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REVIEW PAPER

Review of detection, prediction and treatment of fluid loss events

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Abstract
Lost circulation has the potential to cause formation damage, wellbore instability and a blowout. Many methods have been introduced, but there is no industry-wide solution available to predict lost circulation due to some constraints in the field. It is essential to predict the onset of loss of circulation to mitigate its effects, reduce operational costs and prevent the risk to people and the environment. A wide range of methods, techniques and treatments, including environmentally friendly materials, are reviewed to mitigate the loss of circulation. Conventional and intelligent methods are presented for detecting and predicting lost circulation events. Using oil field data such as fluid parameters, drilling parameters and geological parameters, artificial intelligence can predict fluid losses using supervised machine learning (ML). Several ML models for predicting fluid loss are reviewed in this paper, and other possible applications are discussed. The sample size, field location, input and output features, performance and ML algorithms are extracted. The paper provides an inclusive presentation of the ML workflow for fluid loss prediction and is anticipated to help and support both drilling engineering practitioners and researchers in the resolution of drilling challenges, with recommendations for future development.

Keywords Lost circulation · Fracture formation · Geological parameters · Machine learning · Permeable formations

Introduction

The process of drilling oil and gas wells can be challenging due to the loss of control over the flow of mud into the formation. A significant amount of non-productive time (NPT) can result from the loss of some or all of the drilling mud or cement slurry during drilling operations (Hamza et al. 2019). Fluid loss is indicated by the pit volume, return flow rate and standpipe pressure. Up to 25% of all currently drilled wells worldwide are affected by lost circulation (Sun et al. 2021). Mitigating and preventing lost circulation is costly, with estimates ranging from more than $2 billion USD per year (Ahammad et al. 2019). The following are broad categories of lost circulation: (i) natural fracture formations; (ii) induced or created fractures (i.e. fast tripping or high equivalent circulation density, ECD); (iii) cavernous and vugular formations (i.e. carbonaceous rocks such as limestones); and (iv) Unconsolidated or highly permeable formations. Lavrov (2016) categorises fluid loss during drilling depending on the base fluid of the mud used and the intensity of the loss. This is illustrated in Table 1.

Loss of circulation causes wellbore instability and is a significant contributor to drilling problems (Mardanirad et al. 2021). Resolving the problem and restoring fluid circulation can take significant time and effort, increasing the NPT and overall drilling cost (Sun et al. 2021). In the Gulf of Mexico, 12% of NPTs are caused by loss of circulation, and 18% are caused by wellbore instability, according to Magzoub et al. (2021). The well is sidetracked or abandoned as a result of these vital losses. According to the US Department

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Highlights
- Methods, techniques, and treatments, including environmentally friendly materials, are reviewed.
- Conventional and intelligent methods using formation characteristics and fluids and several machine learning models have been presented.
- An inclusive presentation of the machine learning workflow for fluid loss prediction has been provided.
- Prediction performance analysis is explained to indicate how well predicted values match the field dataset.

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Table 1 Classification of lost circulation based on drilling fluid type (adapted from Lavrov, 2016)

Fluid loss class	Water-based muds (WBMs)	Oil-based muds (OBMs)
1. Seepage losses	< 4 m^3/h	< 2 m^3/h
2. Partial losses	< 4 m^3/h	2–5 m^3/
3. Severe losses	> 16 m^3/h	> 5 m^3/h
4. Total losses	No mud returns to the surface	

of Energy, the costs associated with drilling high-pressure and high-temperature wells are estimated to be up to 20% due to loss circulation problems (Growcock et al. 2009). Furthermore, drilling fluid invasion into the reservoir formation can cause formation damage and reduce productivity (Klungtvedt et al. 2021). A further survey of 103 wells in the Duvernay area of Canada found that the loss of circulation cost $2.6 million and resulted in 27.5 days of NPT (Fox 2018). In the Middle East, an estimated 48% of all drilling issues in Iraq's Rumaila field were caused by lost-circulation issues, resulting in a 295-day loss in the NPT (Arshad et al. 2015). In carbonate formations, conductive natural fractures were found to cause a high frequency of lost circulation. In Iran's fractured carbonate formation, more than 35% of drilled wells experienced lost circulation (Abdollahi et al. 2004).

