Applicability of Anomaly Detection Knowledge from Computer Science and Mathematics Publications to Oil and Gas Research

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***Abstract* — Anomaly detection in equipment processes is crucial for the oil and gas sector. Algorithms for detecting anomalies in measured data are best understood in Computer Science and Mathematics. Therefore, a possible transfer of knowledge from the latter area to the former can have a profound impact. This paper explores the potential for the knowledge transfer by analyzing bibliometric data of Computer Science and Mathematics papers published in MDPI journals, as well as publications available on SPE search platform. The research shows that the main algorithms extensively studied in MDPI publications and found in SPE publications, which address the anomaly detection problem, include Random Forest, Support Vector Machine, Long-term Memory Method and Recurrent Neural Network. The main advantages and disadvantages of these methods are briefly described. This paper provides examples of classical and highly cited publications that describe the work of these algorithms along with examples of articles that illustrate their application in the oil and gas industry. The sections of SPE disciplines with the largest number of publications using the algorithms that are frequently used for anomaly detection are presented.**

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***Index Terms* — anomaly detection, MDPI, SPE, computer science and mathematics, bibliometric data, algorithm.**

I. Introduction

A. Relevance of the subject

Anomaly detection is a vital tool in the oil and gas sector, enhancing safety, security, environmental management, regulatory compliance, maintenance strategies, and operational efficiency. It identifies unusual patterns in sensor data, enabling early detection of anomalies, preventing accidents and equipment failure, monitoring environmental variables, reducing risks, and proactively responding to suspicious activities. Data integrity and anomaly detection are crucial for preventing errors and cybersecurity breaches [1–5].

B. The aim of this study

The objective of this study is to identify the most promising areas for transferring knowledge of “Anomaly Detection” from the fields of Computer Science and Mathematics to the field of oil and gas industry.

To achieve this objective, the following questions are proposed to be answered:

1. Which analytical approaches in the field of anomaly detection are the most developed in publications in the field of “Computer Science and Mathematics?”

2. Which analytical approaches in the field of anomaly detection are most in demand in the oil and gas industry?

Knowledge transfer is assumed to be most appropriate if this knowledge is developed in the field of “Computer Science and Mathematics” and is in demand in the oil and gas industry.

Publications on "Computer Science and Mathematics" are taken from MDPI journals. Publications in the field of oil and gas are taken from the SPE search platform.

The identification of promising issues for knowledge transfer was based on the use of bibliometric methods.

C. Literature review

A review of the literature shows that most publications are devoted to the use of anomaly detection to improve the safety and efficiency of oil and gas operations. The following are typical studies related to this topic.

The paper [6] presents an approach for fault detection and identification using a Self-Organizing Map algorithm, which is crucial for preserving industrial plant health and increasing reliability and efficiency in oil and gas operations. The intuitive and easy-to-understand results of this algorithm are presented.

Machine learning algorithms, including random forest, support vector machine, k-nearest neighbor, gradient boosting, and decision tree, are used to develop anomaly detection models for pipeline leaks in oil and gas operations. The support vector machine algorithm outperformed other algorithms in detecting pipeline leaks, proving its efficiency as an accurate model for pipeline leak detection [7].

A scheme for systematically analyzing flight data to detect anomalies in flight operations, applicable to both online and offline modes, is proposed in [8]. The authors analyze the fundamental aspects of the anomaly detection problem and consider it in the domain of flight operations. The framework relies on the steps of streaming or loading and storing data, creating and explaining the model, while relying on the analysis of domain experts. Logistic operations are important to any industry, so the transfer of the knowledge gained is appropriate for the oil and gas industry.

Random forest and Logistic regression methods used in articles [8, 9] are also used in the oil and gas industry, examples are shown in Table 1.

The paper [9] introduces a two-step methodology utilizing machine learning classification algorithms for anomaly detection in industrial processes. The authors analyze in detail the application of Random Forest Algorithm (RFA) and Decision Jungle Algorithm (DJA) methods to manufacturing processes with multiple phases. The proposed methodology involves first identifying the production phases and then applying an anomaly detection procedure to them. In the oil and gas industry, numerous production processes are multiphase as well. Therefore, the expertise of two-stage anomaly detection, as described in the publication in the field of Computer Science and Mathematics can be highly valuable for the research in the oil and gas sector.

Anomaly detection sensors can be used in oil and gas well-monitoring systems to detect network traffic anomalies, improving safety and efficiency. These sensors are designed to operate within existing well-monitoring infrastructure and compare against pre-set and moving averages to detect and report anomalies [10].

The paper [11] proposes an unsupervised method for anomaly detection in industrial machines, utilizing statistical features to calculate failure severity indicators and interrupt operation before breakdown. The unique feature of this method lies in the fact that it takes a set of time series data from multiple sensors as input. Time series analysis techniques are commonly used in well drilling, making it instrumental to have experience in analyzing recordings from multiple sensors.

Anomaly detection techniques are discussed in [12]. The article provides an overview of current research directions, including definitions, modes, outputs, and literature. It also aims to provide guidance on selecting the most appropriate approach for specific application domains.

In [13], the authors analyze 290 research articles (published in 2000–2020) on ML models for anomaly detection and identify 29 different models used in their application.

