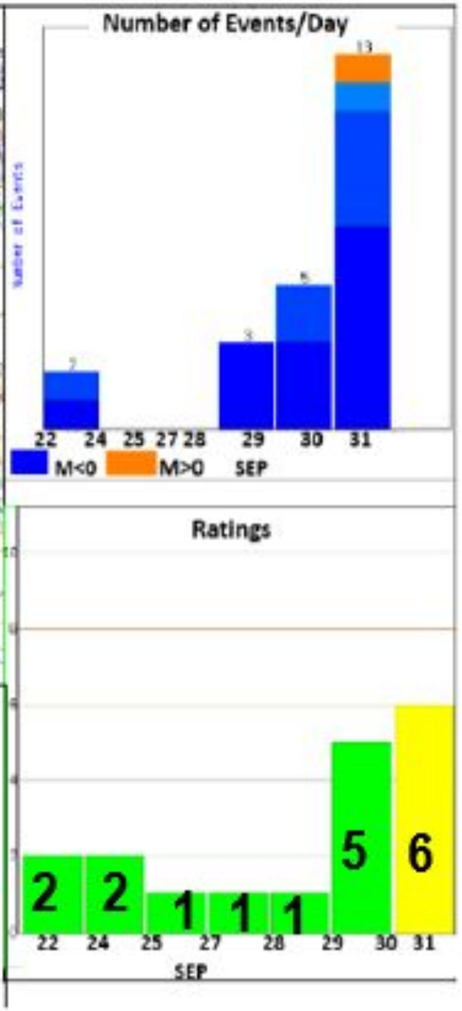
Short Hazard Assessment In The South African Mining Industry

