Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

A Methodology for Missing Well Logs Prediction using AI/ML Models – A Case Study from Volve Oilfield, Norway

Bishnu Kumar[1], Dr. Sunil Kumar Khare[2], Dr. Tanupriya Choudhury[3], Dr. J. Devaraju[4]

[1]PhD Scholar, School of Advanced Engineering, University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, 248007, India.1; bishnukr@gmail.com*
[2]School of Advanced Engineering, University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, 248007, India.2; skhare@ddn.upes.ac.in
[3]School of Computer Sciences, University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, 248007, India.3; tanupriya@ddn.upes.ac.in
4University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, 248007, India4; hspoornimadev@gmail.com

Well log data provides valuable insight into sub-surface lithology and hydrocarbon reservoir. In exploration and production industry, log data acquisition is a continuous process over the lifecycle of an oilfield. However, poor log data quality due to missing, bad or non-recorded data often leads to wrong interpretation and conclusions, leading to poor discovery and recovery of hydrocarbons from subsurface reservoirs. Therefore, it becomes imperative to develop a technique to mitigate poor log data quality issues. With this context, we present an AI/ML based quality control, pre-processing and prediction workflow developed to predict the missing data by utilizing publicly accessible dataset with 24 wells from Volve field within southern Norwegian North Sea.
We present a workflow developed by loading and liberating data from industry's leading petrophysical interpretation platform. AI/ML based workflow is developed on a leading AI platform and suitable tools are used for visualization of input and output. The developed workflow is intuitive and modular comprising of pre-processing, outlier detection, feature selection and clustering to remove irrelevant datapoint, create simple and faster workflow and enable the robust and accurate training and prediction workflow. The workflow has been tested to predict density (DEN) by using a combination of at least two available log curves – compressional sonic (AC), neutron porosity (NEU) and photoelectric factor (PEF), however, is highly flexible and can be deployed in various scenarios and can be used with different vintages and combination of log data. Comparison of uncertainty between predicted and available log curves is within the tool uncertainty confirming the accuracy of prediction and automation brought about resulted in fast tracking the overall well log data interpretation and processing.

Keywords: Oil and Gas; Petrophysics; well logs; volve oil field; reservoir; data analytics;

machine learning; artificial intelligence; well log prediction; well log reconstruction.

1. Introduction

The past decade has seen the escalating implementation towards Artificial intelligence (AI) and Machine learning (ML), across numerous industries, principally among the "Oil and Gas industry" for broader exploring along with production activities levels that have spanned through seismic characterization, reservoir modelling, drilling data interpretation, predictive data monitoring and modelling [1, 2, 3, 4, 5, 6, 7]. In 2018 alone, more than 1000 papers related to AI/ML were published across domains and industries, however, petrophysics is one such domain in E & P industry where periodic accomplishments have been stated, generalization of machine learning-based framework for processing, interpretation and reconstruction of well log data is still in its early stages [5, 7, 8, 9].

The "Oil and Gas industry" regards well log data as an important component that can provide valuable insight into the subsurface and helps develop reservoir dynamic and static models for field development planning and recovery [10, 11]. Density, resistivity and porosity are crucial parameters for the evaluation of the reservoir, helping in determining the existence of producible hydrocarbons, and determining fluid type-gas, oil, and water along with computing porosity, lithology and water saturation [4, 5, 12, 13, 14]. This is ordinary for the log records being missing because of certain reasons including hole conditions, broken instruments, loss of data or instrument failure due to incomplete logging and inapt storage [15, 16], which could lead to the lack of data from certain logged intervals or even from the entire log could be missing from the well data. In the recent years, ML based applications are becoming popular with geoscientists to predict this missing well data using AI/ML methods.

Utilizing Artificial Intelligence for data analysis as a technique, enables learning from data by identifying patterns and making predictions without any human intervention. Interpretation with minimal human intervention does not require any prior petrophysical knowledge and works over a large amount of data, thereby saving critical decision making time.

In this contribution, by using artificial intelligence-based methods, we attempt to develop an automated and rapid way for log data QC for Volve field from offshore Norway. AI/ML based workflow was developed utilizing available regional and domain knowledge to automate data QC, identify outlier and compare similar logs from nearby wells to generate local and regional trend to predict missing logs. This method is unique in the way that in every step we have utilized multiple methods to compare output thereby reducing uncertainties.

1.1 Study area and Consideration

Our study employs data from a public dataset made available by Equinor for field of Volve situated at the Norwegian North Sea's south section at an 80m water depth in Block 15/9. This field was discovered in 1993 with oil being found in the Middle Jurassic Hugin sandstone formation, at around 2700 – 3100 m water depth in western part of heavily faulted the structure. This field has an estimated recoverable reserve of 78.6 MBPOD and 1.5 bcm of gas [17, 18, 19, 20, 21, 22]. Figure :1 shows the 3D view of wells from Volve field (left) and location map of Volve field along Norwegian Offshore.

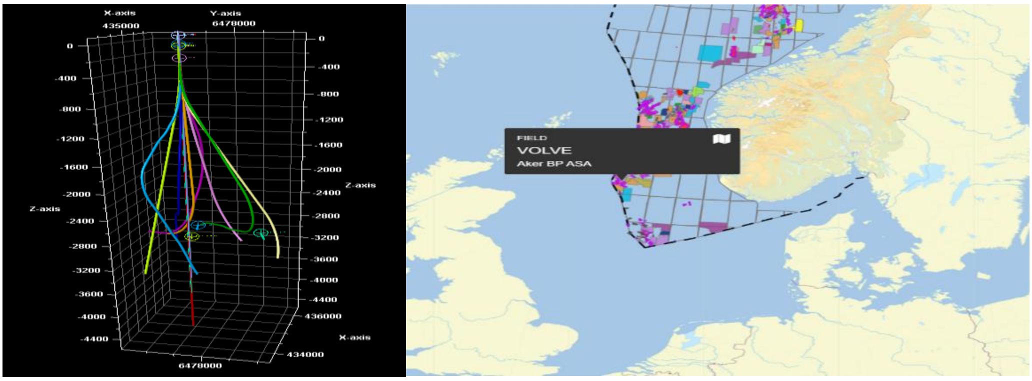


Figure 1: Location Map of field and Well locations in 3D

(Map: Field: VOLVE - Norwegianpetroleum.no (norskpetroleum.no))

In the current study, log data from available 24 wells were scanned for its location, deviation & log data availability. Out of available 24 wells, 14 wells were selected for initial training of the data. The selection of wells was based on overall wider distribution, available log data and depth ranges and hence was utilized for training and predicting log curves. We considered the combination of Triple combo log curves – Bit Size (BS), Caliper (CALI), Deep Resistivity (RDEP), Gamma Ray (GR), Medium Resistivity (RMED), Bulk Density (DEN), Compressional Slowness (AC) and Neutron Porosity (NEU) for analysis, however, utilized the combination of Bulk Density (DEN), Compressional Slowness (AC) and Neutron Porosity (NEU) for training and prediction.

