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A Comprehensive Literature Review for Predicting Petrophysical Well Logs Using AI/ML Techniques

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The integration of artificial intelligence (AI) and machine learning (ML) techniques in the oil and gas sector is increasingly recognized as essential for enhancing the accuracy of petrophysical parameter estimation. This study primarily aimed to conduct a Systematic Literature Review (SLR) addressing how these industries cope with gaps in well log data, including both missing and unrecorded entries. VOSviewer was utilized to analyze the data and identify notable patterns and contributions within this domain. Our findings from the SLR suggest that employing AI/ML methodologies stands out as an optimal approach for developing systems capable of reliably identifying absent or undisclosed well logs. Prior to training models, it is crucial to implement data harmonization practices for refining input data. At this stage, ensuring proper handling of missing values, standardizing datasets, and maintaining consistency across data are pivotal steps. Models are further strengthened by integrating outlier detection algorithms designed to identify and mitigate anomalous datapoints that could skew prediction results adversely. Leveraging clustering algorithms to amalgamate analogous well logs enhance prediction precision concerning reservoir characteristics. For assessing the accuracy and reliability of predicted outcomes, rigorously validated methods must be applied; one method examined in our review involves using sigma values as indicators. In summary, this paper underscores the significance of advanced AI/ML strategies in detecting incomplete or unreported well logs within oil and gas operations while emphasizing meticulous pre-processing protocols for inputs along with robust validation measures for ensuring result fidelity.

Keywords: petrophysics; well logs; non-recorded logs; AI/ML; Oil & Gas; prediction of well logs; reconstruction of well logs

1. Introduction

Our daily life is witnessing an ever-increasing footprint and dependence on AI and ML based technologies – be it handheld devices such as mobile phones or tablets, self-driving cars, virtual voice assistants like Siri or Alexa and with every passing day, every aspect of life seems to embrace automation brought about by AI and ML applications.

In the field of oil exploration & production when it comes to use the terms "wireline logs" or "well logs," usually mean "a documenting versus depth of all of the features of the rock structures encountered by observation devices in a deep-bore." These are gathered using recording gear that can be dropped into the hole following to the drilling bit or on a wired connection. The wiring, composed of one or more conductors that pass transmits observations to a computing device or surface laboratories. The well-log is the documentation of these data on film or papers. In order to capture the geologicaland petrophysical characteristics of the bedrock that the well has penetrated, many separate logs are often run. A drilling log often serves as the trademark of the material and describes the effects of all of the variables present at the moment of settling as well as how the rock has changed throughout the geological history. This information is essential for accurate and reliable assessment of the reservoir.

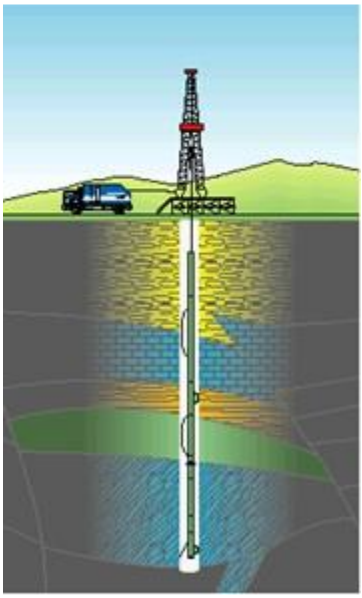

Fig 1: A schematic diagram of Well Logging Operation

(https://seabed.software.slb.com/well_log/WebHelp/well_logging.htm)

Additionally, there are several sorts of cable logs, each of which may be divided into groups based on either their purpose or the form of technology they employ. Once the oil or gas well is cased or enclosed with pipe, "open hole logs" are outing. When the well has been lined by casings or generation pipe, "cased hole logs" are run (SPWLA 1975). According to the physical features that are observed, cable logs may be broadly categorized as Electric Logs (formation Resistivity), Porosity Logs (Formation Density, Neutron Porosity, and Sonic), and Lithology Logs (Spontaneous Potential and Gamma Ray). Artificial intelligence (AI) is a developing area of mathematical research that aims to combine machine computational ability using intelligence from humans to replicate human behaviour and quickly generate intelligent and trustworthy responses to difficulties that are exceptionally difficult to solve. Big data analysis and exploration techniques are provided by machine learning, a branch of artificial intelligence (Tariq et al. 2021). By employing self-determining computations, ML empowers systems to find out how to adapt to individual objectives or human behaviour (Fahad et al. 2020; Elkatatny et al. 2017).