The publications [12, 13] are review-oriented in nature, but their value, especially that of [13], can be useful for oil and gas research when determining which method is best suited for a particular dataset.

No publications were found that explore the potential of transferring anomaly detection knowledge from computer science and mathematics for application in the oil and gas industry. Consequently, the topic proposed in the title of the paper is novel.

II. Materials and Methods

A. Data

This research used bibliometric data from the MDPI publisher website, up to September 11, 2023, for "anomaly detection" query. The query included filters for the years between 2019 and 2023, subjects such as Computer

Science and Mathematics, and article types such as articles and reviews. A total of 2 151 tsv outcomes were exported.

The employment of data from MDPI publisher offers several benefits. Firstly, it provides open access to all publications. Secondly, it encompasses a broad range of topics, as evidenced by the inclusion of the topic “anomaly detection” in 52 journals. Additionally, the exported bibliometric data comprises 16 fields, which include the essential fields required for our study, namely TITLE, JOURNAL, KEYWORDS, ABSTRACT, and DOI.

Journals with 20 or more publications at the time of export are:

Applied Sciences → 735, Electronics → 409, Mathematics → 127, Symmetry → 102, Entropy → 90, Information → 75, Future Internet → 72, Algorithms → 57, Processes → 55, ISPRS International Journal of Geo-Information → 41, Computers → 39, Buildings → 34, Journal of Imaging → 27, Big Data and Cognitive Computing → 25, Journal of Sensor and Actuator Networks → 25, Journal of Cybersecurity and Privacy → 20 articles.

B. Clustering of bibliometric records

The Carrot2 program [14, 15] with the Lingo3G algorithm was used for document clustering with the following parameters that differ from the defaulters: algorithm: minLabelWords: 2, maxWordDf: 0.8, phraseDfThresholdScalingFactor: 0.05. A detailed description of the Carrot2 program, the Lingo3G algorithm, and its parameters can be found at https://carrotsearch.com/lingo3g/.

Clustering was conducted utilizing the KEYWORDS and ABSTRACT fields. The texts of these fields underwent the following preprocessing steps:

1. Stemming texts by the Krovetz method, which allowed the terms to be normalized while preserving their readability.
2. Compiling a dictionary of normalized keywords.
3. Keeping only terms from the above dictionary in the ABSTRACT field.
4. Replacing the original KEYWORDS and ABSTRACT fields in the bibliometric records with the transformed ones.
5. Using the bibliometric data thus obtained further in the demo version of Carrot2.

C. Explanation of text preprocessing in progress

The Krovetz algorithm is characterized by its ability to make minimal alterations to the spelling of terms. In this sense, it can be considered as an intermediate approach that lies between lemmatization and stemming [16,17]. This feature is important not only in the context of record clustering but also when automatically assigning headers to clusters and subclusters. For example, using Porter stemming will render headers unreadable.

A good practice of text pre-processing is to remove stop words, but the choice of the list of stop words is subjective. Here, this procedure was replaced by leaving in the texts of abstracts only those terms that the authors themselves considered significant and included in the list of keywords. A dictionary of terms left in the texts of the abstracts was compiled from the list of all keywords. The common text utilities grep and sed were used for this purpose.

The test version of the Carrot2 program has a limit on the amount of data to be analyzed. Using the full texts of 2151 abstracts caused these limits to be exceeded.

The use of preprocessing not only made the records more consistent, but also allowed meeting the limitations imposed by the test version of the program.

D. Search for publications at SPE research portal (search.spe.org)

After identifying the main methods used for anomaly detection, obtained by analyzing the bibliometric data of MDPI publications, a search was conducted for publications related to oil and gas topics and the problem of anomaly detection. For this purpose, the SPE search engine was used, to which queries of the following form were set: “anomaly detection” AND “method,” for example: “anomaly detection” AND “Random Forest.”

Next, according to the results of each query, reading the abstracts of the found publications and additional information on the method, the following items were compiled: Advantages, Drawbacks, Highly cited publication, Table with Publications demonstrating the application of the method, and SPE Disciplines to which the found publications were referred.

In the absence of publications related to a particular method and anomaly detection problem, examples of publications close in meaning to the problem (Outlier Detection, Deviation Detection, Out-of-Distribution Detection, and Fault Detection) were searched for.

The number of publications found should be considered only as an estimate of the frequency of occurrence of articles on the topic being searched. This may be sufficient to select a specific anomaly detection method. The next stage of the research may require more complex queries, for example, to produce systematic reviews.

III. Results and Discussion

A. Clustering of bibliometric records

The methodology described in the previous section allowed identifying 29 clusters out of 2151 bibliometric records, with 61.0% of the documents falling into the main clusters. Figure 1 shows the clustering results for the six main clusters. In addition, a complete enumeration of all clusters is given in the form of a list to provide more detailed information.

The topics within the clusters and their corresponding subclusters reflect the methods used for anomaly detection, as well as the diverse range of domains in which they can be used.

The full range of clusters and their subclusters are presented in the list below.

The format of the list is as follows: cluster name, number of documents assigned to the cluster, number of subclusters in the cluster. It should be reminded that the algorithm used could assign each document to several categories.