INVENTORY																										
Borehole Names			15/9-19 A	15/9-19 B-T2	15/9-19SR	15/9-F-1	15/9-F-1 A	15/9-F-1 B	15/9-F-1 C	15/9-F-10	15/9-F-11	15/9-F-11 A	15/9-F-11 B	15/9-F-11 T2	15/9-F-12	15/9-F-14	15/9-F-15	15/9-F-15 A	15/9-F-15 B	15/9-F-15 C	15/9-F-15 D	15/9-F-4	15/9-F-5	15/9-F-7	15/9-F-9	15/9-F-9 A
DEPTH		m	101.0-4126.0	101.9 - 4242	101.9 - 4641.0	1970 - 3633	1970 - 3487	1970 - 3269	1970 - 4094	145.9 - 5331.0	183.3 - 347.1	1833 - 3762	1833 - 4770	1833 - 4561.8	245.0 - 3519.9	1070 - 3799	216.5 - 4090.2	145.9 - 4095.6	216.5 - 4095.5	145.9 - 3232.1	145.9 - 4685.1	232.5 - 3509.7	189.8 - 3795.2	239.5 - 1083.5	145.9 - 1114.4	415.2 - 1205.7
MD																										
Log Run			AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0	AIML_0
AC	Compressional Slowness	us/ft	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X		X	X			
BS	Bit Size	in	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
CALI	Caliper	in	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X			
DEN	Bulk Density	g/cm3	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X			
DENC	Bulk Density Correction	g/cm3	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X			
GR	Gamma Ray	gAPI	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
NEU	Neutron Porosity	v/v	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X			
PEF	Photoelectric Factor	b/e	X	X	X	X	X	X	X	X		X	X	X	X		X	X	X	X	X	X	X			
RDEP	Resistivity - Deep	ohm.m			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
RMED	Resistivity - Med	ohm.m			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ROP	Rate of Penetration	m/h				X	X	X	X	X	X	X	X	X		X	X	X	X	X	X		X		X	X
INDEX			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SURVEY			X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X		X	
TL_WellPath			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ZONATION_1						X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	

Table 1: Data Footprint of Volve field

In the workflow we trained the algorithm to predict one of the following logs (Neutron Porosity (NEU) or Bulk Density (DEN)) which are the most critical log curves for understating saturation and hydrocarbon potential of the reservoir. While the method devised in this study could predict multiple well log curves together, however we restricted our discussion and results in this paper to predicting one missing log curve (per interval or per well). Table:1 shows the listing of all log curves available per well along with other information used while creating the well log database in industry standard log interpretation application.

2. Materials and methods

2.1 System Architecture

The complete AI/ML based well logs QC and reconstruction diagram is shown in Figure 2, which is subdivided into three major parts. 1. Wellbore platform which acts as well-database, 2. AI platform where liberated data is put through various AI/ML based workflows and finally 3. UI Software which acts primarily as visualization layer and is integrated across previous 2 steps.

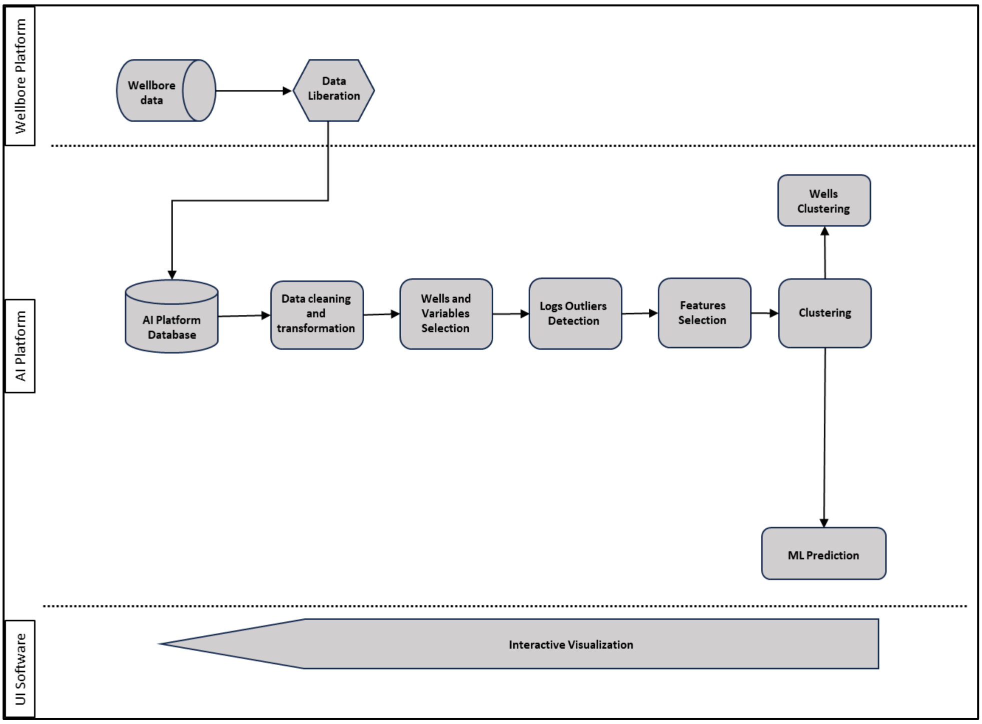


Figure 2: AI/ML Based LogQC, editing and reconstruction workflow.

2.1.1 Wellbore Platform

Wellbore Platform is the key component of system architecture, where data is loaded in an industry standard wellbore interpretation platform to ensure that basic petrophysical parameters e.g. Well Name, Borehole name, units, depth information, well log curve name, units are all available and harmonized across all the wells. A total of 24 borehole data was loaded with 11 log curves per well along with zone and deviation survey information (as per Table 1). Once database is verified to be harmonized across the wells, data is liberated from the wellbore interpretation platform to AI platform for design, deployment and management of AI/ML logic and model.

2.1.2 AI Platform

An Industry standard AI Platform was used to create and run AI logic, wherein liberated database was subjected to train and predict using various AI/ML algorithms. Figure:3 shows the snapshot of AI workflow created in industry's leading platform which is a combination of folders, data sets, flow processes and recipes.

