Recent Application of Machine Learning Algorithms in Petroleum Geology: A brief review

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ABSTRACT

In petroleum geology, machine learning (ML) has shown promise as a method for improving exploration and production. Current uses of ML algorithms in this area have significantly improved data analysis, modeling, and prediction, allowing for better decision-making and cost reductions. ML is utilized for a number of activities, including well-log interpretation, reservoir characterization, seismic data processing, drilling optimization, and production forecasting. The interpretation of well logs is one of the main uses of ML in petroleum geology. Using well logs, ML algorithms can categorize different types of rocks, identify lithology, and calculate porosity and permeability. In order to predict fluid distribution, identify the existence of hydrocarbons, and calculate reservoir parameters like thickness and depth, ML models are also employed for reservoir characterization. To better characterize reservoirs and make well placement decisions, ML algorithms are employed in seismic data processing to locate faults, fractures, and other geological features. ML models have been applied in conventional oil fields and unconventional shale plays in places like the Permian Basin in the United States and the North Sea in Europe. It has also being used in complex geological settings, such as tight gas deposits in the Marcellus Shale and fractured carbonate reserves in the Middle East. By forecasting drilling performance, spotting abnormalities in drilling data, and choosing the most effective drilling parameters, ML is also used to optimize drilling operations. The optimum production techniques are found, the remaining recoverable reserves are estimated, and production rates are predicted using machine learning (ML) in production forecasting. Cost-saving manufacturing optimization is possible with the help of this information. Overall, recent ML applications in petroleum geology have yielded encouraging results, allowing for better decision-making, cost reduction, and increased productivity. The oil and gas sector is expected to see ML approaches play a more significant role as they advance.

Keywords: Machine learning, Algorithms, Petroleum Geology, forecasting, Well logs

INTRODUCTION

The idea of artificial intelligence emerged after (Turing's,1937) "learning machine" and (McCulloch and Pitts', 1943) "threshold logic" as a computational model resembling organic nervous systems. One of the branches of artificial intelligence that has impacted several academic disciplines and is beginning to penetrate new ones is machine learning (ML). Any algorithm that can perform the three steps listed below for an anticipated task, such as forecasting an output value or identifying various classes, is included in machine learning (ML):

1. Take in the facts as input
2. Then analyze it to determine the governing
3. Generalize" those relationships and rules to a fresh dataset.

The second stage, when the algorithm is not directly coded on the data, is what sets ML apart from other computational techniques. The ability of machine learning algorithms to swiftly and accurately evaluate and interpret massive amounts of data has led to their widespread application in petroleum geology in recent years. Artificial neural networks, for example, have been successfully used in seismic data analysis in ML applications dating back to the 1980s (Poulton, 2002; Russell, 2005; Aniwetalu et al., 2018; Ibekwe et al., 2023). More research is being done on the use of ML in geophysics as more algorithms are developed and seismic data quality is improved. By mapping structural boundaries, gas chimneys, and direct hydrocarbon indicators like lithology and fluid classes, as well as reservoir-controlling parameters like porosity and pressure, ML algorithms play a crucial role in comprehending subsurface features in one- to four-dimensional seismic data analysis.

History of Machine Learning Algorithms in Petroleum Geology

Petroleum geology is one of many domains to which machine learning (ML) algorithms have been applied for many years. The history of ML algorithms in petroleum geology is briefly described:

1. **1980s–1990s:** Researchers used methods like artificial neural networks (ANNs) to categorize lithofacies and estimate porosity and permeability in reservoirs during this time period, which is when ML algorithms were first applied to petroleum geology (Rogers et al., 1989; Xie et al., 1994; Pwavodi et al., 2023).
2. Support vector machines (SVMs) and decision trees were used in the 2000s to analyze petrophysical and seismic data in order to predict reservoir characteristics, lithofacies, and hydrocarbon indications (Chen et al., 2001; Wu et al., 2008; Oguadinma et al., 2016; Oguadinma et al., 2017; Nwaezeapu et al., 2018; Oguadinma et al., 2021; Ibekwe et al., 2023).
3. **2010s:** has seen a rise in the use of machine learning (ML) techniques in petroleum geology due to the development of big data and cloud computing. Seismic data has been subjected to deep learning methods for fault detection and classification, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Liu et al., 2016; Liu et al., 2018). For lithofacies classification and reservoir property prediction, ensemble learning approaches like random forests and gradient boosting have been applied (Wang et al., 2017; Xu et al., 2018).