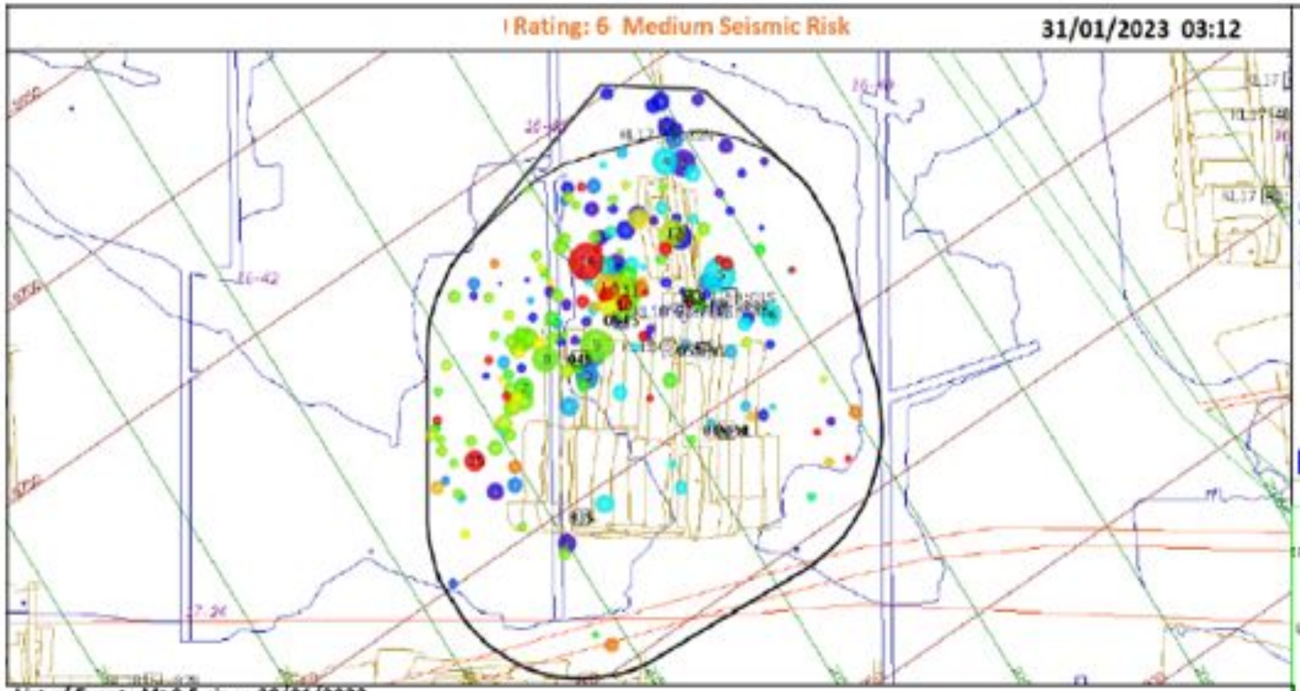


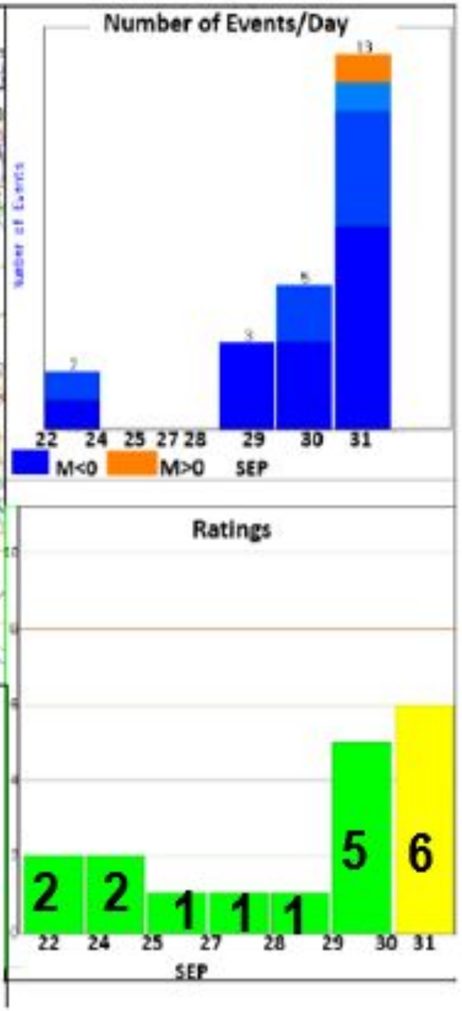


List of Events M>0.5 since 29/01/2023

	Date	Time	Mag	Mpot	Potency	X	Y	Z	Workplace		
1.	29/01/2023	03:19:33	0.3	-0.1	0.80	20435	-8182	-1700	K8_VC KL81 51:RSE1	dXY = 31	HW= +19
2.	29/01/2023	03:19:33	0.0	-0.3	0.80	20255	-8792	-1700	K8_VC KL81 51:RSE1	dXY = 52	HW= +21
3.	29/01/2023	03:19:33	-0.1	0.2	0.80	20355	-8282	-1700	K8_VC KL81 51:RSE1	dXY = 46	FW= -10
4.	29/01/2023	03:19:33	-0.2	0.1	0.80	20475	-8582	-1700	K8_VC KL81 50:03sS	dXY = 31	HW= +17
5.	30/01/2023	03:19:33	1.3	0.1	0.80	20255	-8782	-1700	K8_VC KL81 51:RSE1	dXY = 46	FW= -21
6.	30/01/2023	03:19:33	-0.3	-2.1	0.80	20355	-8782	-1700	K8_VC KL81 51:RSE1	dXY = 22	HW= +10
7.	30/01/2023	03:19:33	-0.5	0.1	0.80	20415	-8782	-1700	K8_VC KL81 51:RSE1	dXY = 46	FW= -33
8.	31/01/2023	03:19:33	0.1	0.1	0.80	20455	-8782	-1700	K8_VC KL81 51:RSE1	dXY = 43	FW= -40
9.	31/01/2023	03:19:33	1.0	0.1	0.28	20455	-8782	-1700	K8_VC KL81 51:RSE1	dXY = 46	FW= -61

Short Hazard Assessment In The South African Mining Industry





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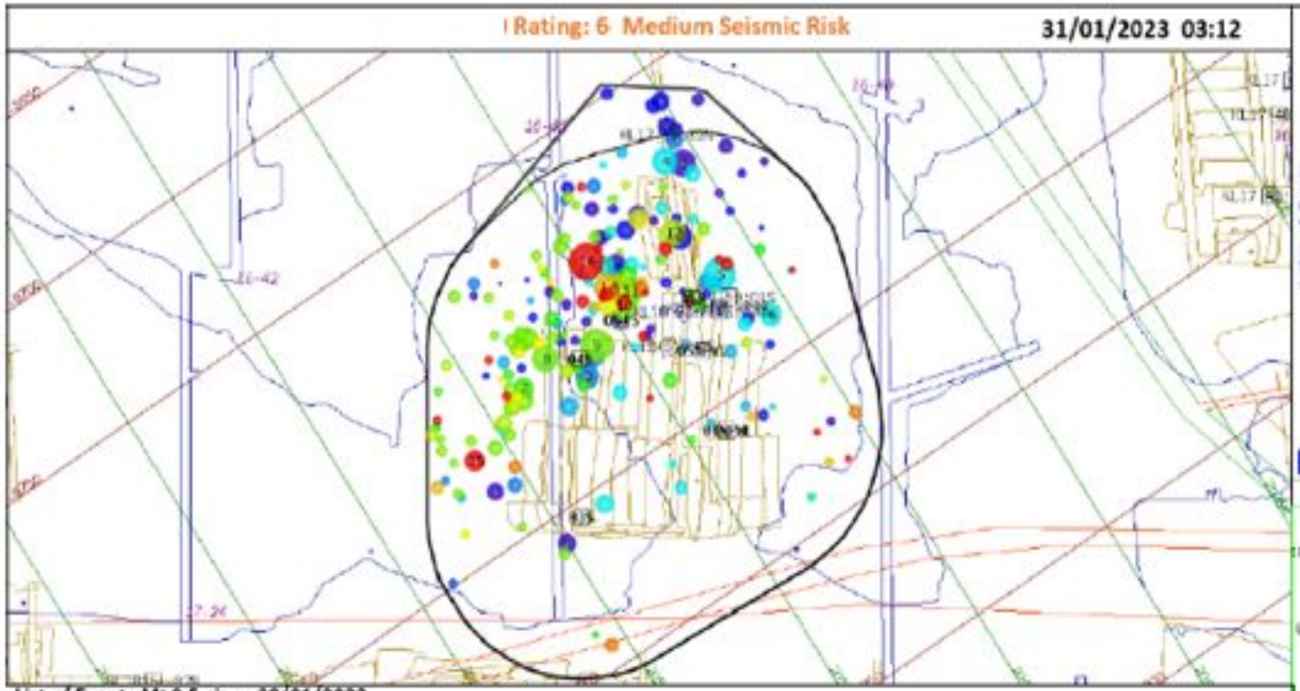