- Anomaly Detection (339 Docs, 14 Subclusters)
- Neural Network (373 Docs, 14 Subclusters)
- Machine Learning (370 Docs, 14 Subclusters)
- Deep Learning (305 Docs, 14 Subclusters)
- Real Time (228 Docs, 14 Subclusters)
- Network Traffic (171 Docs, 14 Subclusters)
- Time Series (125 Docs, 14 Subclusters)
- Future Research (107 Docs, 14 Subclusters)
- Security Privacy (69 Docs, 14 Subclusters)
- Blockchain Technology (38 Docs, 14 Subclusters)
- High Resolution (24 Docs, 11 Subclusters)
- Quality Assessment (18 Docs, 14 Subclusters)

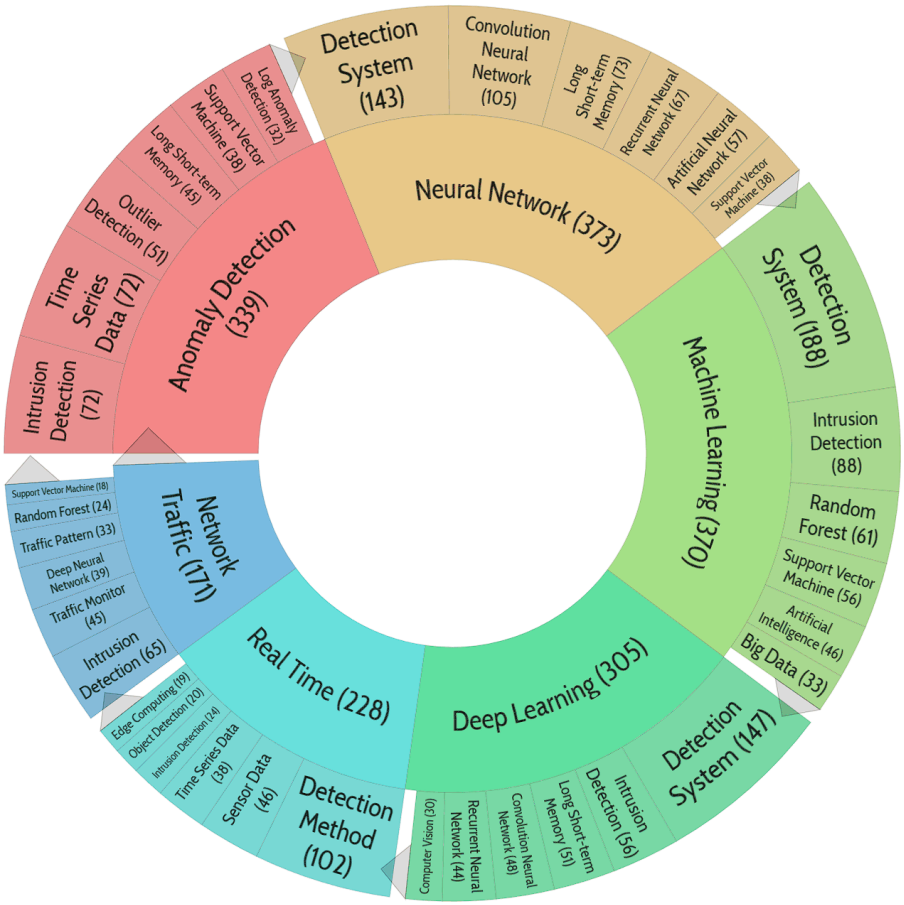

Fig. 1. Themes of the six main clusters and their subclusters of 2151 documents, using the Lingo3G algorithm.

- Wind Energy (19 Docs, 13 Subclusters)
- Signal Ratio (16 Docs, 13 Subclusters)
- Particle Swarm Optimization (15 Docs, 12 Subclusters)
- Knowledge Graph (13 Docs, 10 Subclusters)
- Fuzzy Sets (14 Docs, 12 Subclusters)
- Dimension Reduction (13 Docs, 12 Subclusters)
- Persistent Threat (13 Docs, 10 Subclusters)
- Texture Features (13 Docs, 13 Subclusters)
- Semantic Segmentation (11 Docs, 10 Subclusters)
- Energy Sector (12 Docs, 13 Subclusters)
- Electronic Control (13 Docs, 13 Subclusters)
- Hyperspectral Image (10 Docs)
- Maintenance Activity (9 Docs)
- Useful Life (8 Docs)
- Decision Boundary (8 Docs)
- Damage Severity (7 Docs)
- Other Topics (839 Docs)

The first four clusters show the greatest degree of overlap with the approaches used in anomaly detection. We therefore provide a complete list of their subclusters, emphasizing the methods used.

ANOMALY DETECTION (339 docs, 14 subclusters);

Intrusion Detection (72), Time Series Data (72), Outlier Detection (51), **Long Short-term Memory** (45), **Support Vector Machine** (38), Log Anomaly Detection (32), **Random Forest** (29), Anomalous Behavior (30), Data Mining (29), Cyber-physical System (23), Video Surveillance (18), Industry 4.0 (19), Attention Mechanism (17), Fraud Detection (16)

NEURAL NETWORK (373 docs, 14 subclusters);

Detection System (143), **Convolution Neural Network** (105), **Long Short-term Memory** (73), **Recurrent Neural Network** (67), Artificial Neural Network (57), **Support Vector Machine** (38), **Random Forest** (37), Attention Mechanism (23), Graph Neural Network (23), Computer Vision (21), Generative Adversarial Network (18), Adversarial Attack (10), Activity Recognition (10), Fraud Detection (5).