Well logging has been considered as an integral part of the reservoir lifecycle, where for accurate characterisation, petrophysical evaluation would provide great amount of data to accurate plan for exploitation by developing representative static and dynamic models of the reservoir (Timur 1982).

1.1 Current Challenges

Log data which is often acquired by multiple service providers using multiple runs and passes in the wellbore sections drilled with different mud properties, bit and hole sizes poses multiple challenges in a well. Well log data is lost or is of a poor quality for a variety of reasons, including malfunctioning hardware, poor or washed-out hole circumstances, equipment failure, losing information due to inadequate storage, and even unfinished or incomplete logging that results in lacking log data for an area or perhaps for an entirety log category (Rezaee et al. 1997; Rajabi et al. 2010).

In modern years, a lot of exploration has concentrated on wire-line logging predictions for these reasons. Still, other strategies have shown certain limits and greater application. AI systems include the extraordinary capacity to build a sophisticated linkage amongst exponentially connected data inputs and outputs (Nakutnyy et al. 2008).

One significant obstacle to the broad use of machine learning in the energy sector is the inability of artificial intelligence (AI) algorithms to generalize (Tariq et al. 2021). Several designs have difficulty functioning in situations that differentiate beyond those that were considered when they were developed (VirginiaResearch questions should be, 2018). While training fresh datasets that are comparable to examples from the past, extra assets must be used each time (Ramamoorthy 2018). Another difficult aspect of the computational simulations is their reuse. Being compared to various natural disciplines, developed models from one geographical domain are often less accurate. Provided the data inputs of the supplied dataset fall under the permissible range of the source characteristics that determine how the algorithm is to be carried out, it is strongly advised to apply the model (Mohaghegh 2017). A list of all the restrictions placed on models using machine learning and AI may be found in Table 1

Table 1: A list of the drawbacks of AI and ML algorithms (modified from Tariq et al. 2021)

Limitation	Reason	Solution	References
Overfitting	A shortage of adequate information to be utilized in training.	Considering the proportion of the input points corresponding to all interconnections' net weights ([rho]).	(Andrea et al. 1991; Livingstone et al. 1997)
Coincidence	Obtaining an ideal match for a certain database by accident.	A discriminatory approach is used.	(Livingstone et al. 1993)

Overtraining	If the model's internal makeup is updated and the number of errors keeps dropping, the algorithm might get more complicated to match a specific data set.	The training approach known as "early ending" can be applied. The GAN, for instance, are examples of reinforced learning incorporating in-stream monitoring.	(Hossain 2018)
Data availability	Occasionally the information obtained is sparse.	Single-shot training is the process of enhancing a computerized model after it has been previously learned on a comparable collection.	(Weyrauch 2016)
Interpretability	The findings are affected by the cumulative effects of each of the model linkages rather than just the particular links in the scenarios.	Locally understandable system and unbiased justifications The technique of modified multiplicative designs.	(Shabbir et al. 2018; Bas et al. 2016)
Generalization	Degradation of the framework in conditions that are distinct from those employed to construct the initial model.	It is necessary to use greater assets to train fresh datasets.	(Virgina 2018; Ramamoorthy et al. 2018)
Bias	Black-box simulations are biased by their very characteristics.	Utilizing disturbances without affecting the framework.	(Samek et al. 2018)

1.2 Research questions (RQ)

This comprehensive investigation of the literature attempts to find various released and pertinent publications about petrophysical drilling log quality control, editing, and reconstructing for absent or unrecorded sections using AI and ML. The aforementioned statements on issues are the main focus of this research's major goal:

Research Questions (RQs)	
RQ1	What is the current status of application of AI and ML based techniques for Log reconstruction
RQ2	What are the applicable methods along with their benefits and limitations?
RQ3	What are various considerations like pre-processing and QC?
RQ4	How can we minimize uncertainty and improve overall accuracy and results

2. Materials and Methods

Systematic literature review (SLR) is a remarkable technique that is frequently employed to identify and evaluate important studies for a particular problem or intriguing puzzle. Four basic questions, which are noted in the research questions (RQ) section, is the main focus of the literature review. The Scopus literary database, a prominent resource for scholars worldwide, such as those in the world's oil business, was used to perform the SLR. VOS viewer, a piece of software that is utilized for building and visualizing network diagrams utilizing bibliometric information, was employed for analyzing data from the Scopus collection.