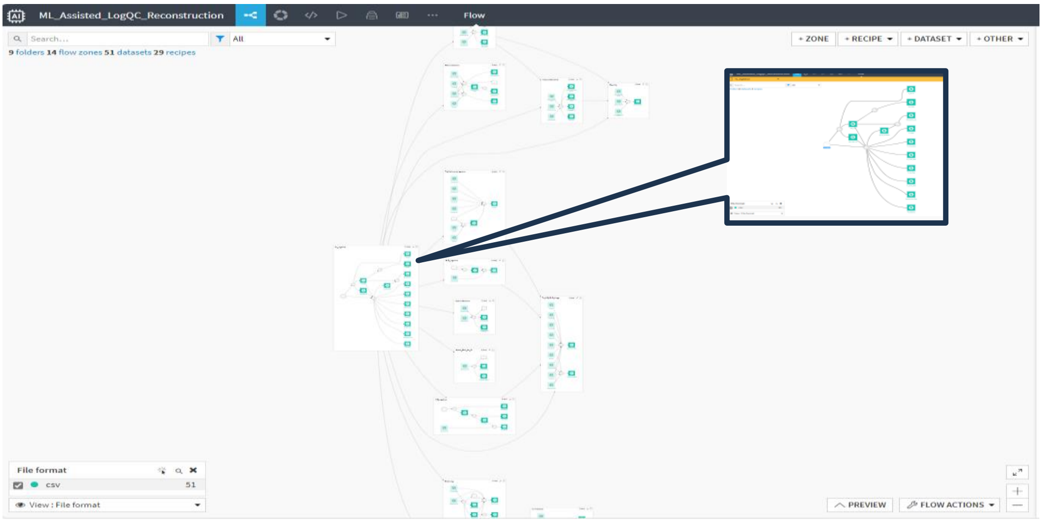


Figure 3: Underlying AI platform workflow

a) AI Platform Database

In AI Platform database, 24 well data which was liberated from wellbore interpretation platform is reviewed and key well list is identified based on completeness of data availability. A total of 14 wells were selected as key wells and a set of 7 log curves – Bulk Density (RHOB), Compressional Slowness (AC), Deep Resistivity (RDEP), Gamma Ray (GR), Medium Resistivity (RMED), Neutron Porosity (NEU), and Photoelectric Factor (PEF) were selected for being utilized in succeeding pre-processing and the processing stages of work.

b) Data Cleansing and Transformation

In this stage basic mathematical equations were created to do quick quality check (QC) of the data which included data clipping (if data present is beyond the specified range), identify and remove anomalous log values, remove constant continuous values or required logarithmic transformation (for certain prediction workflows e.g. permeability). This stage could undertake data QC for all the specified wells in fraction of seconds, thereby providing huge efficiency gain to the interpreter. Figure 4 provides the interface to Data Cleaning and Transformation workflow created and used as part of this work.

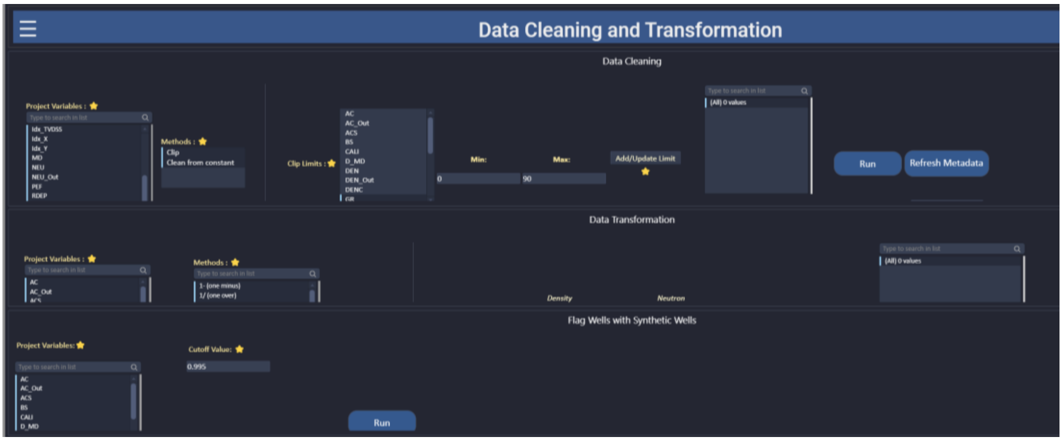


Figure 4: AI/ML Based Data QC, Cleaning and Transformation workflow.

c) Wells and Variables Selection

In this stage of the workflow, wells and log curves are selected for specific part of the ML workflows – outliers' detection, feature selection, clustering and ML training for prediction. This was created specifically to act as central place to manage all the available wells and variables. Specific wells and variables were selected for each part of the workflow. Figure:5 highlights the dataset selection for various AI/ML workflow. Left side of the screen shows data available in database and right-hand side shows dataset selected for a particular workflow.

Figure 5: ML QC and Well Selection workflow.

d) Logs Outlier Detection

Outlier detection is one of the key steps in the current workflow which intends to detect outliers in the data, which are primarily the data points which does not honor the general trends and look significantly different from the other samples. In the current work, Outlier detection was performed utilizing three different algorithms; "One-class Support Vector Machine (SVM)", "Isolation Forests (IF)", and "Local Outlier Factor (LOF)" [12]. Figure6 shows the output (cross-plots) between various log curves after the outlier detection workflow was run using LOF algorithm.

Figure 6: Outlier detection workflow with different methods.

e) Features Selection

Features Selection is yet another important step in the present workflow, wherein predictive model is built free from correlated variables, biases and unwanted noise. Five different methods – Boruta, Correlation Coefficient, Lasso, Principal Component Analysis (PCA) and Variance Threshold were used in the Features selection steps and results were compared to be used for Clustering.