MACHINE LEARNING (370 docs, 14 subclusters);

Detection System (188), Intrusion Detection (88), **Random Forest** (61), **Support Vector Machine** (56), Artificial Intelligence (46), Big Data (33), **Convolution Neural Network** (27), Data Mining (26), Fraud Detection (15), **Generative Adversarial Network** (15), Edge Computing (13), Traffic Pattern (11), Activity Recognition (10), Social Media (9).

DEEP LEARNING (305 docs, 14 subclusters).

Detection System (147), Intrusion Detection (56), **Long Short-term Memory** (51), **Convolution Neural Network** (48), **Recurrent Neural Network** (44), Computer Vision (30), **Random Forest** (28), Artificial Intelligence (29), **Generative Adversarial Network** (21), Big Data (20), **Reinforcement Learning** (18), Video Surveillance (16), Defect Detection (15), Adversarial Attack (13).

For completeness, we present the total occurrence of the highlighted methods in the list of keywords and abstracts of all 2151 records.

Random Forest → 115 rows, 176 matches;
Support Vector Machine → 104 rows, 144 matches;
Long Short-term Memory → 107 rows, 142 matches;
Recurrent Neural Network → 51 lines, 64 matches;
Convolution Neural Network → 15 lines, 20 matches;
Generative Adversarial Network → 57 lines, 96 matches;
Reinforcement Learning → 27 lines, 60 matches.

The Random Forest and Support Vector Machine classification methods are widely studied and are considered classical approaches. Therefore, it is not surprising that they are widely used in the field of anomaly detection when normal and anomalous instances are separated into separate classes.

Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) can be identified as a set of techniques effective for sequential data processing. Different types of sensors and logs serve as suitable data sources for these techniques, especially in the context of time series analysis.

B. *Results of a search of SPE publications and a description of the main features of the methods*

For this purpose, the SPE search engine was used, to which queries of the following form were set: “anomaly detection” AND “method,” for example: “anomaly detection” AND “Random Forest.”

The number of results returned for queries made from December 2018 to December 2023 is:

- ”Support Vector Machine” AND “anomaly detection” → 57
- ”Long Short-term Memory” AND “anomaly detection” → 53

- ”Random Forest” AND “anomaly detection” → 63
- ”Convolution Neural Network” AND “anomaly detection” → 3
- ”Recurrent Neural Network” AND “anomaly detection” → 35
- ”Generative Adversarial Network” AND “anomaly detection” → 6
- ”Reinforcement Learning” AND “anomaly detection” → 0
- ”Reinforcement Learning” → 0

The focus was on bibliometric data alone, not full text.

This simple search provides only a rough estimate of the occurrence of relevant publications on the topic.

For a more comprehensive study, it is necessary to select semantic equivalents of the phrase “anomaly detection” for each analytical technique, such as Outlier Detection, Deviation Detection, Out-of-Distribution Detection, and Fault Detection.

C. Summary characteristics of publications found for the query “Random Forest” AND “anomaly detection”

Advantages. The Random Forest technique is a popular machine-learning algorithm for classification and regression problems due to its high accuracy, robustness, emphasis on feature importance, versatility, and scalability. It combats overfitting by aggregating decision trees and reduces sensitivity to noise and outliers in the dataset.

Drawbacks. Random Forest is a computationally intensive algorithm with disadvantages, including difficulty in interpretation due to the ensemble nature, poor

TABLE 1. Publications Demonstrating the Application of the Random Forest Algorithm to Anomaly Detection Problems

Title and Reference	Short summary
Early Anomaly Detection Model Using Random Forest while Drilling Horizontal Wells with a Real Case Study [19]	This paper presents a machine-learning model to predict drilling surface torque for early detection of operational problems. The model uses real horizontal drilling data from the day before the stuck pipe incident. It predicts surface drilling torque based on typical patterns observed over the past 24 hours, using train and test a random forest model. The model is integrated with the Mahalanobis metric to assess the closeness of real observations to the predicted normal trend.
Explainable and Interpretable Anomaly Detection Models for Production Data [20]	This study compares machine-learning models on two datasets for anomaly detection. It aims to understand how these models make decisions. The models used include K-nearest neighbors, logistic regression, support vector machines, decision tree, random forest, and rule fit classifier. In one data set, the rule fit classifier outperformed the remaining models in both F1 and complexity. In the second data set, random forest outperformed the rest in prediction performance with F1, yet it had the lowest complexity metric.
Leak Detection in Natural Gas Pipelines Using Intelligent Models [21]	This study investigates the effectiveness of intelligent models in detecting small leaks in natural gas pipelines using operational parameters like pressure, temperature, and flowrate. Five models are used: Gradient Boosting, Decision Trees, Random Forest, Support Vector Machine, and Artificial Neural Network. Results indicate that Random Forest and Decision Tree models were most sensitive, with a 0.1% leak detection rate in 2 hours. All models have high reliability, but low accuracy, with Artificial Neural Network and Support Vector Machine performing best.
Assessment of Big Data Analytics Based Ensemble Estimator Module for the Real-Time Prediction of Reservoir Recovery Factor [22]	Estimating reservoir recovery factor is challenging due to high uncertainty, large inexactness, noise, and high dimensionality in reservoir measurements. The paper presents a big data-driven ensemble estimator module, which uses wavelet-associated ensemble models to estimate reservoir recovery factor. The module uses bagging and random forest ensembles to correlate reservoir properties with the recovery factor, and the Relief algorithm to understand their significance. The random forest exhibits the highest coefficient of correlation and minimal estimation errors.
Automating Dynamometer Charts Interpretation with Machine Learning [23]	The aim of the study is to create a mathematical model for the interpretation of Dynamometer Charts from Sucker Rod Pumps. The paper describes a data processing pipeline for obtaining, normalizing, transforming, and evaluating graphs. About 1000 models are trained and tested, including support vector machines, decision trees, K-nearest neighbors, and neural networks. The XGBoost algorithm performs best, although Random Forest algorithms are significantly more accurate in certain conditions.