In Algerian fields, lost circulation is a significant issue during drilling the 6-inch section. The challenge lies in controlling these losses without damaging the reservoir. The average time spent on lost circulation problems and plugging cracks ranges from 50 to over 280 h for the entire phase (Khodja 2008). The problem of loss circulation at the Cambrian level affected over 40% of horizontally drilled wells (Kadi et al. 2004). The volume lost varies from a few tens of m^3 to several hundred m^3. For instance, in the case of the MDZ#576 well, the total volume lost was over 2481 m^3 with the injection of seven plugs, and more than 900 m^3 of sludge was lost in the MDZ#546 well. Drilling costs can range from USD seventy to USD hundred per foot in these circumstances, emphasizing the importance of effectively addressing loss of circulation (Magzoub et al. 2021). Loss circulation events occur in 18–24% of drilled wells in the USA, as estimated by Aljawad et al. (2019) and Ezeakacha and Salehi (2018). Table 2 lists the major oil and gas producing regions along with their approximate fluid loss ranges. Fluid loss varies globally and is between 5 and 207 m^3.

A proactive approach to detecting and mitigating loss of circulation is crucial to reducing its effects, lowering costs, and avoiding environmental and personnel risks. Several approaches have been proposed, including temperature profile and resistivity (Caenn et al. 2017). However, some of these approaches are unreliable due to their high costs, lack of technology or incorrect estimation of thief zones. The main objective of this comprehensive study is to provide ML workflows for fluid loss prediction as well as recommendations for future research developments. The main findings of the ML modelling are presented, along with additional potential applications.

Drilling through highly permeable formations, cavernous and vuggy rocks, fractures and induced formation fractures causes fluid loss. Carbonate formations (dolomite or limestone) with caverns, vugs and fractures, as well as formations with induced fractures and high permeability, are the most likely to experience such losses. Zones with a high incidence of severe, interconnected vugs, cavernous fractures or total losses are of particular concern (Caenn et al. 2017). A sudden increase in the rate of penetration can be seen when such zones are encountered during drilling. This can lead to significant fluid losses that may result in total mud losses. If corrective actions are not taken, a steady drop in the level of the mud pit, indicating fluid loss in natural fractures, can signal total loss. At shallow depths of less than 1000 feet, permeable and unconsolidated formations such as sand and gravel are encountered. These formations have low fracture gradients and high permeability ranges. Without remedial action, the level of the mud pit may gradually decline and persist. Fluid losses may be reduced if a mud

Table 2 Fluid loss ranges in major oil and gas regions

Ranges/m^3	Location	Authors
16–151	North American Region	Aljawad et al. (2019); Ezeakacha and Salehi (2018)
5–8	South American Region	Carpenter (2014); Plazas et al. (2015)
23–207	African peninsular Region	Agwu and Akpabio (2018)
6–280	Algerian fields (North Africa)	Khodja (2008)
48–239	Australian Continent	Tarazona et al. (2014)
7–223	NSSE (North, South and South-East) Asian Region	Yan et al. (2019)
10–159	Middle East Asian Region	Wang et al. (2020)
16–80	Norwegian Region	Zhao et al. (2017)

filter cake is formed on the wall. Additionally, induced fractures can cause loss of circulation. Induced fractures differ from natural fractures primarily in that the loss of mud in induced fractures requires an increase in pressure to break formations, whereas the loss of mud in natural fractures only requires a pressure greater than that of the fluid within the formation (Howard and Scott 1951). Natural fractures that are sealed or closed are primarily planes of weakness in naturally fractured reservoirs. Fractures may occur if the mud pressure exceeds the minimum horizontal stress (Keshavarzi and Mohammadi 2012). Further, lost circulation can cause mud levels to drop, potentially leading to the wellbeing underbalanced and at risk of a kick or blowout (Arshad et al. 2014). In fact, induced fractures are caused by inappropriate hydraulics, including high ECD and excessive pump flow rates, as well as improper drilling techniques, such as tripping too quickly, an excessive rate of penetration and inappropriate mud properties (i.e. gel strength and solid content). The types of lost circulation zones are depicted in Fig. 1 (Magana-Mora et al. 2021). Many methods have been introduced, but there is no industry-wide solution available to predict lost circulation because several interrelated factors affect the severity of fluid loss. There has been a lot of attention given to loss circulation materials (LCMs) for addressing fluid losses; however their use is not always efficient due to unpredictable and uncertain subsurface conditions. It is more efficient to anticipate and identify fluid losses than to attempt to fix the issue after it has already happened (Agwu et al. 2018). Based on the time period in which they were applied, lost circulation treatments can be divided into different categories. It can take place either before the loss of circulation event (preventive) or after it (corrective). There are four general approaches to preventing fluid loss. The overall goal of the preventive method is to optimise drilling parameters such as ECD, drill string running speed, rate of penetration and wellbore strength. Salehi and Nygaard (2012) describe wellbore strengthening as a drilling technique that increases fracture gradients and lengthens the operational window by plugging and sealing fractures caused by drilling. Increasing the wellbore stress and fracture gradient of the formation is the primary benefit of wellbore strengthening. This permits drilling with higher mud density windows, which is particularly advantageous in depleted and weaker formations. In other words,