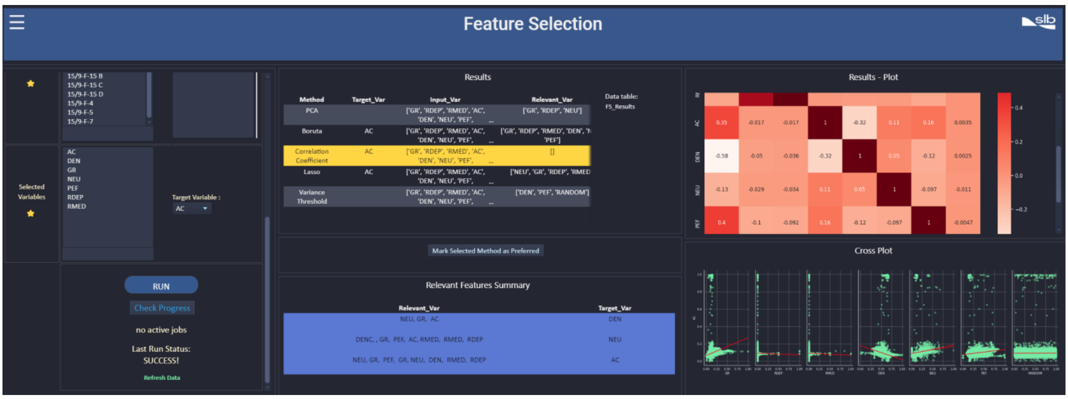


Figure 7: Feature Selection workflow comparing results from various methods.

Figure 7 highlights the key results after the Feature Selection workflow was run to compare results from all 5 algorithms

f) Clustering

Clustering offers ML algorithms to cluster data as per well based on selected logs response and identified wells cluster. A set containing log data points is clustered when they are grouped together to ensure that individuals with comparable features (referred to as clusters) appear more comparable (in some ways) to one another compared to the ones in other categories. In the current work, Gaussian Mixture Models (GMM) [23] based clustering method was utilized as this is more reliable since it can identify rectangular clusters and calculate the likelihood that all samples will be assigned to a certain cluster [24]. Figure 8 highlights the key results (cross plots) after the clustering workflow was run.

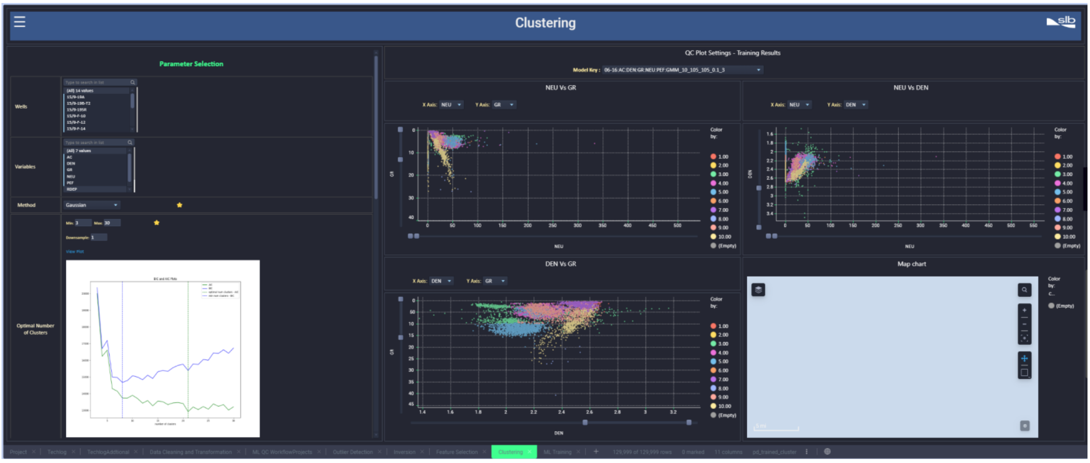


Figure 8: Clustering workflow showing first pass results as displayed in cross-plot.

g) ML Training and Prediction

In the ML training and prediction stage, the workflow first trains the intelligence based on provided data and predicts missing logs where two input logs are present, at minimum. As seen through the present work, the authors leveraged Random Forest [25] algorithm to predict log data, which has proved presence of dominance over preceding “Machine Learning models”. These ML models include “Neural Networks” [26] and “Support Vector Machines” [27]. An ensemble technique where the training of multiple regression trees is undertaken and output is aggregated leading to final prediction is known as Random Forest technique [9]. Figure 9 highlights the key results (cross plots) after the ML Training and Prediction workflow was run.

Figure 9: Machine Learning Training and prediction workflow

3 Results and Discussion

3.1 Outliers Detection

Outlier detection is a significant step among others for the development of Log QC and prediction workflow that aims to detect outliers in data which are data samples significantly different from others. In the current work, authors used "One-class Support Vector Machine (SVM)", "Isolation-Forests (IF)", and "Local Outlier Factor (LOF)" for comparing results. LOF is an unsupervised method which measures the change in a data point's density compared to its neighbors and recognizes points having less density and assigns an anomaly score called LOF score, and "LOF", contrasting to other algorithms, permits a level of anomaly to every one of the samples as an alternative to an outlier or inlier flag allocation to the sample, that is called Local Outlier Factor [28]. One-Class Support Vector Machine (SVM) is also known as an unsupervised outlier detection method; nevertheless SVM captures the majority class density, it tends to classify outliers which falls outside the majority class boundary. In Isolation Forest (IF) is also an unsupervised model and like Random Forest it also utilizes decision tree based on the fact that abnormal samples are few and different.

By comparing the outputs (Figure: 10, 11 and 12 and Table:2) from three algorithms, authors found the LOF method provides most geologically representative and accurate results, which is due to LOF method not taking any of prior assumptions about the data distribution and identifying local outliers rather than global ones. Comparing the three figures – Figure: 10 (LOF), Figure: 11 (SVM) and Figure: 12 (IF), wherein a total of 14,451 log samples were analyzed, Figure:10 clearly depicts the nearby samples to be inliers while further away samples are flagged as outliers due to their lower density. In Figure: 11 and 12, even the nearby sample have been flagged as Outliers, hence geologically not accurate.

Method	LOF	IF	SVM
Total Analyzed Samples	14451	14451	14451
Total Outlier points	195	148	197

Table:2 Comparison of Total Vs Outlier datapoints through algorithms

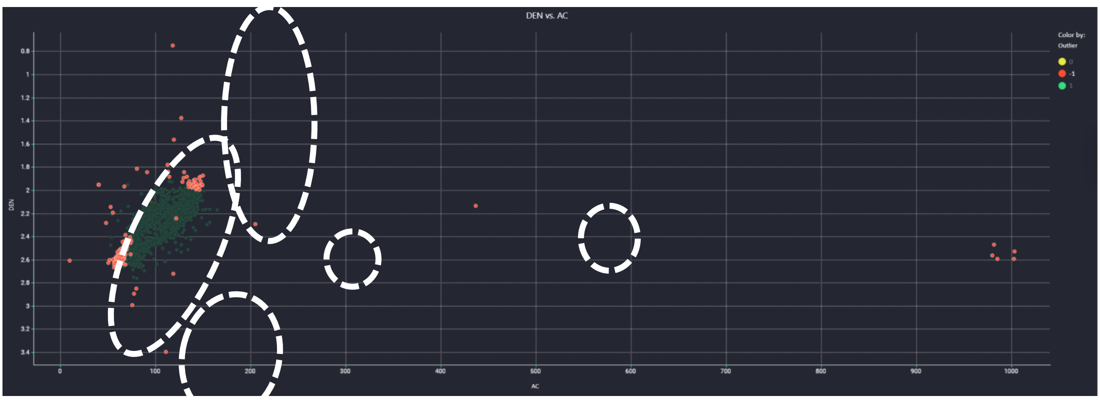


Figure: 10 Cross plot of Density Vs Sonic Curve, showing Outliers identified in RED color using LOF method, marked in circles