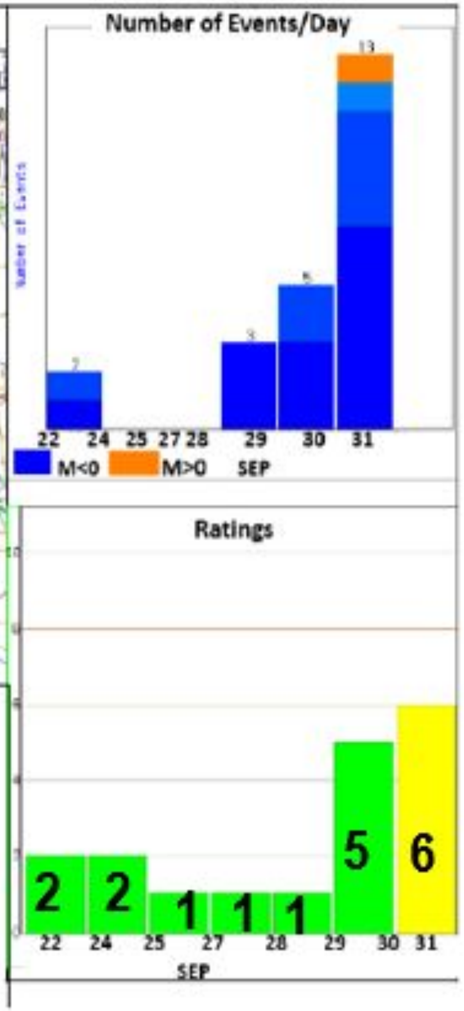

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Four Key Outcomes, As Defined In The Standard Confusion Matrix

	WARNING	NO WARNING
EVENT [M≥1]	0.10 (TP)	0.22 (FN)
NO EVENT [M≥1]	0.38 (FP)	0.30 (TN)
SUM	0.48	0.52

Four Key Outcomes, As Defined In The Standard Confusion Matrix

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SUM	0.48	0.52

Four Key Outcomes, As Defined In The Standard Confusion Matrix

Accordingly, the success rate or threat score/CSI is defined as a ratio of successes to successes and failures using the Equation :

$$Total\ success\ rate = \frac{TP}{TP+FP+FN}$$

The total success rate was **14.3%**

Representing the proportion of correctly predicted events among all actual and predicted positive cases, excluding true negatives

Seismic Data Acquisition

- Seismic data collected using a mine-wide seismic network across active excavations.
- Network used **4.5 Hz** triaxial geophones with a **6 kHz** sampling rate.
- Geophones strategically installed to maximize the accuracy of seismic event locations.
- Seismograms analysed to extract P- and S-wave arrivals and compute seismic source parameters.
- Achieved location accuracies within a few metres in key areas.

Seismicity Data Classification Approach

- The selection of seismic events for analysis focused on those within the area of interest ($M \geq 1$) that are well located and whether they resulted in damage or not.
- The study focused on seismic and mining-related factors influencing rockburst occurrences.
- Analysed 154 (**Platinum**) and 413 (**Gold**) seismic events using eight independent variables (e.g., magnitude, location, PPV).
- Rockburst presence/absence was the binary dependent variable.
- Key predictors: event location, elapsed time between events, and footwall position.
- The dataset provided insights but was limited in size for broader generalisation.
- Predictive analysis supports targeted risk mitigation in high-risk zones.

Modelling Approach

Machine Learning Models for Rockburst Prediction

- Multiple ML models evaluated: LR, SVM, ENS Boosted Trees, ENS Bagged Trees, ENS KNN, and ANN.
- Aim: Identify the most accurate and adaptable model for forecasting rockbursts.
- Focus on model performance across both gold and platinum mining environments.
- MATLAB's Machine Learning apps are used for training and analysis.
- Five-fold cross-validation applied to avoid overfitting and ensure generalisation.
- Input data was normalised to the [0,1] range to improve model performance.