performance in imbalanced datasets, and poor performance in noisy datasets with numerous irrelevant features, as well as in imbalanced datasets with high trees.

Highly cited publication. Random Forest [18].

Example of publication titles and their brief summary demonstrating the application of the Random Forests algorithm for solving anomaly detection problems found using the search.spe.org are presented in Table 1.

The most frequently referenced **SPE disciplines** in the publications found using the **"Random Forest"** query are:

Production and Well Operations (184): Artificial Lift Systems (28); Production Chemistry, Metallurgy and Biology (12); Well & Reservoir Surveillance and Monitoring (**112**).

Reservoir Description and Dynamics (694): Formation Evaluation & Management (276);

Improved and Enhanced Recovery (69); Reservoir Characterization (**285**); Reservoir Fluid Dynamics (72); Unconventional and Complex Reservoirs (154).

Well Drilling (200): Drilling Fluids and Materials (28); Drilling Measurement, Data Acquisition and Automation (12); Drilling Operations (**98**); Wellbore Design (20).

D. Summary characteristics of publications found for the query "Support Vector Machine" AND "anomaly detection"

Advantages. The Support Vector Machine (SVM) is a highly effective machine-learning algorithm known for its high-dimensional performance, resilience against outliers, adaptability to kernel functions, generalization, regularization parameter, efficient memory utilization, and non-linear classification efficacy.

Drawbacks. The Support Vector Machine (SVM) algorithm faces several drawbacks, including poor parameter selection, computational sensitivity to noise, lack of transparency, limited scalability, and binary classification limitations, making it challenging to interpret and handle large datasets.

Highly cited publication. LIBSVM: A library for support vector machines [24].

Examples of publication titles and their brief summary demonstrating the application of the SVM algorithm for solving anomaly detection problems found in the search engine of search.spe.org are presented in Table 2.

The most frequently referenced **SPE disciplines** in the publications found using the query **"Support Vector Machine"** are:

Production and Well Operations (147): Artificial Lift Systems (31); Production Chemistry, Metallurgy and Biology (16); Well & Reservoir Surveillance and Monitoring (**80**); Well Operations and Optimization (7).

Reservoir Description and Dynamics (688): Formation Evaluation & Management (219); Improved and Enhanced Recovery (70); Reservoir Characterization (**336**); Reservoir Fluid Dynamics (69); Unconventional and Complex Reservoirs (110).

Well Drilling (200): Drilling Fluids and Materials (28); Drilling Operations (**85**); Pressure Management (22); Wellbore Design (43).

E. Summary characteristics of publications found for the query "Convolution Neural Network" AND "anomaly detection"

Advantages. Convolution Neural Networks (CNNs) use convolutional layers to learn local patterns and features from input data, extracting meaningful features from raw data, and using parameter sharing for memory efficiency. They are robust to variations in input data and can handle large-scale datasets with modern GPUs' parallel processing capabilities.

TABLE 2. Publications Demonstrating the Application of the SVM Algorithm to Anomaly Detection Problems

Title and Reference	Short summary
An Unsupervised Stochastic Machine Learning Approach for Well Log Outlier Identification [25]	Outlier detection is crucial in Log Quality Control workflows, and machine learning implementations must address challenges. This paper presents a stochastic outlier detection algorithm using the One-Class Support Vector Machine (1CSVM) method. This method creates outlier flags for all data vectors, providing a proxy for uncertainty. It is robust, efficient, and more efficient than processing all wells set at once. The methodology's unique feature is weighting input data vectors based on petrophysics and measurement physics. This automated workflow is ideal for unconventional applications involving large volumes of legacy data.
Real-Time Drilling Models Monitoring Using Artificial Intelligence [26]	Drilling and Workover operations are evolving at a rapid pace, requiring more data to predict drilling problems. This paper presents a new approach using the Wellsite Information Transfer Specification Markup Language, applying an improved mechanism to monitor and evaluate anomaly detection models and demonstrating the benefits of iterative improvements. A regression classifier model using a support vector machine is developed to predict the expected number of alerts.