At this time, ML algorithms are still being developed and used for a variety of petroleum geology-related tasks, such as reservoir characterization, drilling optimization, and well log interpretation. Also, researchers are investigating the application of ML algorithms for production optimization and preventative maintenance. (Abdelaziz et al., 2021; Wang et al., 2021; Ibekwe et al., 2023)

Types of Machine Learning

Machine learning algorithms come in a variety of forms, each with unique advantages and disadvantages (Alpaydin, 2010). Some of the machines learning algorithms that are most frequently employed are listed below:

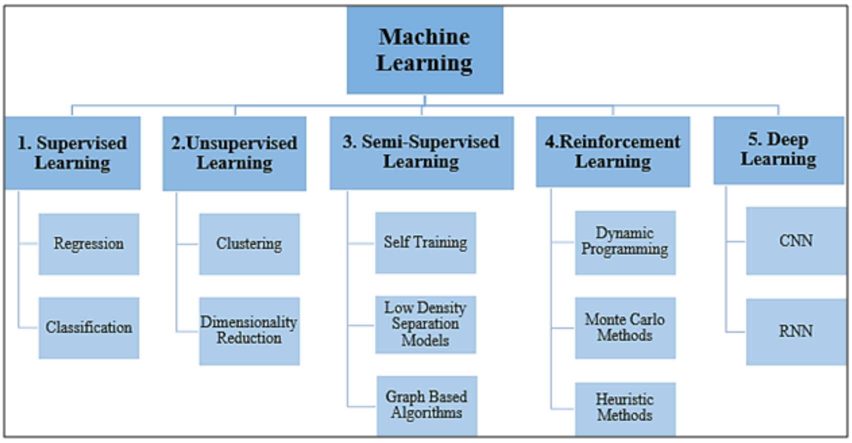

Fig 1: Diagram showing the different types of machine learning (from Nassif et al., 2019)

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Supervised Learning: The model is trained on labeled data, which means the input data has an associated output value, in supervised learning, a type of machine learning. Based on the training examples, the model learns how to map the input data to the output data. Support Vector Machines (SVMs), Decision Trees, Random Forests, and Neural Networks are a few well-known supervised learning methods (Mitchell, 2000)

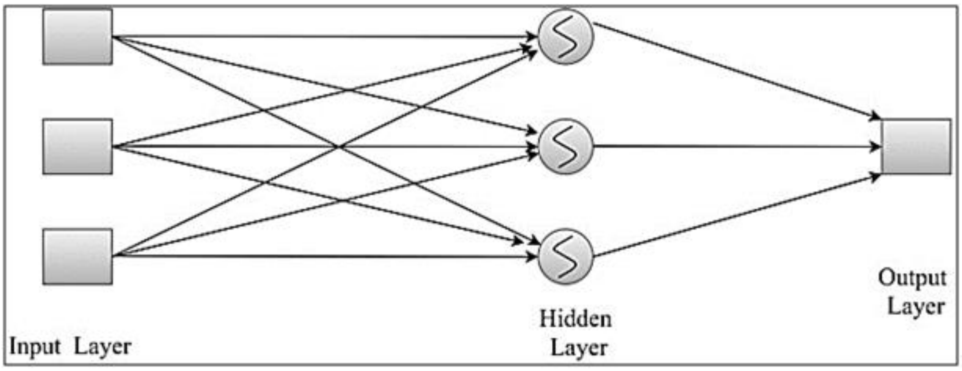

Fig 2: A Simple neural network (Anirbid et al 2021)

Fig 3: Different stages of supervised learning (A. B. Nassif et al., 2019)

Unsupervised Learning: Unsupervised learning is a subset of machine learning in which the model is trained on data that has not been labeled; hence there is no associated output value for the data entered. Without any user input, the model develops the ability to recognize patterns and structure in the data. K-Means Clustering, Principal Component Analysis (PCA), and Hierarchical Clustering are three common unsupervised learning algorithms (Hastie et al., 2009).

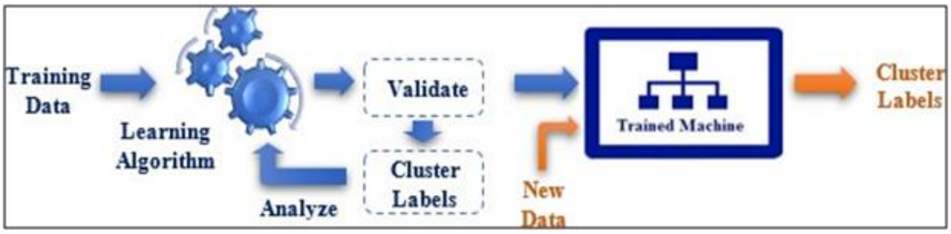

FIG 4. The different stages of the unsupervised learning (A. B. Nassif et al., 2019)

Reinforcement Learning: Reinforcement learning is a sort of machine learning in which an agent learns to make decisions in a given environment by receiving rewards or penalties based on its behaviors. By experimenting with various acts and taking note of the results, the agent learns how to maximize its reward. Prominent reinforcement learning algorithms include Q-Learning, SARSA, and Deep Reinforcement Learning (Sutton and Barto, 2018).