To carry the systematic literature review, a comprehensive review procedure was framed. This review methodology acted as a guide to carry out the review process systematically and comprehensively, thereby eliminating the risk of any sort of publication bias or error. Following structural approach was used to carry out the review process: -

Fig 2: Flow chart for Systematic Literature Review

Search Strategy & Methodology

Search strategy was one of the first key steps in Systematic Literature review process, where following key parameters were established: -

- Identify the key sources of data (e.g. list of databases) to be searched
- Formulate the strategy of keywords to be used to fetch the most relevant results for the review.

The systematic literature review process focused on Geosciences, Petroleum Engineering, and Geology domains to explore the utilization of AI and ML techniques for petrophysical well log reconstruction. Extensive searches were conducted within the SCOPUS, Web of Science & Google Scholar database, encompassing industry/Academic journals, Magazines, Dissertations/Theses, Books and conference proceedings from all providers. Articles were meticulously assessed for relevance and alignment with the research objectives. Permutation and combination of various keywords from 2003 – 2023 returned a total of 1177 articles which were used for VOSViewer analysis in this current review. While AI/ML methods began making inroads into the Exploration and Production (E&P) industry around the early 2000s, their widespread acceptance and popularity have surged notably in the last five years. To ensure a comprehensive literature review, the authors selected a review timeframe spanning the past two decades, from 2003 to 2023.

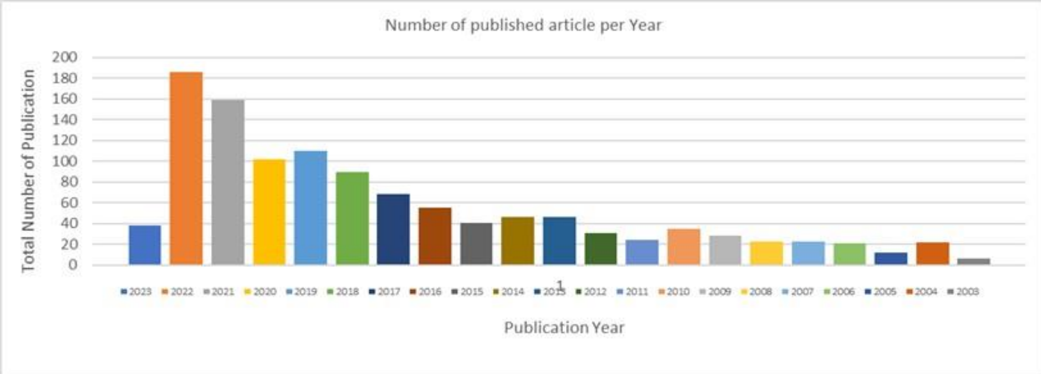

Fig 3: Yearly distribution of published articles

During the literature review, a key strategic approach was to identify appropriate keywords for searching relevant papers, given the interchangeable use of terms like Artificial Intelligence, Machine Learning, Log reconstruction and Log estimation and their combinations including their abbreviations. To address this, a comprehensive list of keywords, including various forms and abbreviations, was employed for article searches (Table 2).

Table 2: Various combinations of keywords used in article search for systematic literature review process.

Key Word Selection and Refinement Criteria	
Criteria – 1	Well log estimation using AI
Criteria – 2	well log estimation using ML
Criteria – 3	well log estimation using machine learning
Criteria – 4	well log estimation using artificial intelligence
Criteria – 5	well log reconstruction using machine learning
Criteria – 6	well log reconstruction using artificial intelligence
Criteria – 7	well log reconstruction using AI
Criteria – 8	well log reconstruction using ML

Inclusion and exclusion procedure for article selection

1177 studies emerged after scanning the aforementioned internet resources and archives. The guidelines for including and excluding study papers have been established in light of the PRISMA criterion established for study reviews in order to pick out among the most pertinent publications and to combat bias in publications. The definition of an acceptable factor is:

(1) Articles in English language only.

(2) Articles meeting keyword search criteria defined in table 2 only.

(3) Articles that can respond to the study queries posed in section RQ.