Drawbacks. CNNs are computationally intensive and time-consuming due to their large training data and resources. They are prone to overfitting, making them difficult to interpret. They require large memory for large input data sets or deep networks, which may limit their usability on devices with limited memory. Furthermore, they lack rotational and translational invariance.

Highly cited publication. Going deeper with convolutions [27].

Examples of publication titles and their brief summary demonstrating the application of the Convolution Neural Network for solving anomaly detection problems found in the search.spe.org search engine are presented in Table 3.

The most frequently referenced **SPE disciplines** in the publications found using the query **"Convolution Neural Network"** are:

Production and Well Operations (5): Artificial Lift Systems (2); Well & Reservoir Surveillance and Monitoring (**4**).

Reservoir Description and Dynamics (54): Formation Evaluation & Management (9);

Reservoir Characterization (**46**).

Well Drilling (10): Drilling Operations (**5**).

TABLE 3. Publications Demonstrating the Application of the Convolution Neural Network to Anomaly Detection Problems

Title and Reference	Short summary
Drilling and Completion Anomaly Detection in Daily Reports by Deep Learning and Natural Language Processing Techniques [28]	Unconventional oil & gas fields generate vast amounts of data, making data-driven methods challenging for analysis. Different activity coding systems and missing data make automatic anomaly detection difficult. An automatic text classification method was proposed using machine learning and natural language processing techniques for daily drilling and completion reports. Based on 460,000 operation records from 1,700 wells worldwide, Word2vec is used, and CNN is found to be the best method for text classification.
Virtual Multiphase Flowmeter Using Deep Convolutional Neural Networks [29]	This paper proposes a low-cost, instantaneous model for measuring oil, gas, and water volume in petroleum wells using artificial intelligence. The system uses pressure and temperature sensors from wells and opening control valve state to train a deep neural network with a convolutional layer to output fluid volume rate. The Schlumberger OLGA multiphase flow simulator software is used to provide data. Tests show the approximation achieves up to 99.6% accuracy, potentially replacing expensive multiphase meters or serving as a redundant digital sensor.
Prediction of Field Saturations Using a Fully Convolutional Network Surrogate [30]	The study focuses on developing surrogate models for predicting field saturations using a fully convolutional encoder/decoder network based on dense convolutional networks. The model extracts multiscale features from input data and uses these to recover input image resolution. It uses static and dynamic reservoir parameters as input features and outputs water-saturation distributions. This approach offers precision and cost-effectiveness, making it useful for production optimization and history matching.

TABLE 4. Publications Demonstrating the Application of the Recurrent Neural Network to Anomaly Detection Problems

Title and Reference	Short summary
Simulating the Behavior of Reservoirs with Convolutional and Recurrent Neural Networks [32]	Recurrent neural networks and convolutional neural networks are applied to model reservoir behavior from data. Recurrent neural networks have the ability to retain information from previous patterns, making them suitable for interpreting permanent downhole gauge records. Convolutional neural networks, with specific design modifications, are as capable as RNNs in modeling sequences of information and are equally reliable in making inferences for cases unseen during training. The study discusses the differences in processing information and memory handling between these two architectures.
Integration of Artificial Intelligence with Economical Analysis on the Development of Natural Gas in Nigeria; Focusing on Mitigating Gas Pipeline Leakages [33]	Artificial intelligence is used to develop models using gas flow data to detect potential gas leakages in Nigeria's natural gas pipelines. Machine learning algorithms such as Recurrent Neural Networks and K-nearest neighbors are trained and evaluated for accuracy and precision. The results indicate that recurrent neural networks outperform K-nearest neighbors in leak detection, but all models show high reliability.
Machine Learning for Deepwater Drilling: Gas-Kick-Alarm Classification Using Pilot-Scale Rig Data with Combined Surface-Riser-Downhole Monitoring [34]	Deepwater drilling often faces gas kicks due to the narrow mud-weight window. Traditional methods have time lag and can lead to severe gas influxes. A novel machine-learning model uses pilot-scale rig data and surface-riser-downhole monitoring for early detection and risk classification. Four ML algorithms are developed. The long short-term memory recurrent neural network algorithm shows the best performance, it is selected and deployed to early detect gas kicks and classify the corresponding kick alarms. The model achieves high recall, accuracy, precision, and detection time delay.

F. *Summary characteristics of publications found for the query "Recurrent Neural Network" AND anomaly detection"*

Advantages. Recurrent Neural Networks (RNNs) are effective when sequential data are involved, for example, in natural language processing, speech recognition, and time series analysis. They can handle variable input lengths, maintain internal memory, and make context-based decisions. They can be pre-trained on large datasets and fine-tuned for specific problems.

Drawbacks. RNNs, due to their recurrent nature, are slow and computationally intensive, making training time challenging. They struggle to learn complex patterns, capture long-term dependencies, and can suffer from vanishing or exploding gradients.

Highly cited publication. Recurrent Neural Networks [31].

Examples of publication titles and their brief summary demonstrating the application of the Recurrent Neural Network for solving anomaly detection problems found in the search engine of search.spe.org are presented in Table 4.

The first publication can refer to both Convolutional and Recurrent Neural Networks.

The last work can also be attributed to long short-term memory algorithm as a special case of recurrent neural network.