Semi Supervised Learning: This method of machine learning involves training the model on both labeled and unlabeled data. The model gains identification skills by employing labeled data to direct its learning and unlabeled data to explore the space of potential solutions, the model learns to recognize patterns and structure in the data. Prominent semi-supervised learning techniques include Label Propagation, Co-Training, and Graph-Based Learning (Chapelle et al., 2009).

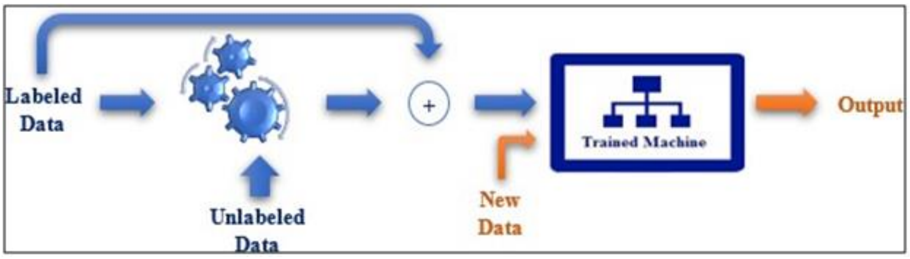

FIG 5: Different stages of semi-supervised learning (A. B. Nassif et al., 2019)

Deep Learning: Deep learning is a sort of machine learning in which representations of the data are learned using neural networks with several layers. These representations can be used for a variety of machine-learning issues, including speech recognition, image classification, and natural language processing. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers are a few well-known deep learning techniques (Goodfellow et al., 2016).

DISCUSSION

The several machine learning techniques are ANN, FL, SVM, DT, RF, KNN, RNN, CNN, and fuzzy C-means clusters. All these techniques are used in different applications of oil and gas.

Application of Machine Learning

Fault and salt body delineation:

Fault detection and delineation of the salt body boundary from 3D seismic data are essential for building a realistic model (Bahorich and Farmer,1995; Melville and Guruswamy, 2002). Seismic analysis has been traditionally used to map faults& salt bodies. Examples of such attributes are coherence (Bahorich and Farmer, 1995; Qi et al., 2017), edge detection (Di and Gao, 2014), and semblance (Marfurt et al.,1998). Due to the complex geology & the noise level frequently encountered in 3D seismic data, the use of multiple seismic attributes is frequently needed to detect faults or salt-body geometry (Berthelot et al.,2013; Hale, 2013). Machine language has been used in several studies to integrate multiple seismic attributes for better detection and faster operation. Machine learning techniques have been employed for fault detection in subsurface structures. In one case, a neural network was used to identify flaws in seismic data (Jiang et al., 2018). To identify defects from well-log data, another study employed a decision tree (Chen et al., 2019).

Petro facies classification and fractures identification:

Reservoir rocks can be classified based on their petrophysical rock properties. Examples; porosity, permeability, and pore size and geological features such as textures, diagenetic overprints, and pore size. Petro facies is usually the combination of petrophysical and geological attributes, which is essential for reservoir characterization (Avseth and Mukerji, 2002). It is done using both core samples and wireline log data. The utilized logs for facies identification are usually Gamma Ray(GR), resistivity(Rt), neutron (NPHI), density(RHOB), and lithology(PEF). Other features can also be extracted from these logs to improve the prediction, such as total organic matter (TOC), matrix grain density (RHOMAA), and apparent volumetric cross-section (UMA). One major challenge that remains for the success of machine learning in this application is to have the right petrophysical and geological features to distinguish between facies. Such

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tasks remain mainly subjective and far from being automated or objective.

Well Correlation:

Correlating different reservoir units and formation tops across different wells is essential in reservoir characterization and modeling. The use of machine learning to handle this issue has been recognized many years back (Luthi and Bryant,1997; Oguadinma et al., 2016; Oguadinma et al., 2021; Oguadinma et al., 2023). An interpreter has first to pick formation tops and perform well correlations in several wells, which will be used as a training dataset to perform interpretation in tens to hundreds of other wells. An interpreter has first to pick formation tops and perform wells. An increasing body of studies (Maniar et al.,2018; Zheng et al.,2019)has demonstrated that a deep convolutional neural network(CNN)can provide an accurate and efficient approach for well-log correlations.