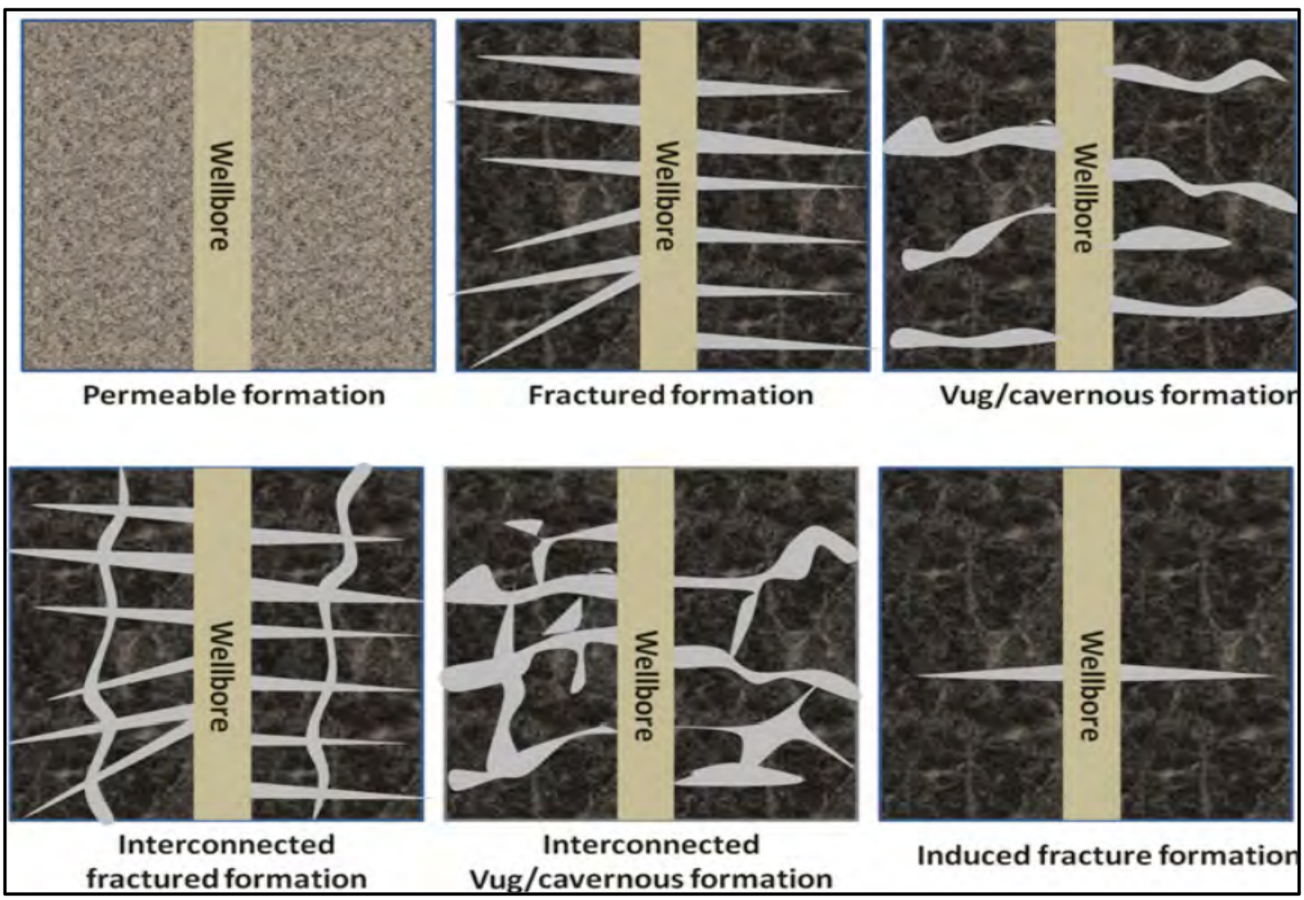

Fig. 1 Types of loss of circulation formations (adopted from Magana-Mora et al. 2021)