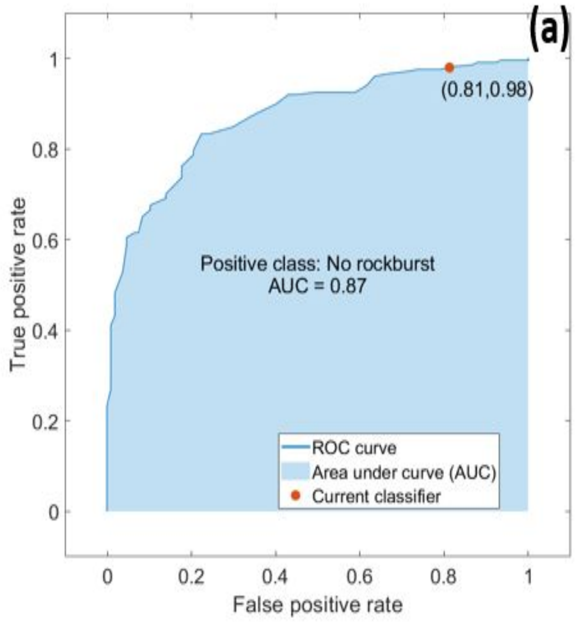
Sample data with normalised values (gold mine)

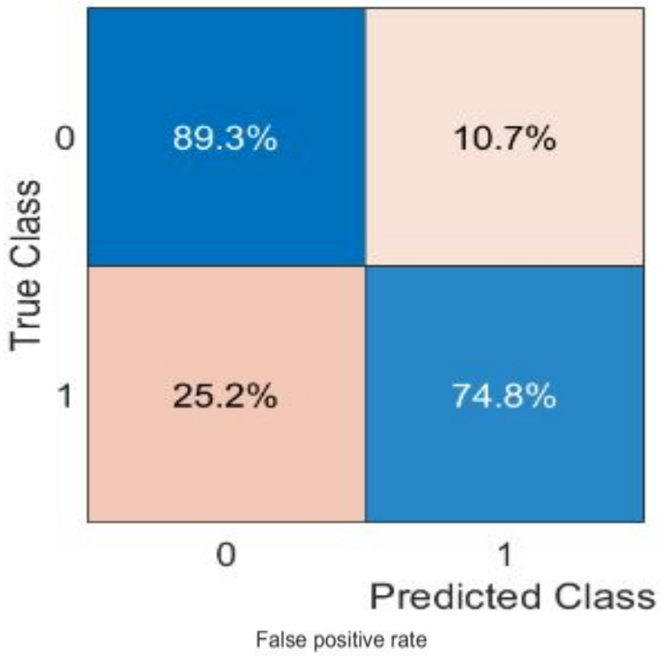
Gold Mine

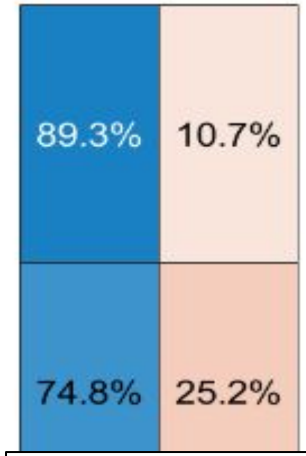
P1	P2	P3	P4	P5	P6	P7	P8	Damage (Yes/No)
0.52	0.84	0.52	0.22	0.09	0.05	0.25	0	0
0.05	0.51	0.21	0.17	0.11	0	0.25	0	0
0.48	0.49	0.58	0.58	0.08	0.06	0.26	1	0
0.19	0.48	0.56	0.54	0.07	0.04	0.26	1	0
0.1	0.57	0.19	0.21	0.09	0.02	0.27	0	0
0.67	0.84	0.57	0.32	0.01	0.12	0.32	1	1
0.33	0.45	0.45	0.43	0.05	0.09	0.32	1	1
0.05	0.88	0.56	0.31	0.1	0.01	0.32	1	1
0.38	0.5	0.49	0.46	0.07	0.1	0.32	0	1
0.14	0.49	0.49	0.5	0.06	0.02	0.32	1	1
0.62	0.19	0.04	0.41	0.2	0.03	0.34	1	1