Duplicated documents, irrelevant documents, abstract-only publications, and studies that were not comparable to the study topics were excluded from consideration. The research comprised papers and parts that were published in reputable publications as well as meeting proceedings from major worldwide and national gatherings. Based on this inclusion and exclusion criteria, a VOSviewer analysis was carried out to find out dependencies and relationships.

3. Results & Discussion

Co-occurrence Analysis

The study's co-occurrence analysis, which used results of available literature fetched using the keywords from SCOPUS, Web of Science & Google Scholar database in VOSviewer analysis. VOSviewer analysis focused on examining the various available research literature fetched using the keywords. The study specifically sought to determine the relatedness of words based on how frequently they appeared together throughout the study documents. The authors focused their analysis on the co-occurrence trends in well logging, well logs, AI and ML in order to be consistent with the research aims. Although there were no keywords that precisely matched "reconstruction," the phrase "estimation" served as a good stand-in. Within the wider collection of 6767 keywords, a threshold of 50 repetitions per term produced an overall total of 58 keywords having co-occurrence patterns.

The total weight of the object was strategically chosen as an incidence in this investigation, determines the dimensions of the mark and the circular shape of an entity. The label and circular of a commodity grow in size in proportion to its frequency. The group in which a thing corresponds determines the colour of the object. Links are shown by arrows across objects. The distance that exists among the two elements in the network representation, roughly reflects how closely connected the items are in regard to co-occurrence relationships (Figure 4-7). In broad terms, the more powerful the co-occurrence of two elements is the closest they are positioned to one another. Lines are used to depict the mutually reinforcing linkages between the things that are the greatest.

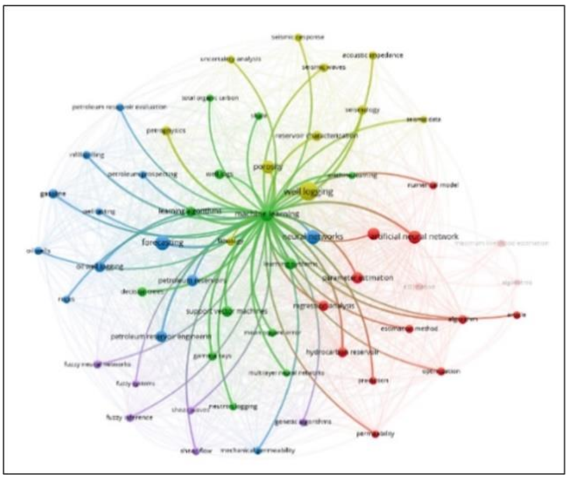

Fig 4: Co-occurrence of various index keywords (Machine Learning)

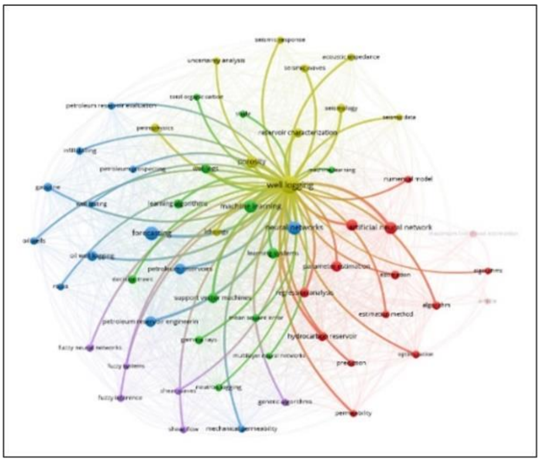

Fig 5: Co-occurrence of various index keywords (Well Logging)

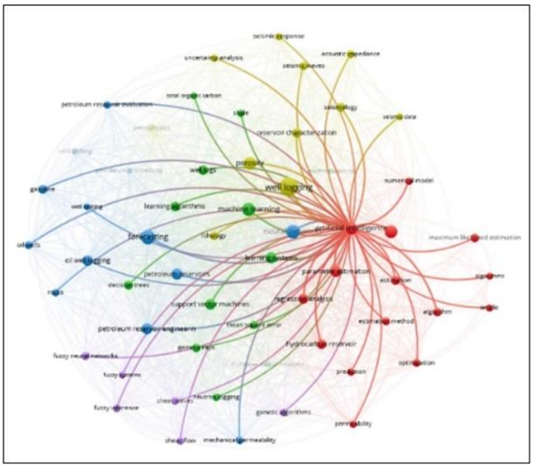

Fig 6: Co-occurrence of various index keywords (Artificial Intelligence)