Reservoir characterization:

Machine learning can be applied in various fields of geosciences. The areas discussed are petrophysical properties prediction from the seismic, core and well-log data. Other properties such as water saturation, petroleum geochemical parameters and reservoir geomechanics will be predicted.

Production Optimization:

The production of oil and gas has been enhanced using machine learning algorithms. To improve the gas field's production plan, one study used a genetic algorithm (Mohammadpour et al., 2019). A machine learning model was employed in a different study to forecast how well a water injection system will work (Wu et al., 2019).

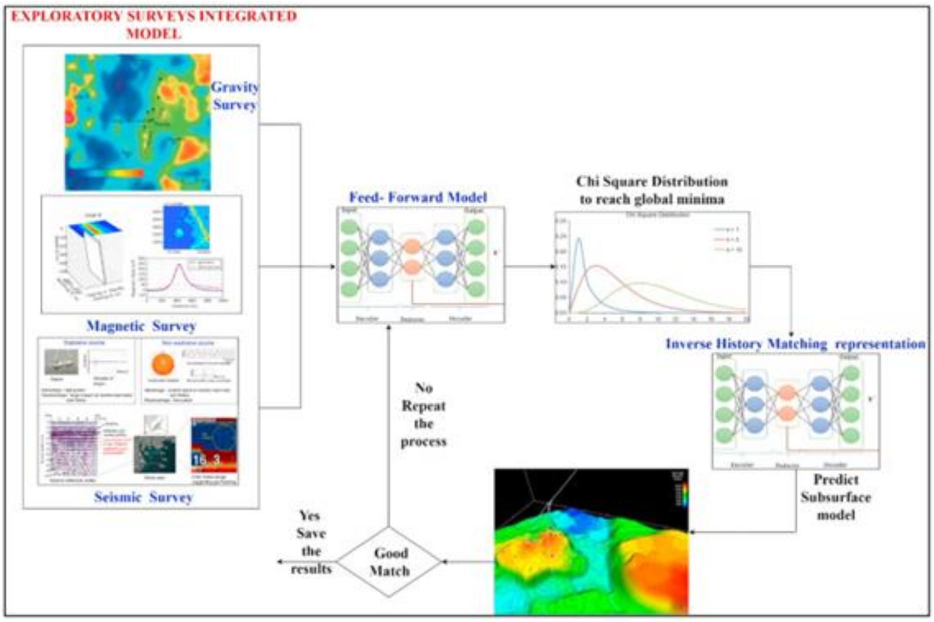

Fig 3: Exploration outline for data processing and interpretation using machine learning technique (adapted from Anirbid et al., 2021)

Petrophysical Properties prediction

Reservoir characterization plays a critical role in the oil and gas industry, such as developing optimal production and reservoir management strategies. One of the properties which determine the ability and direction of flow is permeability which is a very important property in reservoir characterization

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(Oguadinma et al., 2014; Oguadinma et al., 2016; Oguadinma et al., 2017; Nwaezeapu et al., 2018; Oguadinma et al., 2021; Ibekwe et al., 2023; Oguadinma et al., 2023). An accurate permeability determination is essential for material balance calculations, reservoir flow simulation, estimating oil production rate, stimulation strategies, and enhancing oil recovery. However, it is very difficult to determine due to its complexity and high nonlinear nature. Machine learning techniques are widely used to predict petrophysical parameters such as bulk density, capillary pressure, relative permeability, permeability, and porosity.

Water saturation prediction

This can be defined as the fraction of pore space occupied by water. A good estimation of water saturation is considered a difficult task in petroleum engineering and is an essential parameter in petrophysics and reservoir engineering calculations such as material balance calculations, simulation model optimizations, history matching, and oil and gas reserves estimation In 1942, Archie was the first to present an equation to determine water saturation in a clean, non-clay reservoir. However, no consensus exists among log analysts about the model to be universally used. The most commonly utilized models/correlations are Simandoux (Simandoux, 1963), Fertl and Hammack (Fertl and Hammack, 1971) and Waxman and Smith models; however, the variables involved in each contain inherent uncertainties and eventually lead to misconstrued results.