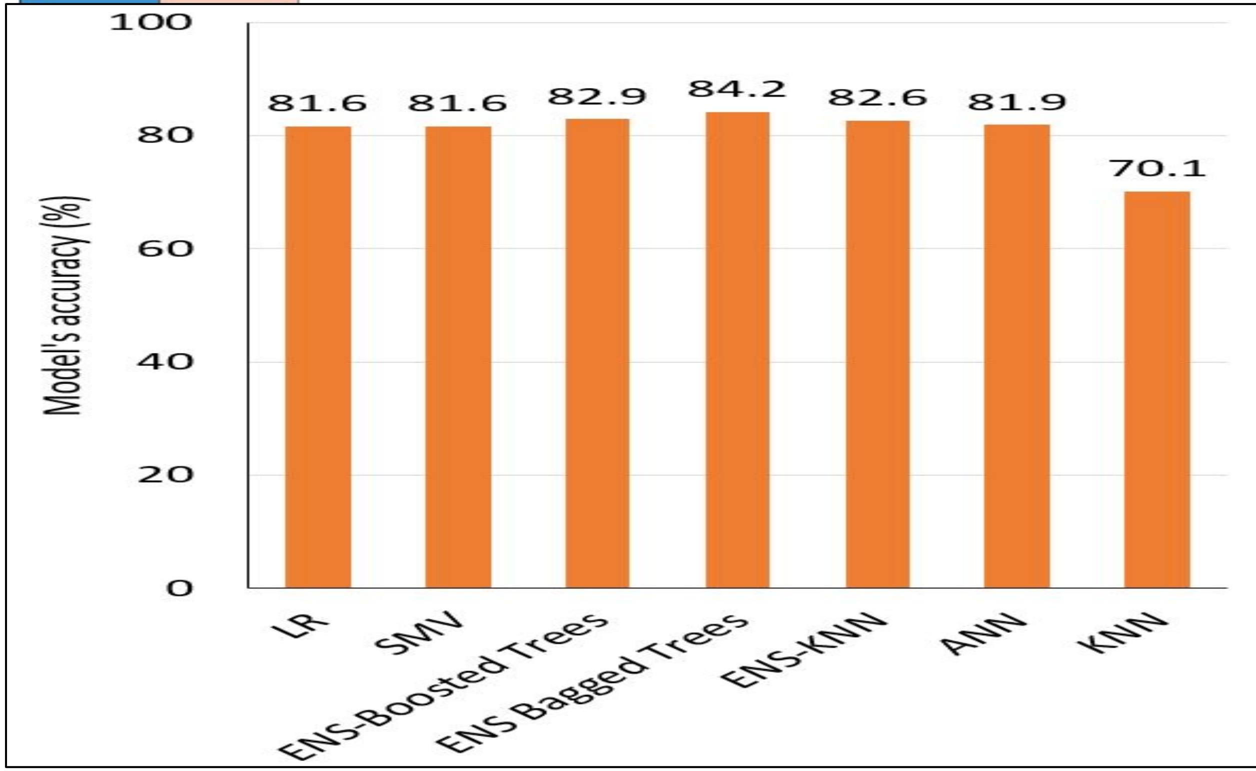
Platinum Mine

P1	P2	P3	P4	P5	P6	P7	P8	Damage (Yes/No)
0.26	0.76	0.35	0.67	0.29	0.05	0.16	0	1
0.01	0.19	0.71	0.10	0.31	0.08	0.18	1	1
0.16	0.05	0.49	0.17	0.33	0.03	0.02	1	1
0.46	0.24	0.35	0.67	0.26	0.04	0.20	0	1
0.77	0.38	0.82	0.35	0.15	0.02	0.46	0	1
0.72	0.05	0.29	0.73	0.31	0.49	0.12	1	0
0.33	0.00	0.23	0.63	0.27	0.12	0.12	0	0
0.80	0.14	0.63	0.83	0.44	0.06	0.12	1	0
0.40	0.00	0.31	0.66	0.31	0.13	0.12	0	0
0.35	0.57	0.32	0.67	0.31	0.10	0.12	0	0
0.82	0.14	0.28	0.71	0.31	0.34	0.12	1	0