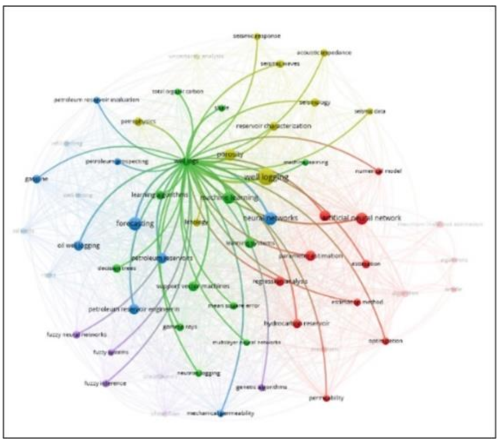

Fig 7: Co-occurrence of various index keywords (Well Logs)

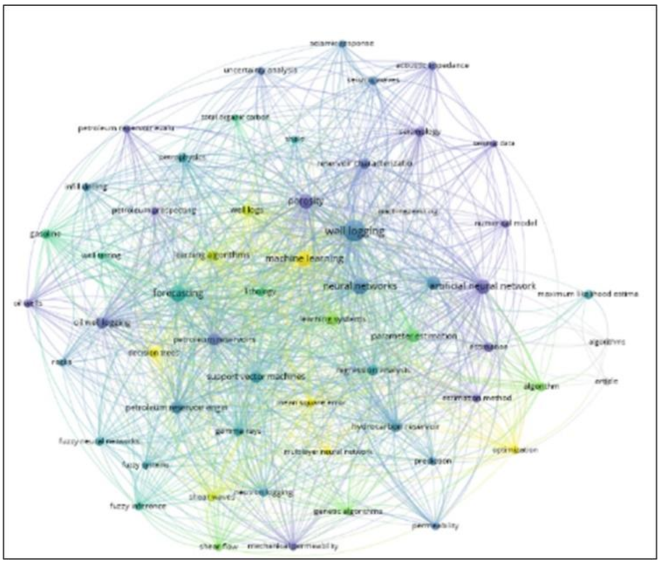

Fig 8: Co-occurrence of various index keywords (Published Year)

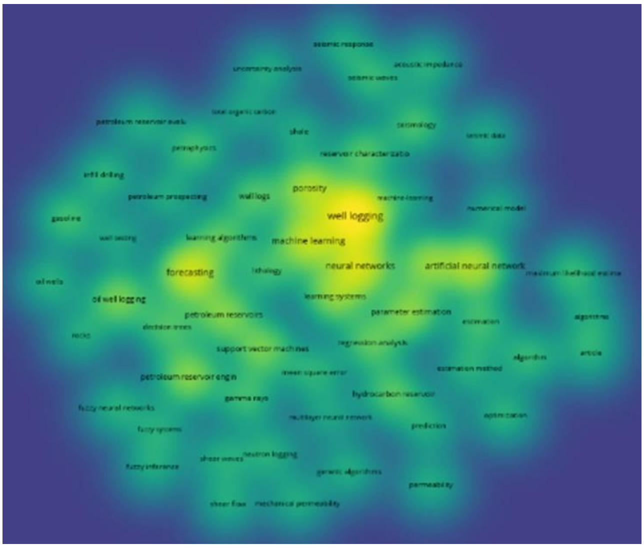

Fig 9: Co-occurrence of various index keywords (total co-occurrence)

Fig 4 – 7 represents the network diagram of VOSviewer, wherein a circular shape and a description symbolize co-occurrence items. Fig 8 analyses the amount of literature that has been released over the previous four years (2018-2021), and Fig 9 shows the rate of occurrence for a certain phrase.