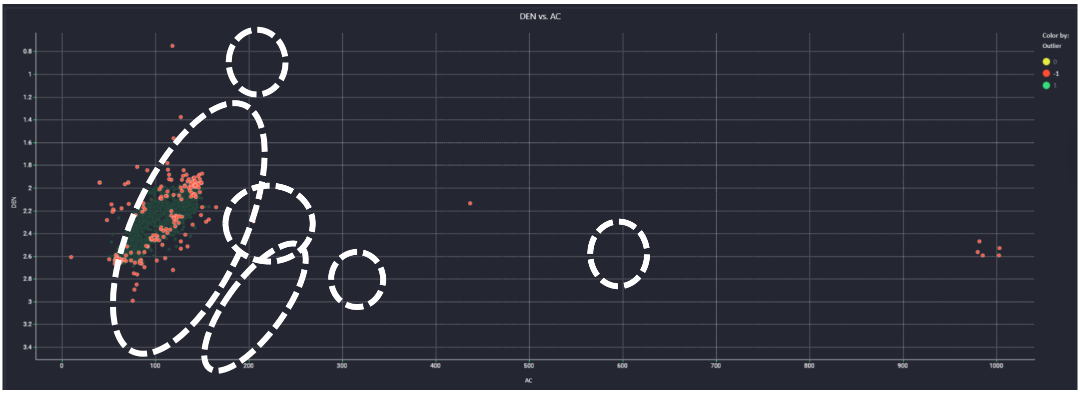


Figure: 11 Cross plot of Density Vs Sonic Curve, showing Outliers identified in RED color using SVM method, marked in circles

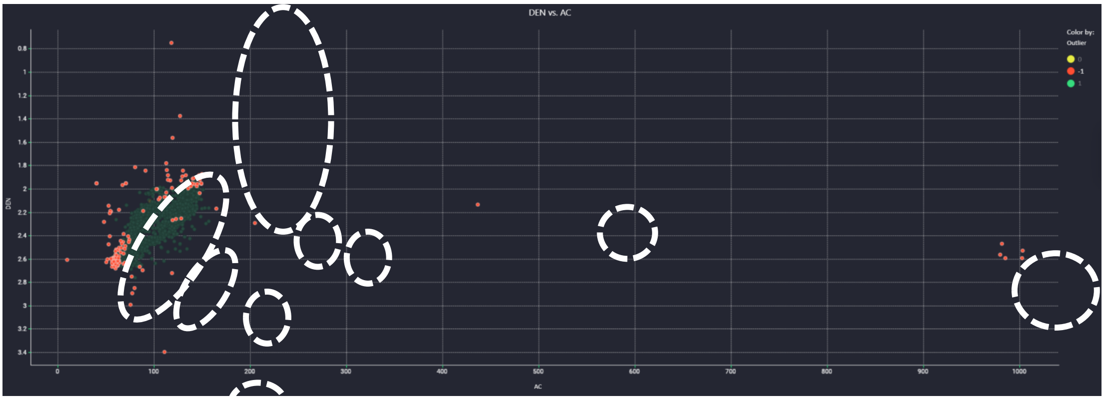


Figure: 11 Cross plot of Density Vs Sonic Curve, showing Outliers identified in RED color using IF method, marked in circles

3.2 Feature Selection

The procedure of selecting relevant features in relation to input in ML algorithms is known as "Feature selection". The goal of this feature selection in ML is to decrease the amount of input features through eradicating unrelated or unnecessary features thus simplifying the ML models, and improving the runtime required for ML training and consequently accuracy of the models. In the present work, authors utilized and implemented 05 different methodologies - Boruta, Correlation Coefficient, Lasso, Principal Component Analysis (PCA) and Variance Threshold to help select the most appropriate and relevant features for clustering and log prediction steps. In Figure: 12, Feature selection was executed for three target variables: Sonic (AC), Density (DEN) and Porosity (NEU). The Target_Var was being compared to all the input variables and

Method	Target_Var	Input_Var	Relevant_Var	Preferred_Flag
Boruta	DEN	['GR', 'AC', 'DEN', 'NEU', 'RANDOM']	['GR', 'AC', 'NEU', 'RANDOM']	
Correlation Coefficient	DEN	['GR', 'AC', 'DEN', 'NEU', 'RANDOM']	[]	
Lasso	DEN	['GR', 'AC', 'DEN', 'NEU', 'RANDOM']	['GR', 'AC']	
Boruta	AC	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	['GR', 'RDEP', 'RMED', 'DEN', 'NEU', 'PEF']	Yes
Correlation Coefficient	AC	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	[]	
Lasso	AC	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	['NEU', 'GR', 'RDEP', 'RMED']	
PCA		['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	['GR', 'RDEP', 'NEU']	
Boruta	NEU	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'PEF', 'RANDOM']	
Correlation Coefficient	NEU	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	[]	
Lasso	NEU	['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	[]	
Variance Threshold		['GR', 'RDEP', 'RMED', 'AC', 'DEN', 'NEU', 'PEF', ...	['DEN', 'PEF', 'RANDOM']	

Figure: 12 Feature Selection process results after successful execution.

and Output was compared in the form of relevant_var. Corresponding plots Figure:13 and 14 provides correlation and trends with respect to input vs target variables. In Figure:13, it can be visualized that Sonic (AC) shows good correlation with DEN, NEU and PEF.