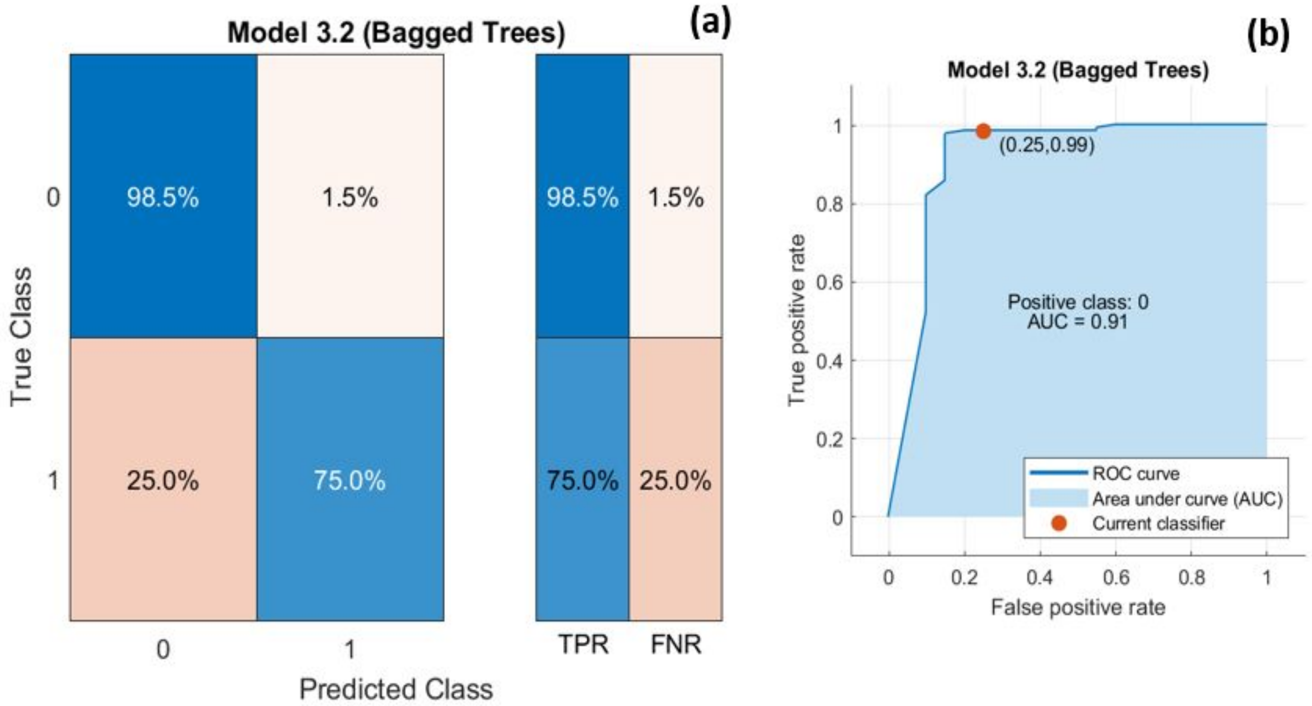


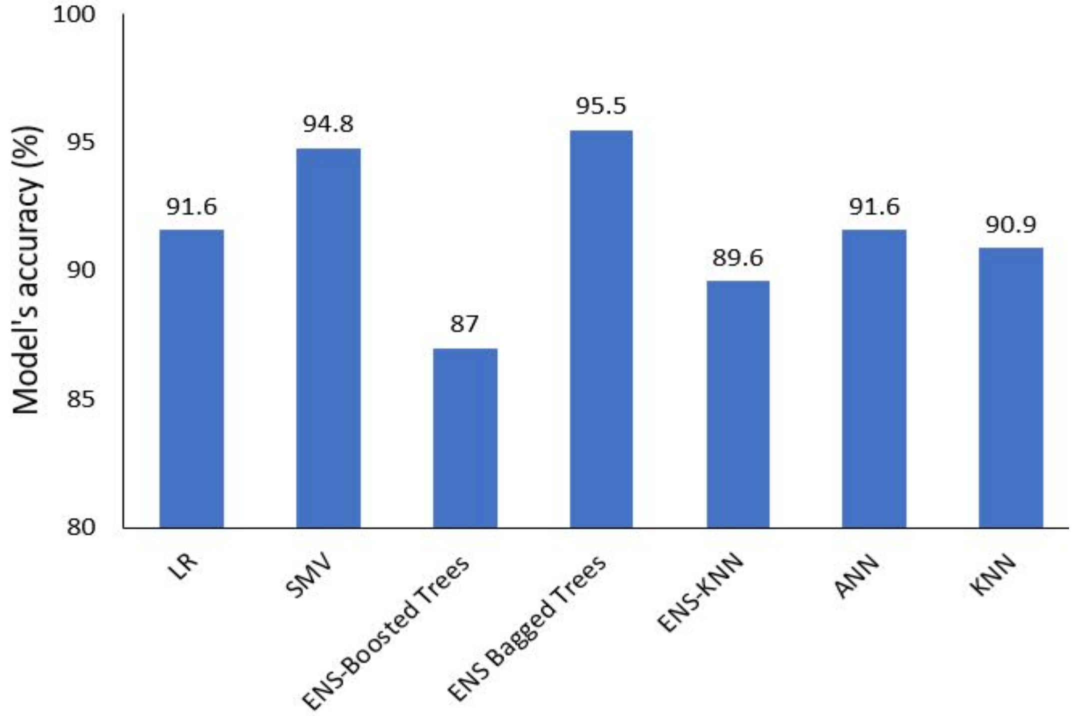




- Ensemble Bagged trees model correctly identified 89,3% of events (did **not** result in Rockburst)
- Only 74.8% of Rockburst-related events were accurately classified
- This corresponds to a false prediction rate of 25.2%.

PLATINUM MINE





- Ensemble Bagged trees model correctly identified 98,5% of events (did **not** result in Rockburst)
- Only 75% of Rockburst-related events were accurately classified
- This corresponds to a false prediction rate of 25%.

