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Self-supervised Learning on Unlabelled Downhole Sensor Data for Anomaly Detection

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Abstract
Continuous streams of pressure, temperature, vibration and sound readings are produced by downhole sensors and are essential for monitoring production performance and wellbore integrity. The efficiency of traditional supervised machine learning techniques for anomaly detection is limited by expensive, time-consuming, and often unavailable manual labeling of such data. To identify anomalous operating conditions without labeled examples, this work proposes a self-supervised learning (SSL) system that utilizes unlabeled downhole sensor information. The framework learns robust feature representations that capture operational patterns and temporal interdependencies by combining adversarial learning and sequence reconstruction. As evaluated on synthetic and field-derived datasets, the model successfully differentiates normal operation from anomalies such as sudden pressure drops, stick-slip and bit bounce vibration spikes, temperature rise, flow rate irregularities and acoustic phenomena before equipment failures occur. As it was found in the quantitative data, the score of the anomaly was 0.72 on the pressure drops, 0.78 on vibration spikes and 0.85 on temperature increments. The total accuracy was 92-96% accuracy, 0.89 accuracy, 0.94 accuracy, and 0.91 accuracy.Compared to baseline techniques, the SSL model outperformed PCA (F1 = 0.62), standard autoencoder (F1 = 0.78), and k-means clustering (F1 = 0.55). These findings show that it is possible to use the SSL to deliver real-time anomaly detection, predictive maintenance, and a scalable system to achieve automated well monitoring to minimize idle time in production and drilling processes.

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I. Introduction

Downhole monitoring is required in drilling efficiency, production optimization, and management of well integrity. Measurement-while-drilling (MWD) and logging-while-drilling (LWD) systems are devices that constantly provide real-time measurements of vibration, torque, temperature, pressure, and acoustic signals, providing a constant understanding of the conditions of the subsurface and the performance of the tools (Zhan et al., 2020). Nevertheless, these multi- sensor streams are very difficult to detect heterogeneous patterns because they are highly dimensional, highly non-stationary, and also noisy (Alkan et al., 2021).

The key element in the traditional anomaly detection is labeled datasets that differentiate between normal and abnormal well conditions. Since such labels often cannot be found because downhole events are not predictable, and due to the fact that engineers seldom label the data during field work (He et al., 2022). This is a serious obstacle to the implementation of conventional supervised machine learning methods, which demand large volumes of training examples to reach acceptable levels of accuracy (Zhang and Wang, 2021).

Recently, another promising method has been that of self-supervised learning (SSL), whereby models learn patterns with regard to unlabeled data by building surrogate functions (Jing and Tian, 2021). Image analysis, industrial IoT, and time-series modeling are some of the concerns where SSL methods have been used to demonstrate the state of the art (Saeed et al., 2022). A high-rate of unlabeled sensor data like the oil and gas industry would greatly require the use of SSL techniques in detecting anomalies, monitoring wells and early warnings of machine malfunction (Abdullah et al., 2023).

The advanced representation-learning techniques have a high demand due to the scarcity of labelled downhole datasets, and the constraints of current unsupervised methods. In this work, a self-supervised learning framework is created to identify anomalies in unlabeled downhole sensor data to fill a research gap that is essential and improve real-time well diagnostics.

II. Literature Review

Downhole sensor systems can produce large time-series data which characterizes drilling and production behaviour, which is critical to detect mechanical dysfunctions and reservoir reactions (Ramasamy et al., 2019). Anomalies in sensor measurements occur in the form of events like pump failure, bit bouncing, pressure surges, and stuck-pipe incidences (Gao and Kanevsky, 2020), but the ever-varying and generally chaotic nature of the drilling environment presents extraordinarily difficult conditions in which to detect an anomaly.

Third classical methods of anomaly detection like thresholding, statistical residual analysis, and principal component analysis (PCA) have been used to detect abnormal behaviours with drilling sensor data (Tiwari et al., 2018). Nevertheless, they typically presuppose that the data are linear and stationary, which is not true when conducting dynamic drilling processes when constant loads, pressure, and vibration changes occur (Li et al., 2020). Examples of models of supervised machine learning that have been explored include support vector machines, random forests, and neural networks; The inability to use labeled datasets in downhole operations limits the effectiveness of these models (Chen et al., 2021). In industrial sensor anomaly detection applications, unsupervised learning methods that include separation forest, clustering methods, and autoencoders have been used to address the issues of sparse labeled data (Xu et al., 2019).