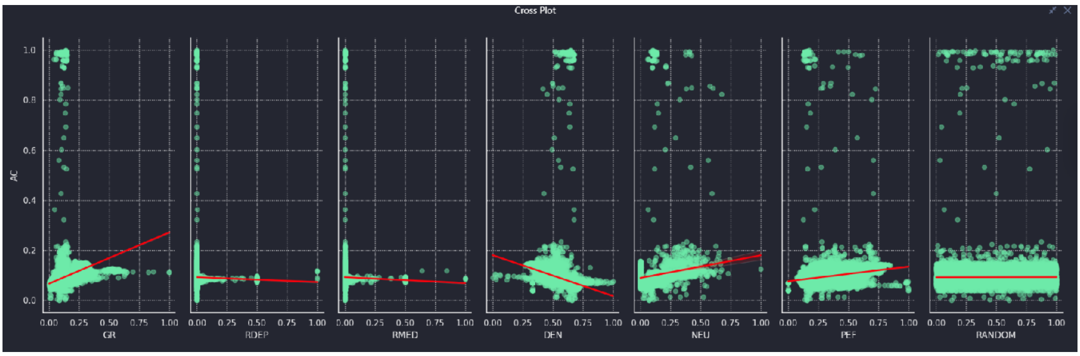


Figure: 13 Cross Plot of Sonic Curve (AC) along y-axis Vs Various input curves (x-axis) along with predicted trend line

Figure: 14 Results from Corr-Coeff, PCA, Lasso and Variance threshold for Feature Selection

From Figure: 14, comparing results from Correlation Coefficient, Principal Component analysis and variance threshold plot, similar observations that Sonic (AC) shows good correlation with DEN, NEU and PEF. All plots display ‘RANDOM’ variable, which is generated automatically and randomly to QC and check methods results. In the current work, more off the variable having lower correlation (RMED, RDEP, GR) with target (AC, DEN or NEU) comparing to ‘RANDOM’ will only introduce noise in the model. Hence for clustering and ML log interpretation, AC, DEN and NEU has been selected as key variables.

3.3 Clustering

Following the execution of Feature selection and removing irrelevant features in data and identifying most co-relatable variables, Clustering detection process was run in the present study. Probabilistically, it can be presumed that clustered data can be derived from various distributions of probability (for example, t-disatribution or Gaussian). Either that, otherwise it is derived from a parametrized matching distribution in a different way [9]. Mixture models clustering intends to obtain the data distribution parameters [29]. In the present study, two algorithms were designed - Gaussian Mixture Models (GMM) [23] and Stratigraphy based. Since for Stratigraphy methods, not all data was available for Volve field, authors decided to use Clustering based on GMM which follows multivariate Gaussian distributions. To identify the cluster optimal quantity, an “Akaike Information Criterion “/”Bayesian Information Criterion” plot had been employed, which provided a range of 8-21 to be the ideal range of clusters. In the present work, total 10 clusters were used to be predicted.

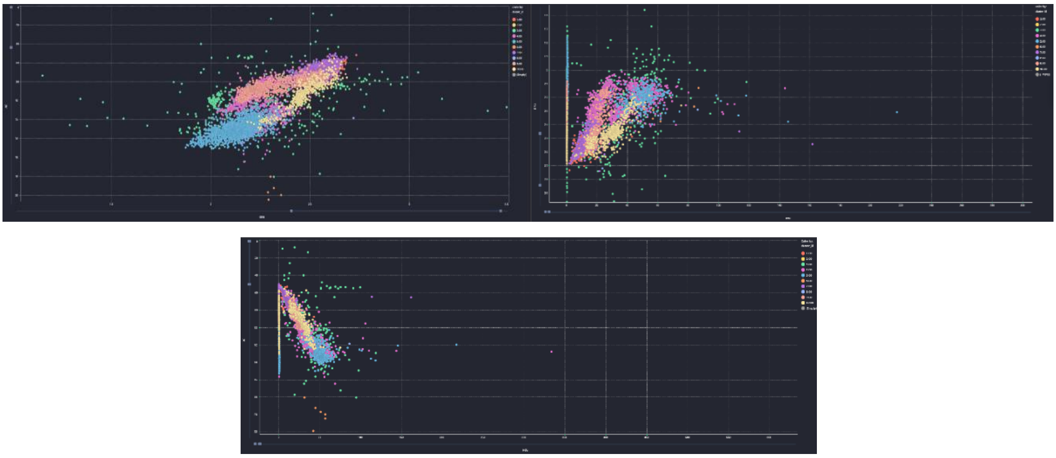
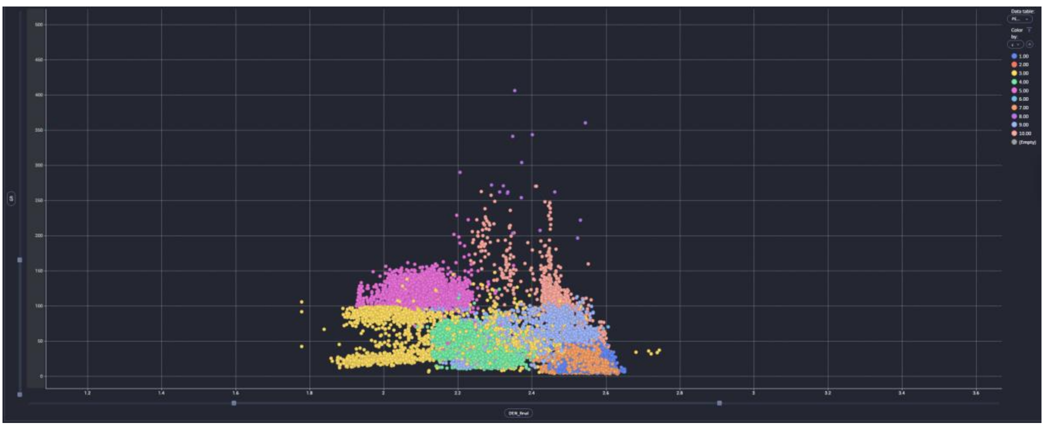


Figure: 15 AC-DEN-NEU Cross plots highlighting identified clusters following GMM Clustering

In Clustering, first a data subset was used for training the data and the results were saved in model for prediction. Subsequently, the model was run on the entire dataset using the trained data. Figure:15, highlights well defined clusters in the dataset which correlates all across the wells and range of values which signifies the model is ready to be used for ML training and prediction.

3.4 Machine-Learning Log Prediction

After the Clustering process was executed and 10 clusters of data was predicted, first ML Training and then ML Prediction using the Random Forest method. In our data set, DEN was predicted, whenever at least two of the curves AC, NEU, PEF was available in the well. The results were visualized using Cross-plots of both input and final logs. Figure: 16 highlights the input and prediction NEU, DEN and AC with 10 cluster and excellent correlation.