RQ – 1 & RQ – 2

Figure 4, 5 & 7 helps in finding the answers for RQ -1 (What is the current status of application of AI and ML based techniques for Log reconstruction) and partially RQ – 2 (What are the applicable methods along with their benefits and limitations). Figure – 4, 5 & 7 highlights the co-occurrence of Machine Learning and Well Logging/well Logs (they occur quite close with higher density) along with Porosity, Permeability, Estimation, Artificial Neural Networks, Regression Analysis, and Fuzzy Neural Networks etc. Figure – 6 highlights the co-occurrence of Artificial Intelligence with Well Logs/Well Logging and Machine Learning. Based on density and availability of network in Figure 4,5 & 7 it can be observed that Well Logs has been used along with conventional ML methods (e.g. ANN, Regression Analysis, Fuzzy Neural Networks) to estimate the following:

1. Porosity & permeability (Petro physical property modelling and forecasting)
2. Lithology, Facies or Rock-typing
3. Acoustic Impedance or other seismic rock properties

The overall co-occurrence analysis done through VOSViewer can be summarized in Table – 3, which highlights that Machine Learning (ML) based methods have been used in variety of applications to estimate porosity, Lithology, TOC utilizing Well Logs. Whereas Artificial Intelligence (AI) based methods has been used for various types of estimations, prediction & optimization, however there is immense potential to expand on estimation/prediction of various well logs where the current available work is limited (Figure 8 & 9).

(Table – 3 Summary of Co-occurrence analysis via VOSViewer)

Method	Applications	Method	Applications	Method	Applications
Machine Learning		Well Logging	Porosity	Artificial Intelligence	
			well logs		Numerical Model
	Porosity		reservoir characterization		Maximum Likelihood estimation
	Well Logs		petrophysics		estimation
	Well Logging		uncertainity analysis		regression analysis
	Neural Networks		seismic response		well logging
	Learning Systems		seismic waves		prediction
	Lithology		acoustic response		optimization
	TOC		seismology		porosity
			lithology		permeability
					parameter estimation

Figure 6 highlights the scarcity of modern AI applications for log estimation and limited research addressing missing well logs (RQ-1), while RQ-2 shows that most research on predicting petrophysical property using well logs and associated methods, advantages, and limitations has emerged in the last five years.

1. Artificial neural networks (ANN) (Parapuram et al. 2017)
2. The genetic algorithm (Rahmanifard et al. 2018; Rajabi et al. 2013)
3. Least squares-support vector regression (LS-SVR) (Venna et al. 2018; Zhao et al. 2015)

4. Extreme machine learning (ELM) algorithm (Sayyafzadeh et al. 2016; Bishop 1995)
5. Fuzzy logic (FL) (Karimpouli et al. 2015)
6. Random Forest (RF)
7. Bayesian network (BN)

Table 4: Summary of the AI & ML methods via VOSviewer network analysis along with advantages/limitation to be used with well logs (modified after Tariq et al. 2021; Fahad et al. 2020)

Algorithms	Description	Application	Advantage	Limitations
Artificial neural networks (ANN)	Mathematical design called ANN was developed by biological neural structures, designed to emulate their information processing abilities. These networks learn from input data, identify patterns, and subsequently make predictions based on the trained model (Auda et al. 1999; Ayala et al. 2005)	Regression	Basic algorithms to learn It might be preferable to any other algorithm using the information at hand. Never depends on any function's linearity	They are blackbox in nature hence hard to understand or interpret Lack the ability of generalisation as tend to memorise data
The genetic algorithm	Genetic algorithms (GAs) mimic natural evolution, making them suitable for multi-objective optimization tasks and adept at resolving conflicting objectives, providing robust solutions in scenarios with multiple feasible solutions. (Velez-Langs 2005)		Although GA is very effective and simple to use, its operations are uniformly unpredictable, inconsistent, extremely fluctuating, and non-differentiable.	Limiting the quantity of data sets, additional sets of data will produce more precise findings.
Least squares-support vector regression (LS-SVR)	LS-SVR comprises supervised learning methods that analyse data, recognize patterns, and solve linear equations for classification and regression analysis, avoiding convex quadratic programming.	Regression	The LS-SVR provides results with higher accuracy. It handles noise efficiently and over fitting occurrences is less.	Since the LS-SVR system uses the binary categorization method, it must take a long time to cross-validate the variables.
Extreme machine learning (ELM) algorithm	A extended one-layer neural network with feed forward processing that uses a random set of parameters across both input and output stages is the foundation of ELM.		This method may be utilized for issues where finding a solution is difficult or impractical.	Smaller datasets does not provide accurate results