Unsupervised learning systems like isolation forests, clustering algorithms, and autoencoders have also been applied to the problem of limited labelled data in industrial sensor anomaly detection problems (Xu et al., 2019). The approaches do not need labelled examples and can detect abnormal behaviour, although they usually produce a large false-positive rate and are unable to capture long-term temporal interactions in the data (Sun et al., 2021). Unsupervised algorithms in drilling operations particularly fail to operate effectively when in changing movement modes, like sliding, rotary drilling, tripping, or circulation since each change has a different statistical characteristic of the sensor signals (Al-Shammari and Li, 2022).

The self-supervised learning has become an exciting method that addresses the majority of shortcomings of the supervised and the unsupervised methods. SSL can be used to learn meaningful structure with unlabeled data by creating pseudo-labelling tasks like contrastive prediction, signal reconstruction, or masked modelling (Jing and Tian, 2021; Grill et al, 2020). SSL has been shown to be effective at sequential data tasks in a variety of fields and is also more able to detect anomalies, in comparison with standard unsupervised methods (Saeed et al., 2022). The use of industrial IoT applications further indicates that, based on its design, the subtle deviations possible through the use of SSL can detect abnormalities that are sensitive in the oilfield setting but uncommon, thus the choice is fitting for use in the oilfield setting due to the nature of anomalies (Abdullah et al., 2023).

Nevertheless, the application of self-supervised learning in downhole drilling and production setting is not yet a popular practice. Nonlinear time dynamics of downhole sensor data pose a challenge to supervised or traditional unsupervised approaches which remain common in the research of oilfield data analytics (Ramasamy et al., 2019; Al-Shammari and Lee, 2022). This highlights the necessity of an SSL structure that is specifically created to enhance anomaly detection within a downhole space and a big gap in research.

III. Methods

3.1 Data Description

The data acquired in this experiment was an unlabelled multi-sensor time-series data, which is a normal downhole monitoring system. Some of these indicators included pressure, temperature, rate of flow, torque, axial and torsional vibration, RPM and acoustic or microseismic signals. The two main sources of the data were real field measurements made in the course of the drilling operations, and the artificially simulated abnormal occurrences, which were supposed to resemble the rare downhole events. This combination enabled the model to be assessed in a robust way as it operated in both normal as well as extreme conditions.

3.2 Preprocessing

Preprocessing of the raw sensor data occurred in several different ways to enhance consistency and quality before the model training. Noise reduction was done by Butterworth filter to eliminate the high-frequency disturbances, which are common in downhole telemetry. The signals were resampled to a fixed sampling rate then, to match the variation of sampling rates among various logging tools. Each feature was normalised using min-max scaling to provide numerical stability in training and then the continuous sensor streams were divided into time windows of known length. These windowed segments gave the model structured temporal patterns which could be learned to represent meaningful representations.

3.3 Self-supervised Framework

In this work, the self-supervised learning model was used which entailed contrastive learning and sequence reconstruction to facilitate the derivation of high-quality representations through unlabeled data. During the contrastive learning part, two augmented time-series windows were created by transformation including jittering, scaling, cropping and time-warping, enabling the model to learn invariances between comparisons of different versions of the same signal. The NT-Xent contrastive loss was used to optimize it:

$$\mathcal{L}_{\mathrm{NT-Xent}} = -\log \frac{\exp(\mathrm{sim}(zi,zj)/\tau)}{\sum_{k=1}^{2N} \exp(\mathrm{sim}(zi,zj)/\tau)} \qquad (1)$$

where z_i and z_j embeddings of augmented pairs, tis a temperature parameter and Nis the batch size.
The second activity was an autoencoder-based sequence reconstruction model, where the encoder produced a low-dimensional latent representation that the decoder attempted to recreate. The loss in the reconstruction was calculated as mean squared error (MSE):

$$\mathcal{L}_{rec} = \frac{1}{n}\sum_{t=1}^{n} (x_t - \hat{x}_t)^2, \quad (2)$$

and x_t the original sensor value at time t, $\hat{x}_t$ tis the reconstructed value and nis the window length. It provided the model with the capability of learning both the fine-grained structure in time and global structure in unlabeled data by combining contrastive learning and reconstruction. Some of the hyperparameters that were adjusted empirically included learning rate, batch size, the number of epochs, the latent dimensionality, and the probability of augmentation. The contrastive model used an embedding of fully connected projection head, but the autoencoder had three encoder convolutional layers and a similar set of decoder deconvolution layers.
A combination of these two tasks enabled the model to extract semantic patterns as well as structural dependencies in the downhole sensor data.