Results And The Discussion

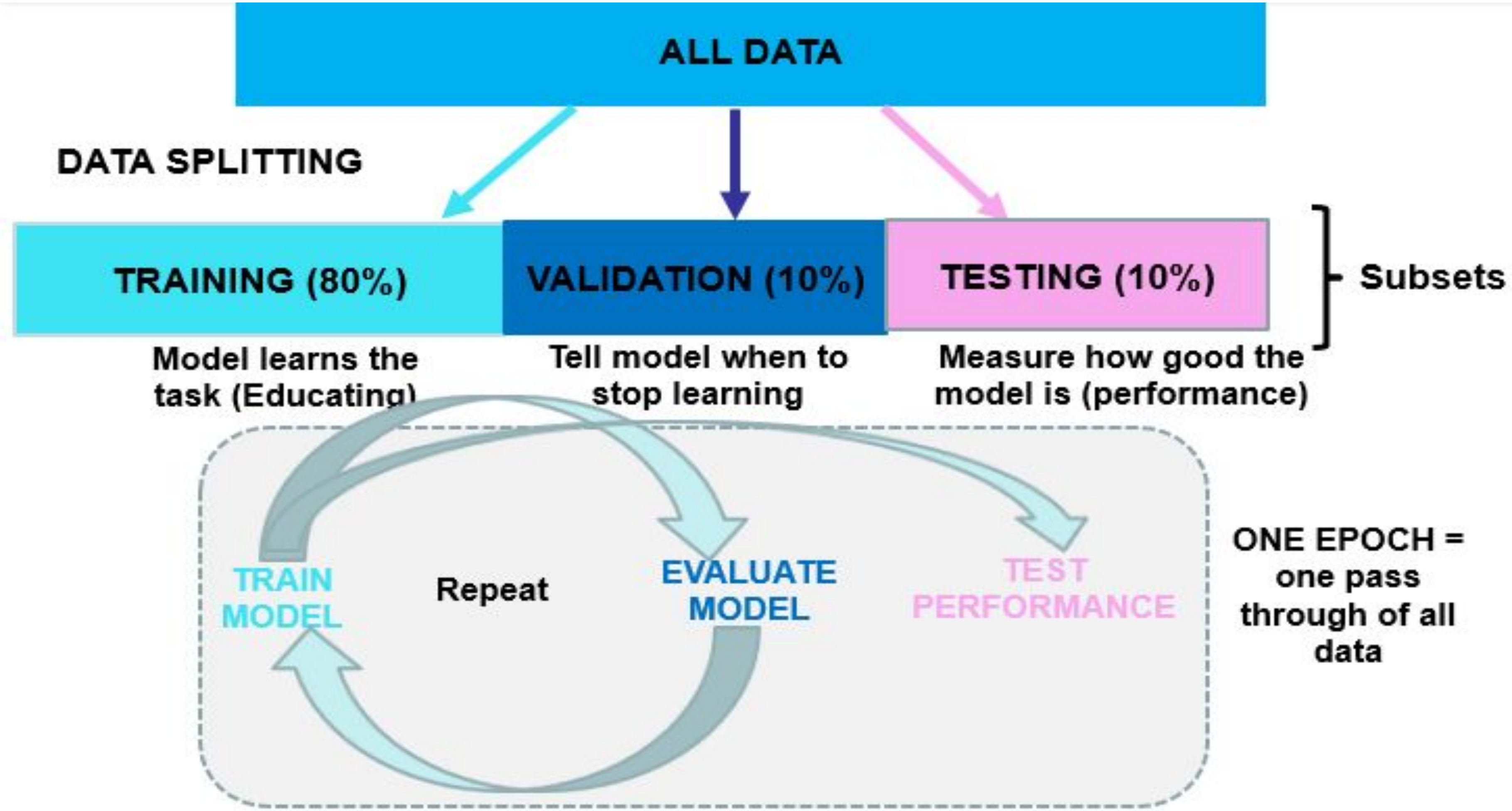
The performance of machine learning models

Mine Type	Model	Accuracy (No Rockburst Case	Accuracy (Rockburst Case)	False Prediction Rate
Gold	ENS bagged trees	84.2%	74.8%	25.2%
Platinum	ENS bagged trees	95.5%	75.0%	25.0%