The most frequently referenced **SPE disciplines** in the publications found using the query **"Recurrent Neural Network"** are:

Production and Well Operations (68): Artificial Lift Systems (8); Production Chemistry, Metallurgy and Biology (6); Well & Reservoir Surveillance and Monitoring (**43**).

Reservoir Description and Dynamics (288): Formation Evaluation & Management (80); Improved and Enhanced Recovery (29); Reservoir Characterization (**135**); Reservoir Simulation (43); Unconventional and Complex Reservoirs (35).

Well Drilling (49) → without subcategories.

G. *Summary characteristics of publications related to those found for the query "Long Short-term Memory" AND "anomaly detection"*

The Long Short-Term Memory (LSTM) algorithm is a type of Recurrent Neural Network (RNN) known for its ability to process and analyze sequential data.

Advantages. LSTM overcomes the vanishing gradient problem, capturing long-term dependencies in sequential data. Its memory cell can retain information for long periods, making it suitable for speech recognition and natural language processing. LSTM also allows efficient transfer learning.

Drawbacks. The Long Short-term Memory (LSTM) algorithm has drawbacks such as higher computational cost, overfitting risk, and difficulty in implementing dropout. It also struggles with long-term information storage, making it difficult to refer to previously stored data.

Highly cited publication. Long Short-Term Memory [35].

Examples of publication titles and their brief summary demonstrating the application of the Long Short-term Memory algorithm for solving anomaly detection

TABLE 5. Publications Demonstrating the Application of the Long Short-term Memory Algorithm to Anomaly Detection Problems

Title and Reference	Short summary
A Machine Learning Workflow to Predict Anomalous Sanding Events in Deepwater Wells [36]	This study develops a predictive machine learning model using sensor and simulation data to inform Control Room Operators before significant damage occurs, using an anomaly detection architecture. The problem is addressed using Principal Component Analysis and Long Short-Term Memory Autoencoders, which reconstruct the original input. An alarm is triggered when the real-time anomaly score exceeds the training threshold.
Towards Real-Time Bad Hole Cleaning Problem Detection Through Adaptive Deep Learning Models [37]	The study presents an adaptive predictive deep-learning model that uses equivalent circulating density measurements, model results, and drilling data to predict potential bad hole cleaning conditions. The model has two components: an anomaly detector and a predictor. It uses Long Short-Term Memory cells to account for data correlations and generate future data conditioned to past observations. The approach is demonstrated on two real examples from offshore Norway.
Development of an Artificial Intelligence-Based Well Integrity Monitoring Solution [38]	The goal of an artificial intelligence-based well integrity monitoring solution is to build models to identify well annulus leakage events, given the well type and all relevant anomalies. Artificial intelligence models are created using Long Short-Term Memory Autoencoders and classifier to identify complex irregularities.

problems found in search engine of search.spe.org are presented in Table 5.

The most frequently referenced **SPE disciplines** in the publications found using the query **"Long Short-term Memory"** are:

Production and Well Operations (94): Artificial Lift Systems (9); Production Chemistry, Metallurgy and Biology (7); Well & Reservoir Surveillance and Monitoring (**62**).

Reservoir Description and Dynamics (314): Formation Evaluation & Management (95); Reservoir Characterization (**124**); Reservoir Fluid Dynamics (31); Reservoir Simulation (42); Unconventional and Complex Reservoirs (49).

Well Drilling (71): Drilling Operations (**31**); Pressure Management (8); Wellbore Design (8).

H. Summary characteristics of publications found for the query "Generative Adversarial Network" AND "anomaly detection"

Advantages. Generative Adversarial Networks (GANs) are an unsupervised learning method that can be trained using unlabeled data. They generate data similar to real data, including images, text, audio, and video. GANs have strong discrimination power, allowing them to distinguish between training data and generated data samples. They also generate realistic data instances that resemble the training-data distribution, making them a valuable tool for data analysis.

Drawbacks. GANs pose challenges in training due to instability, mode collapse, and hyperparameter sensitivity. They can cause a stalemate between generator and discriminator networks, resulting in limited or repetitive samples. Hyperparameter choices like learning rates, batch sizes, and network architectures are crucial. GANs can produce fake data. Additionally, they require significant computational resources.

Highly cited publication. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network [39].

Examples of publication titles and their brief summary demonstrating the application of the Generative Adversarial Network for solving anomaly detection problems, which are found in the search engine of search.spe.org are presented in Table 6.

TABLE 6. Publications Demonstrating the Application of the Generative Adversarial Network to Anomaly Detection Problems

Title and Reference	Short summary
Broadband reconstruction of seismic signal with generative recurrent adversarial network [40]	The resolution of seismic data depends on frequency and bandwidth, and complex exploration objects require higher resolution algorithms. Traditional methods can affect signal to noise ratio, reducing data reliability. A new method based on a generative recurrent adversarial network (GRAN) is proposed to generate pseudo sample sets constrained by geological layers and train the GRAN model for broadband seismic data reconstruction. The method's applicability is proven through blind well tests and is applied to actual work area seismic data processing, achieving excellent results.
Self-Supervised Subsea SLAM for Autonomous Operations [41]	The study proposes a deep learning-based Simultaneous Localization and Mapping (SLAM) method to estimate the 3D structure of a vehicle's surrounding environment from a single video. This method predicts a depth map of a given video frame while estimating the vehicle's movement between frames. The method is self-supervised and uses Generative Adversarial Networks to improve depth map prediction results. The study evaluates the method on the KITTI dataset and a private dataset of subsea inspection videos, showing it outperforms existing SLAM methods in depth prediction and pose estimation.