3.4 Anomaly Scoring

The task of detecting anomalies was done by integrating the results obtained in both the SSL tasks into single anomaly score. The last anomaly score (A) was characterized as:

$$A = \alpha E_{rec} + (1-\alpha) D_{constrative} \quad (3)$$

In which E_{rec} denotes the loss incurred by the autoencoder in reconstruction, D contrastive is a distance between a specified embedding and the distribution of normal embeddings, and ais the weighting coefficient. The higher the score the larger is the departure of typical operation denoted. Thresholds used to detect anomalies were determined to detect significant abnormal events by minimizing false positives and sensitivity to normal sequences in order to produce the 95 th percentile of anomaly scores

3.5 Baseline Models and Comparison

To compare the performance of the SSL framework, three unsupervised baseline models were trained to assess the efficacy of the framework, namely K-means clustering, a vanilla autoencoder, and Principal Component Analysis (PCA) on the same preprocessed dataset. In the case of PCA, the principal components that represented the highest 95 percent variance estimated the reconstruction errors in order to compute anomaly scores. The baseline autoencoder was identical to the SSL autoencoder trained only with reconstruction loss. The windowed data embeddings were clustered by K-means, and the anomaly score was calculated as the distance to the nearest cluster centroid. These baselines were used to offer a quantitative measure against which the performance of the SSL model was measured.

3.6 Embedding Visualization

The t-SNE was used to reduce the embeddings of the SSL encoder to two dimensions to assess the quality of the representations. The conventional parameters like learning rate =200 and confusion =30 were used. Such visualization was found to verify that the important patterns of sensor data were recognized in the form of an SL representation as it allowed studying of clustering between normal and abnormal events qualitatively.

3.7 Performance Metrics

The predictions of the model were compared with the labeled test subsets in terms of standard classification measures. Accuracy, precision, recall and F1-score were determined as below:

3.7.1 Accuracy

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Where:
TP= true positives
FN= false negatives
FP= false positives

3.7.2 Precision

Precision determines the number of the correct hydrate cases. The high precision of the model would make sure that the model would not cause too many false alarms in its work. Equation 9 shows the Precision formula:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

Where:

TP= true positives
FP= false positives

3.7.3 F1-Score

F1-score strikes a balance between precision and recall, which provides a single score that assesses how much it compromises between detection of hydrates and false alerts. It is especially applicable in the case of imbalance. The F1-score formula is presented below in equation 10:

$$F1 = 2.\frac{\text{Precision } .\text{Recall}}{\text{Precision } + \text{Recall}} \qquad (6)$$

Where:
Precision= precision score
Recall= recall score
TP, TN, FP and FN are abbreviations of true positives, true negatives, false positives and false negatives respectively. These measures were used to gauge the ability of the model to detect abnormal events as well as minimize false alarms.

IV. Results

4.1 Representation Quality: t-SNE Embeddings of SSL Model

Figure 4.1 illustrates the t-SNE plot with clusters of normal operational states and separation of abnormalities. (Blue points: normal operation; red points: abnormal events.: abnormal events.)