Fuzzy Logic	Instead of the typical true or false method that today's machine uses, fuzzy reasoning is an algorithm-based strategy for computation focused on levels of significance to the real data being input.	Classification, clustering	Quickly, easily, powerfully, and with just small effects on the natural world Provides a representation of networks that combines numbers and symbols.	If a computational framework already exists, FL uses it only when computer power is limited. Due to the structure's absence of arithmetic it is difficult to verify its qualities.
Random Forest (RF)	Random Forest (RF) is a group learning approach that, while being trained for regression, sorting, and other tasks, creates a large number of trees of choices.	classification, regression, clustering	Resilient to data noise May succeed in learning	Poor outcome with training information connected to attributes

RQ – 3 (What are various considerations like pre-processing and QC) and RQ – 4 (How can we minimize uncertainty and improve overall accuracy and results)

Log data, integral to oil companies' on-going well programs, spans several years with variable quality and origins affected by borehole conditions, logging tools, mud type, and processing parameters. Essential petro physical modelling and interpretation demand rigorous log quality control, with initial processing often handled by acquisition services companies.Work performed by (Gerges et al. 2022; Akkurt et al. 2018; Liang et al. 2019; Singh et al. 2020) highlights the prominence of subsequent to be considered in AI/ML based log QC and reconstruction.

Domain Input:

- Each ML algorithm using drilling data at a field dimension must take into account topographical and geographical information since it could prove to be just as useful as well statistics.
- ML algorithms surpass human data processing in efficiency and accuracy but still rely on expert evaluation for parameter selection and quality control, necessitating user-interaction tools to ensure transparent and efficient workflow management.

Pre-processing Input:

- Data collection and harmonization for mnemonics and Units
- Identification of correct log interval for reconstruction
- Identification of correct set of log responses to be used for Artificial Intelligence and Machine Learning based training for log QC and reconstruction.

- Pre-processing of data, conducted prior to AI/ML training, includes handling bad hole intervals, constant values (usually at start and stop depth intervals), and linearizing resistivity logs to ensure compatibility with other log data for tasks such as Log Normalization and clustering.

Outlier Detection:

Outlier Detection, which is the identification of data anomalies, is one of the key steps in the growth and deployment of AI and ML model for log reconstruction. Based on work published by (Gerges et al. 2022; Singh et al. 2020), Density-Based Local Outlier Factor (LOF), which is an unconfirmed approach for outliers' detection (Breunig et al. 2000) provide comparatively better results in comparison to one-class support vector machine (SVM) and isolation forests (IF) outlier detection algorithm. LOF calculates a score for anomalies for each point of data by comparing the degree of density variance for that point to its surroundings. According to (Han et al. 2011), an example is deemed to be unusual if it possesses an elevated anomalous score, or in simpler terms, if it's regional density is significantly lower compared to those of its nearby instances. As opposed to simply labeling every observation as an inlier or an anomaly, LOF offers a level of oddity, in contrast with some outliers' identification techniques. Local Outlier Factor (LOF) is the term used to describe this level of oddity.

Result Uncertainty and Accuracy

It is very critical that the output of AI & ML based Log reconstruction has low uncertainty and high confidence and accuracy (Khare 2022; Sircar et al. 2021), which would be ascertained based on sigma (σ) factor between reconstructed (predicted) logs and blind wells. Sigma (σ) relates to how variable a specific piece of data is: either the information's points have a close association or widely dispersed.

5. Summary & Conclusions

In recent times, the oil and gas industry has seen a downturn in profits owing to multiple challenges. These range from volatile market conditions and the global health crisis to overproduction and other factors. Yet, well logging remains an indispensable activity within the reservoir management process. The sector is often hampered by the lack of essential logging data for various reasons. Consequently, there's been an increased focus on predicting wireline log data as a means to circumvent economic constraints associated with gathering these logs. Table 5 presents a synopsis of commonly employed strategies in AI/ML-driven predictions used within this sector, particularly for filling in gaps where log data is missing. Over two decades, analysis using VOSviewer tools on Scopus database entries reveals sporadic application of artificial intelligence (AI) and machine learning (ML), or their combined approaches when it comes to interpreting absent logs. Additionally, scrutiny of upwards of one thousand scholarly articles indexed by Scopus highlights a traditional dependence on established machine learning frameworks like Artificial Neural Networks, Regression Analysis, and Fuzzy Neural Networks for deducing diverse petrophysical properties. It is noteworthy that despite these developments, there appears to be a relatively small number of studies specifically employing AI/ML techniques aimed at projecting incomplete or unrecorded log information. This insight points towards potential areas for further research and innovation within the field's predictive methodologies.

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