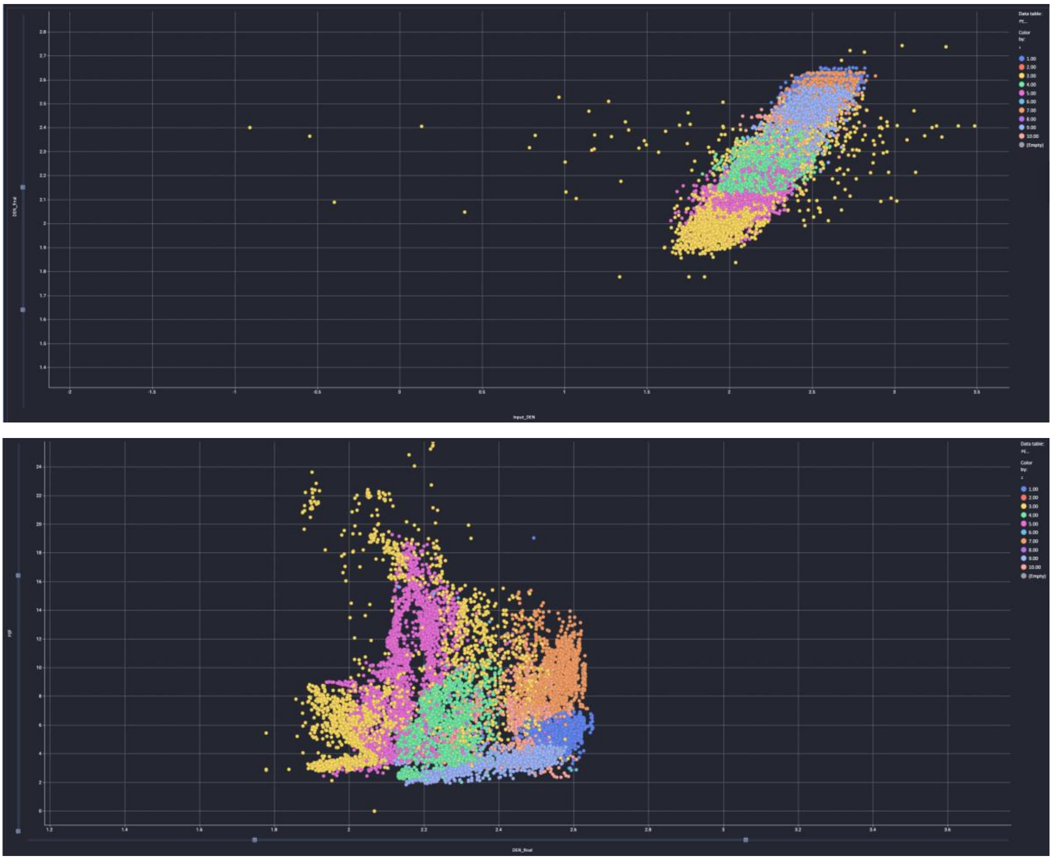


Figure: 16 ML Log Prediction results display in AC-NEU-DEN Cross plots

3.5 Validation and Uncertainty

In the present work, the uncertainty was calculated by comparing the values of predicted logs Vs original logs for all 24 wells and the uncertainty of prediction was comparable to the acquisition tool uncertainty.

4 Conclusions

In the present work we built interactive AI/ML assisted well log data QC prediction workflow and tested on publicly available Volve dataset from Norwegian Offshore. The dataset loaded in industry leading petrophysics interpretation platform is used to quickly load, prepare and liberate data to AI platform where data undergoes pre-processing, outlier detection, Feature selection and clustering to enable the robust Training and prediction workflow. Data available for 24 wells and triple combo log curves – AC, NEU, DEN and PEF along with GR, RDEP and RMED were used in the workflow, to predict DEN by using a combination of at least two available log curves – AC, NEU and PEF. The uncertainty of prediction was comparable to tool uncertainty thereby signifying the confidence in the predicted results. The developed workflow is highly flexible and can be deployed in various scenarios and can be used with different vintages and combination of log data.

The quality of predicted logs highlighted does not need any further manual intervention for more than 80% of the cases and can be used directly in various geological and petrophysical workflows thereby significantly automating the overall workflow and reducing the overall interpretation time.

Use of AI tools declaration

The authors proclaim no AI tools were used during this article's formation.

Acknowledgment

Authors intend to recognize and confirm that the current work has received no external or internal funding of any kind.

First Author would also like to acknowledge the support provided by Dr. Arvind Sharma, Dr. Hussein Mustapha, Ivan Velikanov, Sushant Shekhar, Manish Kumar Singh, Midhun Madhavan, Alaa Maarouf from Schlumberger, for innumerable discussion, troubleshooting sessions on python code and workflow while creating and running the workflow. First author would also like to acknowledge its gratitude and thanks to Patricia Manceron, Global AI & INNOVATION FACTORI Manager and Schlumberger for the support provided to enable to undertake part time PhD work. Authors would also like to acknowledge its gratitude to Equinor to provide Volve dataset for public use for research, study and development (https://www.equinor.com/energy/volve-data-sharing)

Conflict of interest

No conflicts of interest were faced by the authors.

Study Data

Data used in this study can be made available on request.

References

1. Khare, Sunil Kumar. "Machine vision for drill string slip status detection." Petroleum Research 7, no. 1 (2022): 115-122. https://doi.org/10.1016/j.ptlrs.2021.08.001
2. Sircar, Anirbid, Kriti Yadav, Kamakshi Rayavarapu, Namrata Bist, and Hemangi Oza. "Application of machine learning and artificial intelligence in oil and gas industry." Petroleum Research 6, no. 4 (2021): 379-391. https://doi.org/10.1016/j.ptlrs.2021.05.009
3. Mohaghegh, Shahab D. "Subsurface analytics: Contribution of artificial intelligence and machine learning to reservoir engineering, reservoir modeling, and reservoir management." Petrol explor develop 47, no. 2 (2020): 225-228. https://doi.org/10.1016/S1876-3804(20)60041-6
4. Salehi, Mehdi Mohammad, Mehdi Rahmati, Masoud Karimnezhad, and Pouria Omidvar. "Estimation of the non records logs from existing logs using artificial neural networks." Egyptian Journal of Petroleum 26, no. 4 (2017): 957-968. https://doi.org/10.1016/j.ejpe.2016.11.002
5. Syed, Fahad I., Abdulla AlShamsi, Amirmasoud K. Dahaghi, and Shahin Neghabhan. "Application of ML & AI to model petrophysical and geomechanical properties of shale

reservoirs–A systematic literature review." Petroleum 8, no. 2 (2022): 158-166. https://doi.org/10.1016/j.petlm.2020.12.001