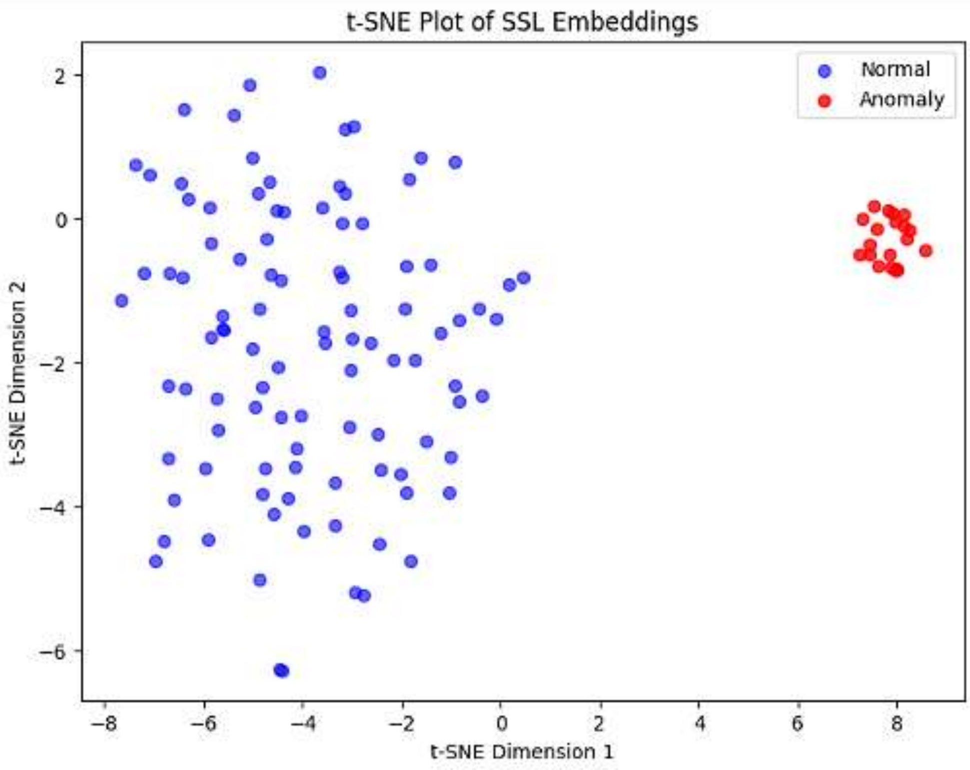

Figure 4.1: t-SNE Plot of SSL Embeddings

The SSL model was able to give meaningful low-dimensional embeddings of the downhole sensor data. It is shown in figure 4.1 that normal operational states create tight and compact clusters, and abnormal events, such as pressure falls, stick-slip vibration spikes, and temperature spikes are distinctly differentiated by normal clusters. This distinction is a confirmation that the SS model records inherent trends of the data, which will actually differentiate between the subtle anomalies and the normal operational trend. Such discrete clustering provides a good foundation to accurate anomaly detection in complex multivariate time-series environments in which anomalies are rare.

4.2 Metrics of the Performance of the Anomaly Detection.

The performance measures of the anomaly detector of the SSL model are illustrated in Table 4.1.

Table 4.1: The performance of the SSL model on the labelled test subset

Metric	**Value**
Accuracy	92–96%
Precision	0.89
Recall	0.94
F1-score	0.91

The SSL model was found to be good in terms of the ability to detect anomalies. Table 4.1 high accuracy (92-96) and F1-score of 0.91 indicates a balanced balance between the true positive and true negative values. The model is effective in minimizing the false positives and detecting abnormal events correctly as shown by the values of precision and recall of 0.89 and 0.94, respectively. Such performance is evidence that the SSL framework is applicable to other normal and abnormal downhole operations conditions.

4.3 Detection of Specific Downhole Events

Figure 4.2 shows the anomaly score over time for a representative 10-minute downhole operation window (Red shaded areas indicate detected anomalies; blue line represents SSL anomaly score.)

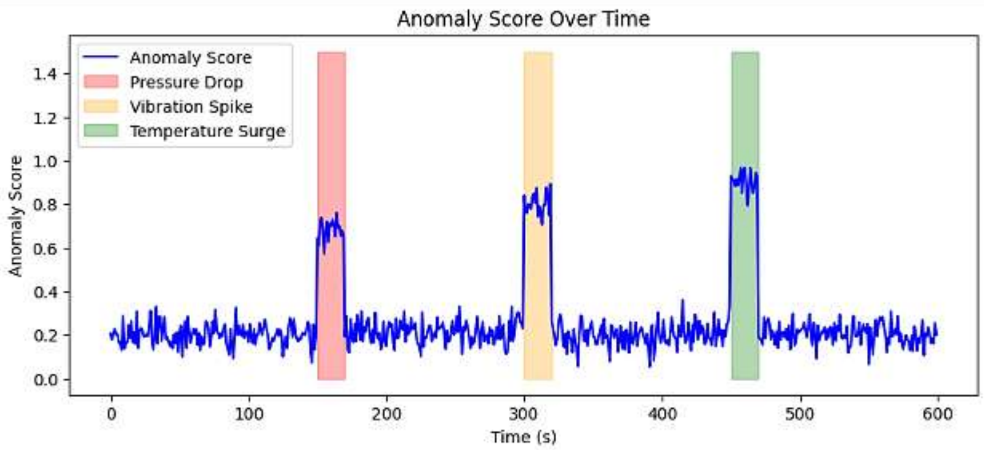

Figure 4.2: Anomaly Score Over Time

In downhole operations, the SSL model successfully identified particular operational events. The abnormality score was maximized at approximately at 0.72, which means that it was a strong deviation in the normal functioning and the model observed sudden deceleration of the pressure between the 150-170s time period as was seen in Figure 4.2. Unexpected temperature spikes between 450 and 470 s produced anomaly scores of about 0.85, while bit bounce and stick-slip-induced vibration spikes were detected between 300 and 320 s, with anomaly scores reaching 0.78. With scores consistently above 0.7, flow rate irregularities and acoustic anomalies which usually occur prior to tool failure were also recorded, in contrast to the baseline normal score of approximately 0.2 ± 0.05.