TABLE 7. Publications Demonstrating the Application of the Reinforcement Learning Algorithm to Anomaly Detection Problems

Title and Reference	Short summary
Novel Stuck Pipe Troubles Prediction Model Using Reinforcement Learning [43]	This paper defines the stuck pipe prediction problem as a multi-class problem considering the dynamic nature of drilling operations. A reinforcement learning-based algorithm is proposed to solve this problem, with performance and evaluation results shared. The algorithm's accuracy is demonstrated, and performance improvement through feedback channel retraining is demonstrated. The reinforcement logic connects solutions to operation reporting, enhancing accuracy through neural networks.
Deep Reinforcement Learning: Reservoir Optimization from Pixels [44]	This paper uses Deep Reinforcement Learning to optimize the Net Present Value of water flooding by altering the water injection rate. This is the first demonstration of AI's potential in understanding reservoir physics directly, without considering reservoir petrophysical properties or the number of wells in the reservoir.

The most frequency referenced **SPE disciplines** in the publications found using the query **"Generative Adversarial Network"** are:

Production and Well Operations (11): Artificial Lift Systems (2); Well & Reservoir Surveillance and Monitoring (**8**).

Reservoir Description and Dynamics (172): Formation Evaluation & Management (27); Reservoir Characterization (**143**); Reservoir Simulation (17).

Well Drilling (5): Drilling Measurement, Data Acquisition and Automation (2); Drilling Operations (2).

I. Summary characteristics of publications found for the query "Reinforcement Learning" AND "anomaly detection"

Since no documents were found upon direct request, this section presents an analysis of documents that can be only indirectly related to this topic.

Advantages. Reinforcement learning (RL) is an AI model that trains agents to learn sequences of actions, making it useful in complex environments. It is adaptive and intelligent, allowing agents to learn from their actions and rewards without explicit supervision. RL focuses on optimal behavior to maximize reward, making it suitable for decision-making problems and similar to human learning.

Drawbacks. RL is a time-consuming, expensive and complex learning method that involves interacting with the environment to find the optimal policy. It requires numerous interactions and may not be practical in real-world scenarios. The balance between exploration and exploitation, high dimensionality, deferred reward, security and hyperparameter sensitivity are also challenges.

Highly cited publication. Reinforcement Learning: An Introduction [42].

Examples of publication titles and their brief summary demonstrating the application of the Reinforcement Learning algorithm for solving anomaly detection problems found in the search engine of search.spe.org are presented in Table 7.

The first paper does not satisfy the search criterion "anomaly detection," but it is related to the identification of an anomalous situation, i.e., it satisfies only the extended search for publications, revealing the topic at hand.

The most frequently referenced **SPE disciplines** in the publications found using the query **"Reinforcement Learning"** are:

Production and Well Operations (43): Artificial Lift Systems (7); Well & Reservoir Surveillance and Monitoring (**18**);

Reservoir Description and Dynamics (157): Formation Evaluation & Management (43); Improved and Enhanced Recovery (33); Reservoir Characterization (**55**); Reservoir Simulation (33); Unconventional and Complex Reservoirs (33).

Well Drilling (54): Drilling Equipment (7); Drilling Operations (29); Well Planning (5); Wellbore Design (6).

IV. CONCLUSION

Clustering Computer Science and Mathematics related documents according to their bibliometric entries on the topic of anomaly detection provides an easily interpretable list of publication topics, which can be further extended for an in-depth literature analysis. The dominant anomaly detection methods include Random Forest and Support Vector Machine for classifying normal and abnormal states, while Long-term Memory Method and Recurrent Neural Network are effective when sequential data such as time series from sensors or logs are involved.

The SPE search platform publications primarily use the same anomaly detection methods for engineering problems in the oil and gas sector, suggesting that the knowledge gained from Computer Science and Mathematics can be applied to these problems. The SPE search platform found no studies on methodology for addressing the limitations of anomaly detection methods. It seems more practical to search for solutions in articles related to Mathematics and Computer Science to mitigate the problems encountered when using these techniques in applied engineering problems.

In the oil and gas industry, anomaly detection problems are most often encountered in Production and Well Operations (Well & Reservoir Surveillance and Monitoring), Reservoir Description and Dynamics (Reservoir Characterization), and Well Drilling (Drilling Operations). The result is easily understandable, as the above applications form the foundation of engineering tasks in development.

V. Possible Applications of the Findings

This study could serve, for example, as a preliminary step towards preparing a systematic review on the suitability of the Long Short-term Memory method for anomaly detection in well integrity monitoring. When justifying the feasibility of the Long Short-term Memory method, the review should not only demonstrate its applicability but also consider ways to overcome possible shortcomings based on the relevant literature. This approach is analogous to a typical systematic review in medicine, looking at the side effects of a drug in the treatment of a particular disease.

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