# Use of ML in CSS micro-seismic monitoring workflow in Cold Lake, AB

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## Summary

Imperial Oil is using micro-seismic monitoring for operations integrity in high-pressure, high temperature oil/bitumen/hydrocarbon recovery technologies. Data recorded with approximately 90 monitoring systems is around 1.5 TB/day, generating 8,000 or more triggered files, of which, historically, less than 1% are deemed of interest for further analysis. Imperial Oil has developed a machine learning (ML) tool, SA-DEEP (Seismic Analyzer using Deep learning), to reduce the volume of data requiring manual review by classifying and filtering out noise event files. To date, about 96% of the total event files are accurately classified as noise by SA-DEEP, and hence are excluded from further manual review.

## Background

In operations related to heavy oil production, particularly those involving enhanced oil recovery techniques such as Cyclic Steam Simulations (CSS), the activity related to the recovery process (use of steam at high temperature and pressure) may impact the distribution of in-situ stresses across overlaying/adjacent ground layers. The change in stresses in the surrounding rock and/or chemical processes generated by production fluids in wellbores, may cause well-integrity issues such as casing or liner failures and impairments, casing or liner slips, or cement de-bonding around a production well. Some of these outcomes could seriously affect the integrity of operations resulting in negative economic and environmental impacts. In addition, shear stress induced mechanical slips along weak rock planes or pore pressure increases due to operations can generate small movements within the rock, away from production wells. The operations-related outcomes described above are mechanical in nature and can generate earthquake-like seismic signals, which are several orders of magnitude lower amplitude than an earthquake felt at the surface, on a logarithmic scale. These signals, known as micro-seismic signals, can be detected by seismic sensors (receivers) installed at the surface of the earth or in a monitoring well. The analog seismic signal measured at the receivers is converted into a digital record by specialized acquisition equipment. In general, a micro-seismic signal over a user-defined threshold of amplitude is set to trigger an event file that is processed and classified to aid the monitoring of CSS operations. Currently, at Imperial Oil's Cold Lake CSS operations, more than eight thousand micro-seismic triggered event files daily are processed by empirical, and machine learning automated classifiers and are subsequently analyzed through manual interpretation to monitor the operations. Historically, less than 1% of the triggered event files may be of interest to operations, and the rest of the triggered files are deemed to be noise. From an operational integrity standpoint, sources of noise in the micro-seismic signal include, but are not limited to, human activities at the surface (e.g., trucks or other equipment), electrical noise due to system malfunctioning (e.g., electrical spikes) and noise due to oil recovery activities (pumpjacks, rod pumps or fluid flow in production pipes) and downhole system clamping noise. Defined in this way, noise does not bring any useful information for operations integrity monitoring, and therefore files that are classified as noise can be filtered out prior to manual review, resulting in significant manual work reduction.

## Theory / Method / Workflow

The work presented in this paper addresses the following problem areas related to the described process.

1. Micro-seismic triggered files were analyzed and classified manually, which adds to the cost of oil production.
2. Manual analysis and classification of a large number of micro-seismic triggered files requires many person hours of work which may cause a significant delay in the identification of a critical event for operations integrity (i.e., delay of 1-2 days).
3. Automated classifiers implemented by Imperial Oil operations in development/ testing mode were designed to classify a limited number of micro-seismic signal types. Computerized processing a of large volume of data requires sufficient available memory and CPU capacity for the automatic classifiers to run.

The tool presented in this paper, SA-DEEP, consists of an automated micro-seismic event classification pipeline. The machine learning tool removes a large volume of files deemed to be noise and is a scalable cloud-hosted deep learning application. The tool uses advanced supervised and unsupervised deep learning algorithms based on convolutional neural networks (CNN) techniques. The ML tool has two parallel CNN pipelines for classification. One is based on acoustic features and the other is based on visual features (see schematic below). The CNN is trained with a training dataset comprised of approximately 25,000 historical triggered files. The historical files are divided into 8 different event type classes through manual interpretation and verification performed by a Passive Seismic expert. This has enabled SA-DEEP to produce accurate and reliable classifications of new/validation micro-seismic triggered files into noise files and ‘events of operational interest’ files, without a manual screening.