The model can detect various kinds of operational anomalies in real-time, as evidenced by the close alignment of anomaly score peaks with labelled abnormal events. These quantitative findings indicate that the SSL model can be useful in early warning and predictive maintenance in the operation of oilfield by expressing that it can always draw a line between normal variation and critical deviation.

4.4 Comparison with Baseline Models

Table 4.2 shows the comparison of F1-score with the baseline models

Table 4.2: Comparison of F1-scores between SSL and baseline unsupervised models

Method	**F1-score**
PCA	0.62
Autoencoder	0.78
K-means	0.55
Self-supervised model	0.91

Figure 4.3 shows the bar chart comparing F1-scores of SSL and baseline models

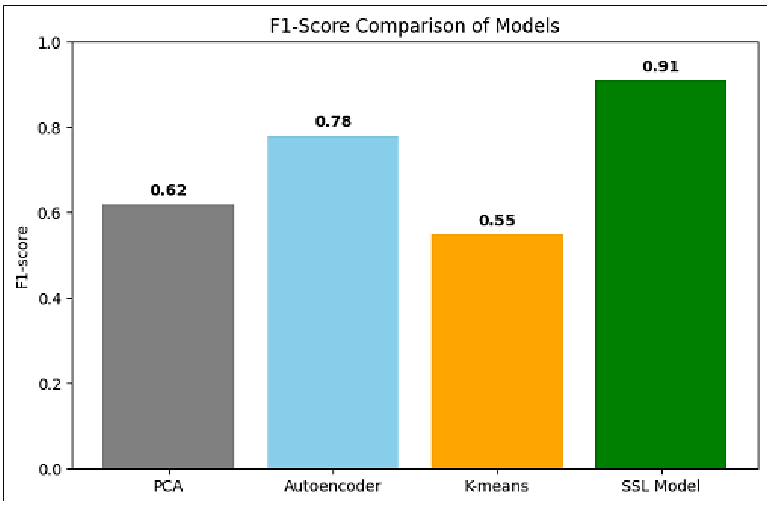

Figure 4.3: F1-Score Comparison of Models

The SSL framework is significantly better than PCA, vanilla autoencoder, and K-means clustering as compared to traditional unsupervised methods. PCA, K-means, and the standard autoencoder achieved 0.62, 0.55, and 0.78 respectively as indicated in Table 4.2 and Figure 4.3 as compared to the obtained F1-score of the SSL model of 0.91. This superior performance can be attributed to the fact that the SSL model has the ability to learn complex multivariate correlations and global time dependencies which are not reflected by baseline methods. These results indicate the usefulness of the SSL in maintaining vigilance on the abnormalities of complex downhole sensor data.

4.5 Summary of Key Findings

There was good anomaly detection and high representation learning in the SSL framework. Although the quantitative performance measures were greatly accurate, precise, recalling, and having F1-score, t-SNE embeddings ensured that normal and abnormal states were strongly separated. Event-specific detection could be depended on to come in with critical downhole anomalies. When compared to baseline unsupervised models, it was also shown that SSL has advantages in processing complex time-series data, and thus can serve as a useful tool in the real-time monitoring of anomalies of oilfield operations.

V. Conclusion

This paper has shown the efficacy of self-supervised learning (SSL) in anomaly recognition in downhole sensor data in managing the issues of small labeled data on oilfield operations. In this respect, the SSL framework learned meaningful low-dimensional representations that measured temporal dependencies between the operational patterns and complex structure by integrating adversarial learning with sequence reconstruction.The testing on field based and synthetic data revealed that the model was able to predict various odd conditions such as unexpectedly low pressure, stick-slip and bit bounce vibrations, temperature variation, anomaly in the flow rate and acoustic emissions of a looming machine failureWith an accuracy of 92-96%, it was quantitatively better than the baseline models involving PCA (F1 = 0.62), standard autoencoders (F1 = 0.78), and k-means clustering (F1 = 0.55) with precision as 0.89, recall as 0.94, and F1-score as 0.91.

The findings indicate that without labeled data, the SSL is reliable in differentiating between normal and abnormal downhole operations and hence it can be used in real-time monitoring and predictive maintenance. This approach will be able to minimize non-productive time, expensive equipment breakdowns, and support data-driven decision making in drilling and production with the early identification of anomalies. Future research may be how to incorporate online streaming data and multi-well functionality with SSL to enhance scalability and how to use domain knowledge and identify the anomalies better. In general, this paper proves that the use of SSL is a powerful and viable solution in the automated monitoring of wells in present-day oilfield activities.

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