

Using an artificial neural network (ANN) to identify coals from drilling and logging-while-drilling (LWD) data

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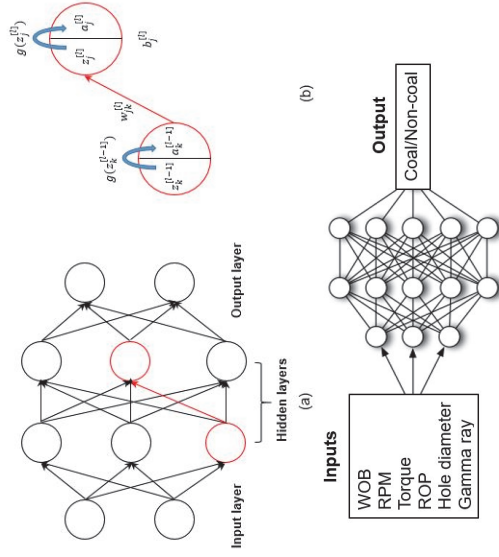
Objective

Saving logging cost by quickly identifying coal pay zones for completion packers and slotted casing placement.

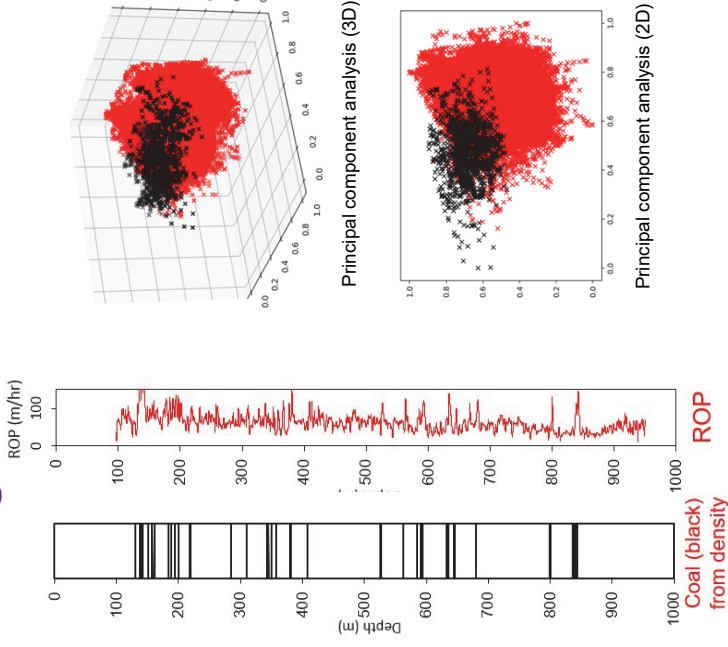
Method	Disadvantages
Well logging	Expensive (tool and rig time) Acquired on a few wells Potential logging failure (especially in deviated and horizontal sections)
Laboratory tests	Scale effects Time/resource intensive Require lab & quality samples

Machine learning: fast, accurate, and low-cost.

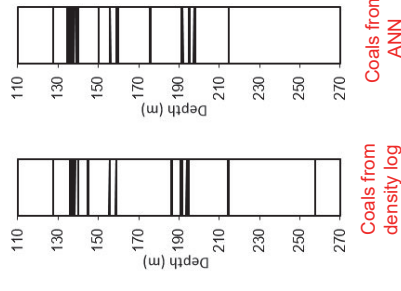
Methodology



Drilling data vs. coal

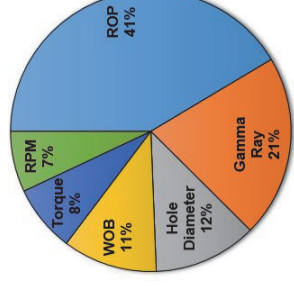


Results



Summary of results for the test section

	Precision	Recall	F1 score	Samples
0 (non-coal)	0.98	0.99	0.98	1318
1 (coal)	0.77	0.79	0.78	135
Avg/total	0.96	0.96	0.96	1453



Feature importance

Confusion matrix

Predicted Condition	True Condition	
	Coal	Non-coal
Coal	True positive	False positive
Non-coal	False negative	True negative

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$$

$$\text{F1 Score} = 2 \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Acknowledgements

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