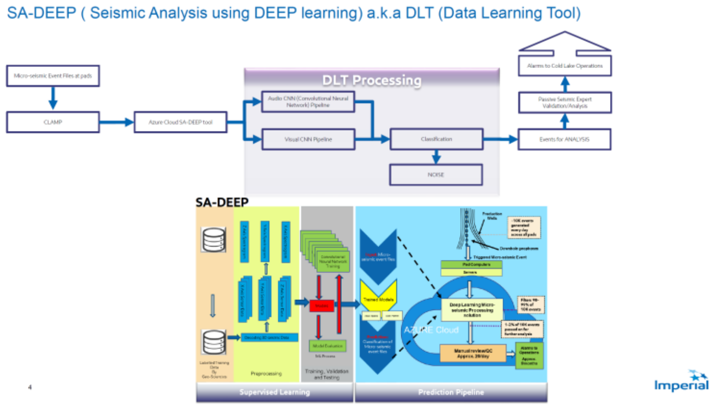


Fig 1 – Schematic of SA-DEEP and production deployment.

## Results, Observations, Conclusions

SA-DEEP has been trained several times to reach the desired level of KPIs (key performance indicators). Over 100,000 validation files recorded over 3 years were tested for classification accuracy. The results show an accuracy of 96% for noise file identification with no critical false negatives. The confusion matrix for the 8 different event type classes showing an accuracy of 90+ % is shown in the plot below. Currently, SA-DEEP is partially deployed in production workflows, with the last phase of production deployment scheduled for Q1 2023.

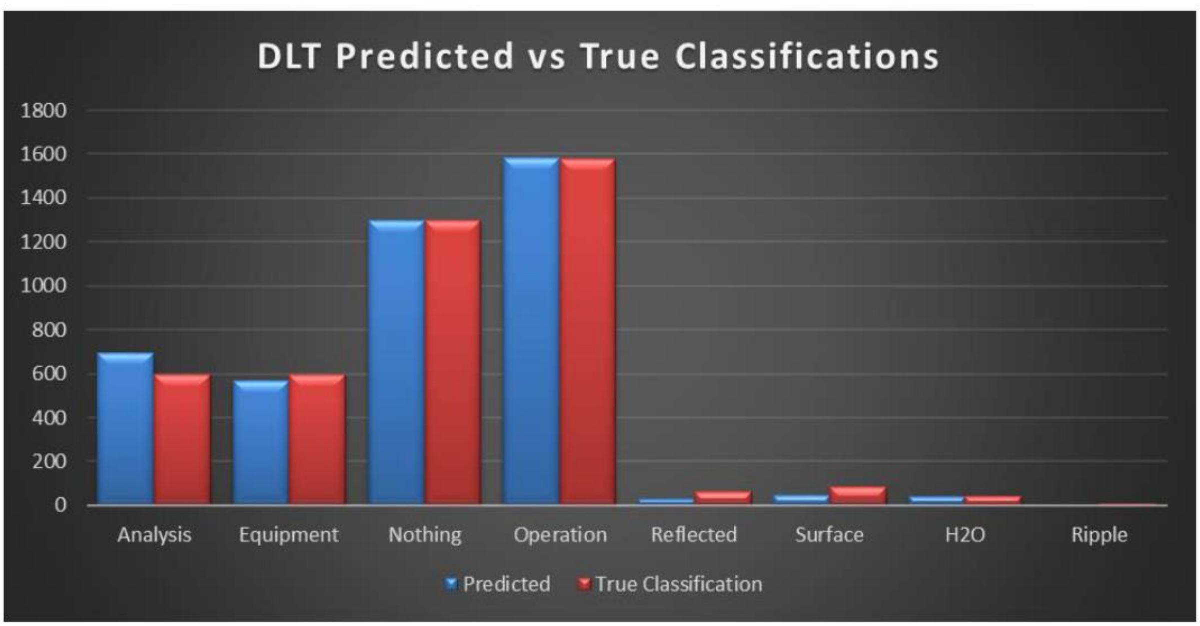


Fig 2 – True and predicted classifications obtained from the most recent SA-DEEP release.

## Acknowledgements

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### References