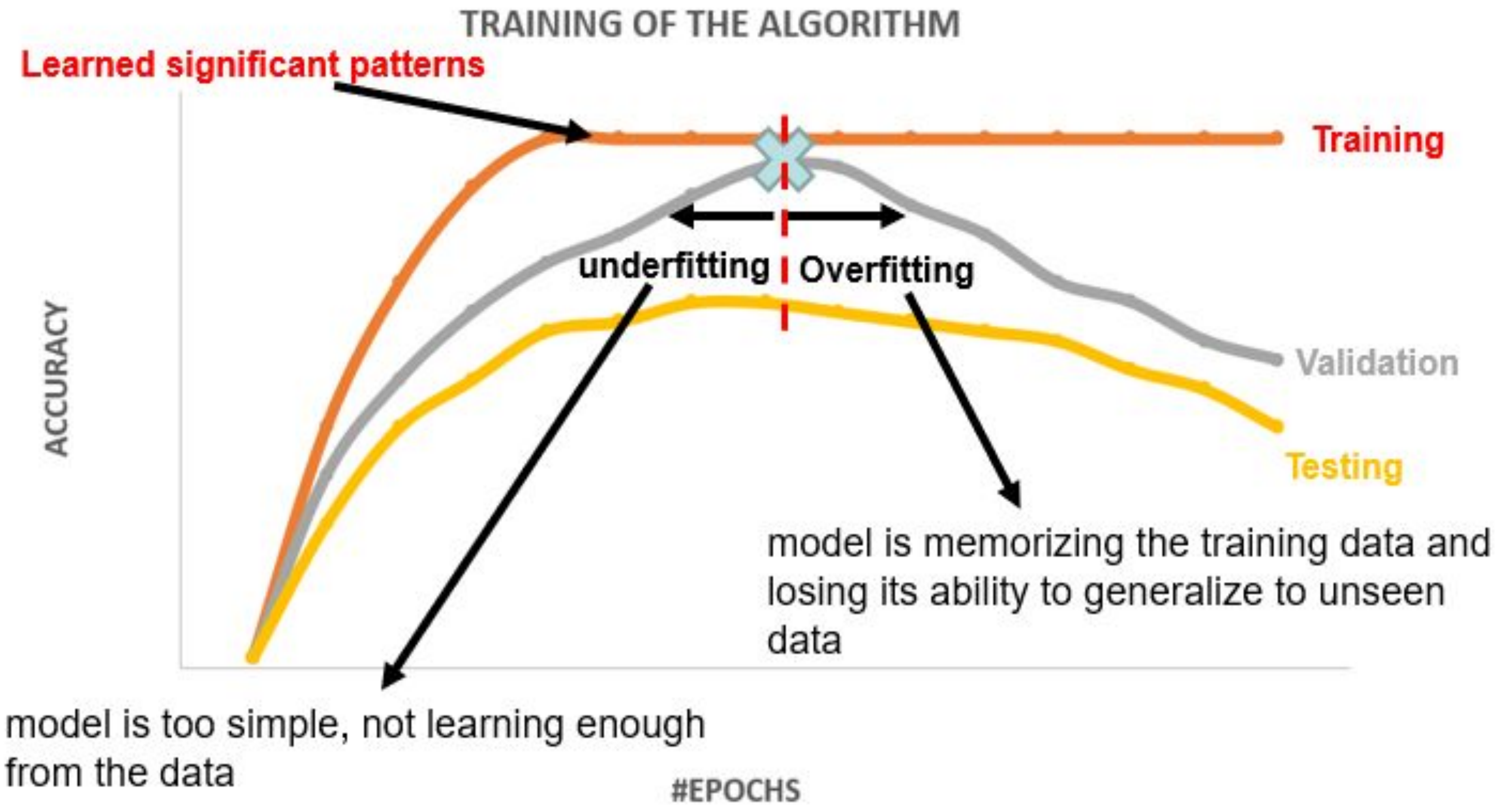
The model accuracies varied between the two mine types:

- Platinum mine: Accuracy ranged from 87% to 95.5%, with the best-performing model showing a false positive rate of approximately 25%.
- Gold mine: Accuracy ranged from 70.1% to 84.2%, with a similar false positive rate of around 25% for the best-performing model.

WHAT IS NEXT?


ALL DATA
DATA SPLITTING
TRAINING (80%)
VALIDATION (10%)
TESTING (10%)
Subsets
Model learns the task (Educating)
Tell model when to stop learning
Measure how good the model is (performance)
TRAIN MODEL
Repeat
EVALUATE MODEL
TEST PERFORMANCE
ONE EPOCH = one pass through of all data

Accuracy Vs Epoch Graph



Conclusion

- ENS bagged trees consistently demonstrated the highest classification accuracy among the tested ML models, making it a promising approach for developing real-time rockburst prediction tools in seismically active mines.

- These results suggest that ensemble-based learning techniques, particularly bagged trees, provide greater robustness and predictive performance in differentiating between seismic events associated with rockbursts and those that are not

- However, a key limitation observed in this study was data imbalance, where models demonstrated higher accuracy in recognising no-damage seismic events compared to correctly identifying rockburst occurrences

Conclusion

- This highlights the need for advanced techniques such as data augmentation, synthetic resampling (e.g., SMOTE), and cost-sensitive learning to improve the model's ability to detect rockburst-related seismic events.

- Furthermore, the study suggests that expert systems, combined with ML, could enhance predictive capabilities by integrating domain knowledge with data-driven models

- To refine the predictive power of these models, future research should focus on multi-class classification to distinguish between different types of rockbursts rather than treating them as a binary problem

THANK YOU