6. Hassan, Amjed, Abdulaziz Al-Majed, Mohamed Mahmoud, Salaheldin Elkatatny, and Abdulazeez Abdulraheem. "Improved predictions in oil operations using artificial intelligent techniques." In SPE middle east oil and gas show and conference, p. D032S085R003. SPE, 2019. https://doi.org/10.2118/194994-MS
7. Bello, Opeyemi, Catalin Teodoriu, Tanveer Yaqoob, Joachim Oppelt, Javier Holzmann, and Alisigwe Obiwanne. "Application of artificial intelligence techniques in drilling system design and operations: a state of the art review and future research pathways." In SPE Nigeria Annual International Conference and Exhibition, pp. SPE-184320. SPE, 2016. https://doi.org/10.2118/184320-MS
8. Jain, Vikas, Po-Yen Wu, Ridvan Akkurt, Brooke Hodenfield, Tianmin Jiang, Yuki Maehara, Vipin Sharma, and Aria Abubakar. "Class-based machine learning for next-generation wellbore data processing and interpretation." In SPWLA Annual Logging Symposium, p. D043S007R008. SPWLA, 2019. https://doi.org/10.30632/T60ALS-2019_SS
9. Singh, Maniesh, Gennady Makarychev, Hussein Mustapha, Deepak Voleti, Ridvan Akkurt, Khadija Al Daghar, Arwa Ahmed Mawlod et al. "Machine learning assisted petrophysical logs quality control, editing and reconstruction." In Abu Dhabi International Petroleum Exhibition and Conference, p. D021S054R001. SPE, 2020. https://doi.org/10.2118/202977-MS
10. Mawlad, Arwa Ahmed, Richard Mohand, Praveen Agnihotri, Setiyo Pamungkas, Osemoahu Omobude, Hussein Mustapha, Steve Freeman, Kassem Ghorayeb, and Ali Razouki. "Embracing the digital and artificial intelligence revolution for reservoir management-Intelligent integrated subsurface modelling IISM." In Abu Dhabi International Petroleum Exhibition and Conference, p. D011S004R004. SPE, 2019. https://doi.org/10.2118/197388-MS
11. Akkurt, Ridvan, Tim T. Conroy, David Psaila, Andrea Paxton, Jacob Low, and Paul Spaans. "Accelerating and enhancing petrophysical analysis with machine learning: a case study of an automated system for well log outlier detection and reconstruction." In SPWLA Annual Logging Symposium, p. D043S008R004. SPWLA, 2018.
12. Gerges, Nader, Gennady Makarychev, Luisa Ana Barillas, Alaa Maarouf, Midhun Madhavan, Sonal Gore, Lulwa Almarzooqi, Sylvain Wlodarczyk, Chakib Kada Kloucha, and Hussein Mustapha. "Machine-Learning-Assisted Well-Log Data Quality Control and Preprocessing Lab." In Abu Dhabi International Petroleum Exhibition and Conference, p. D011S009R002. SPE, 2022. https://doi.org/10.2118/211719-MS
13. Timur, Aytekin. "Advances in well logging." Journal of Petroleum Technology 34, no. 06 (1982): 1181-1185. https://doi.org/10.2118/10947-PA
14. Wyllie, M. R. J., and M. B. Spangler. "Application of electrical resistivity measurements to problem of fluid flow in porous media." AAPG Bulletin 36, no. 2 (1952): 359-403.
15. Rezaee, Mohammad R., and James K. Applegate. "Shear velocity prediction from wireline logs, an example from Carnarvon Basin, NW Shelf, Australia." In SEG Technical Program Expanded Abstracts 1997, pp. 945-947. Society of Exploration Geophysicists, 1997. https://doi.org/10.1190/1.1886175
16. Rajabi, Mojtaba, Bahman Bohloli, and Esmaeil Gholampour Ahangar. "Intelligent approaches for prediction of compressional, shear and Stoneley wave velocities from conventional well log data: A case study from the Sarvak carbonate reservoir in the Abadan Plain (Southwestern Iran)." Computers & Geosciences 36, no. 5 (2010): 647-664. https://doi.org/10.1016/j.cageo.2009.09.008
17. Wang, Baozhong, Jyotsna Sharma, Jianhua Chen, and Patricia Persaud. “Ensemble Machine Learning Assisted Reservoir Characterization Using Field Production Data–An Offshore Field Case Study.” Energies 14, no. 4 (February 17, 2021): 1052.

https://doi.org/10.3390/en14041052
18. Sen, S.; Ganguli, S.S. Estimation of Pore Pressure and Fracture Gradient in Volve Field, Norwegian North Sea. In Proceedings of the SPE Oil and Gas India Conference and Exhibition, Mumbai, India, 8 April 2019; p. 8.
19. Equinor. Volve field dataset. Retrieved August 14, 2020, from https://data.equinor.com/dataset/Volve.
20. Szydlik, T.J.; Way, S.; Smith, P.; Aamodt, L.; Friedrich, C. 3D PP/PS Prestack Depth Migration on the Volve Field. In Proceedings of the 68th EAGE Conference and Exhibition incorporating SPE EUROPEC 2006, Vienna, Austria, 12–15 June 2006; doi:10.3997/2214-4609.201402177.
21. Equinor Volve Field. 2020. Available online: https://www.equinor.com/en/what-we-do/norwegian-continental-shelf-platforms/volve.html (accessed on 14 August 2020).
22. Equinor. 2016. Volve Reservoir Model and History Match Report. Available online: https://data.equinor.com/dataset/Volve (accessed on 14 August 2020).
23. Rasmussen, Carl. "The infinite Gaussian mixture model." Advances in neural information processing systems 12 (1999): 554-560.
24. Kumar, Bishnu, Sunil Kumar Khare, J. Devaraju, and Tanupriya Choudhary. "A Comprehensive Literature Review for Predicting Petrophysical Well Logs Using AI/ML Techniques.", J of Min Sci & Tech, 3, (2024): 1-15.
25. Breiman, Leo. "Random forests." Machine learning 45 (2001): 5-32.
26. Hornik, Kurt, Maxwell Stinchcombe, and Halbert White. "Multilayer feedforward networks are universal approximators." Neural networks 2, no. 5 (1989): 359-366.
27. Cortes, Corinna, and Vladimir Vapnik. "Support-vector networks." Machine learning 20 (1995): 273-297.
28. Han, Jiawei, Jian Pei, and Hanghang Tong. Data mining: concepts and techniques. Morgan kaufmann, 2022.
29. McLachlan, Geoffrey J., and Kaye E. Basford. Mixture models: Inference and applications to clustering. Vol. 38. New York: M. Dekker, 1988.