Geomechanics

A better estimation of the reservoir rock elastic and failure properties is instrumental to minimizing wellbore instability problems, avoiding differential sticking, improving casing placement, improving hole cleaning, improving hydraulic fracturing operations, minimizing subsidence, and many more (khamidy et al.2019). Carrying out mechanical rock tests such as triaxial compression, uniaxial compressions, scratch, and impulse hammer is an accurate way to determine these properties (Elkatatny et al., 2019). These tests are usually carried out on the downhole samples retrieved from some depth of interest. When core samples and well-log data are absent, analytical and empirical models determine the rock’s mechanical properties.

Drilling and completions

This method is very expensive; therefore, several approaches are utilized to reduce the cost of operation by improving drilling efficacy and reducing the drilling time. The drilling performance is improved by selecting proper drilling fluids, improving cementing jobs, maximizing the drilling rate of penetrations, and minimizing the required drilling energy(Bilgesu et al.,1997; Dupriest and Koederitz, 2005; Hegde and Gray, 2018; Pwavodi et al., 2023). Therefore, accurate prediction of the drilling fluid parameters, cement strength, and rate of penetrations(ROP) is an essential element for evaluating or improving the drilling performance.

Drilling performance prediction

Several analytical models were developed to evaluate and optimize the drilling performance; however, most of these models were developed based on weak assumptions, reducing their reliability (Aadnoy et al., 2010; Reiber et al., 1999). (Mehrad et al., 2020) used a machine learning approach to develop a rigorous ROP model for vertical wells. They used different parameters to determine the ROP, including logging, drilling, and geochemical parameters. They found that the best ROP prediction can be obtained by using the uniaxial compressive strength (UCS), mudflow rate, weight on bit (WOB), depth, mud density (MD), and revolutions per minute (RPM) as input parameters.

Drilling fluids

Drilling is one of the most critical tasks with challenges such as lost circulation, clogged pipes, wellbore

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instability and kicks occurring regularly. It is also known as "blood of the drill". It prevents the pipe from sticking by building thin filter cake on the wellbore wall as well removing drilling cuttings out the wellbore. The operation's success or failure is largely determined by the drilling fluid's performance and compatibility (Agwu et al., 2018). Each well design includes a drilling fluid program that specifies drilling fluid, additives, rheology, density, filtration, and other drilling fluid parameters. The majority of drilling fluid design is done in the laboratory through trial and error. Regression approaches are utilized to predict rheological proficiencies such as an ANN. For greater accuracy, the ANN model can be trained continuously with more data sets. It gives a more comprehensive view of how to comprehend the drilling performance. For example, if there is a reduction in pump pressure during the drilling operation, which happens for several reasons, including thinning effect on the drilling fluid, quick transport of the cuttings to the surface, reservoir fluid influx in the wellbore, and lost circulation, etc. When this happens, I interlink different parameters, improves the decision-making process, and brings back the engineers on the right track within a short time.

Oil well cementing

The oil well prevents the movement of fluid between the geological formation and behind the casing string (Murtaza et al., 2020; Tariq et al., 2020). A slurry of cement is pumped down the annulus between the casing and the geological formation.AI is used for the prediction of cement strength development and rheological properties. Accurate prediction of compressive strength development can save a lot of money by reducing the wait on the cement after cementing operation.

Reservoir and Production

Production in the Reservoir: ML methods have been used to accelerate oil reservoir simulations and achieve higher accuracy as well. He et al. (2021) developed a methodology to optimize the field development plans (FDPs). This includes optimizing well counts, well locations and the drilling sequence.

Stimulation: (Rastogi and Sharma, 2019) used machine learning tools to find the impact of fracturing chemicals on the production using one-year production data. Different algorithms were used for feature selection such as F-Regression. Decision tree-based regressions, recursive feature elimination etc. The data was gotten from different fracture jobs in the Power River Basin.

Challenges Faced Using The Machine Learning

Inasmuch as machine language has been used to offer solutions to the oil and gas industry, it also has limitations which are:

1. When building a relationship between several parameters, which is done whenever there is a high, correlation is not necessarily an indication that these parameters are having "causation" unless there is a proven physical or scientific relationship between them.
2. The data has to be accurate in order to produce a useful model.

CONCLUSION

The use of machine learning algorithms in petroleum geology has produced encouraging results in a number of fields. Including reservoir classification, seismic interpretation, and well log data processing. Machine learning algorithms will play a bigger role in maximizing the potential of these data as the volume of data collected in the petroleum business keeps growing. Overall, the use of machine learning algorithms in petroleum geology has the potential to greatly increase exploration and production efficiency while lowering

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costs, resulting in more environmentally friendly and financially successful oil and gas operations.

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