the borehole strengthening approach will broaden the mud density window's range. In the corrective strategy, lost circulation treatments are either spotted as a concentrated pill or continuously added to the drilling mud to reduce losses. LCMs are classified according to their appearances and applications into fibrous, granular, flaky, swellable, hydratable, high-fluid-loss squeezes, water-soluble (sized salts) or acidic (sized calcium carbonate) materials, as well as nanoparticles. Fluid losses in reservoir sections could be restored using non-damaging LCMs that are water- and acid-soluble. LCM or treatment method selection is influenced by a variety of variables, including the type of drilling mud, the formation type where fluid losses occur, the magnitude of fluid loss circulation events, the mud properties and the drilling operating parameters and the size of drill bit nozzles. This is partially caused by the additional difficulties some LCMs in field applications encounter, such as the damage of production zones, the plugging of downhole tools by relatively large LCM particles and poor filtration control. Moreover, fibrous materials could alter the emulsion properties of OBM, and oil-wetting chemicals could be added to keep the oil wet. As a result, it is recommended to conduct a standard test to determine the best type of LCM materials. Conventional methods for treating or managing seepage and partial loss of circulation include adding LCM (fibrous, granular and flaky materials) or spotting high-viscosity pills mixed with LCM. Based on field experience, combinations outperform single LCMs. With greater severity (such as severe or complete losses), other solutions, such as cement (Cui et al. 2021) and nanocomposite gels (Al-Hameedi et al. 2018), can be used.

Smart LCMs have the ability to be programmed to change in shape, bridge and expand when stimulated by a specific temperature. A fully coupled simulation was developed to test the sealing efficiency of the newly introduced smart LCMs. Various particle size distributions and fracture sizes were used to further understand the properties of the smart LCM (Mansour and Teleghani 2018). Environmentally friendly materials are being used in the global industrial community to replace harmful products (Amish et al. 2022). One of the most effective ways to achieve this goal is to use LCMs and eco-friendly mud additives derived from plants and other vegetal tissues (Table 3).

Several bridging theories for LCMs, their mechanisms and applications are available. The primary objective of these theories is to enhance the particles' ability to bridge and seal fractures (Abrams 1977; Whitfill 2008; Vickers et al. 2006; Alberty and McLean 2004; Wang et al. 2008; Jaf et al. 2023).

Loss of circulation detection methods

As shown in Table 4, there are two types of loss of circulation detection methods. The first is known as conventional methods, and the second is known as intelligent methods. Various conventional methods are used to identify loss and gain issues in drilling operations, such as monitoring mud tank volume, calculating delta flow rates (the difference between the inflow rate and the outflow rate) and measuring annulus pressures. A drop in mud levels in the annulus or lower mud returns in the tanks can indicate fluid loss during drilling (Maus et al. 1979; Speers and Gehrig 1987). Pressure surges from tripping the drill string or casing into the hole can lead to significant drops in hydrostatic and annular pressure (Krishna et al. 2020). During trip-in and trip-out operations, trip tank volumes are compared to ensure the correct fluid volume is taken by the well. Two common methods used to monitor mud tank fluid levels and hole returns are employed to estimate partial or complete loss of circulation. Surface mud logging and downhole measurements, including standpipe pressure, discharge pressure and annular pressure, are used for detection. Combining standpipe pressure and annulus discharge pressure helps in early detection of fluid loss, kicks, drill string leaks and plugging. Various tools like temperature survey tools, hot wire surveys, radioactive tracer surveys, spinner surveys, PWD tools and others are used for detecting fluid loss issues in drilling operations (Mitchell and Miska 2010; Mills et al. 2012).

Table 3 Sample of environmentally friendly LCMs

Material	Classification	Authors
Calcium carbonate	Granular	Ezeakacha and Salehi (2018)
Apple skin	Fibrous	Ghazali et al. (2015)
Eucalyptus camaldulensis bark	Fibrous	Sedaghatzadeh et al. (2021)
Crushed palm date seeds	Granular	Alawad et al. (2019)
Nut shell	Franular	Sedaghatzadeh et al. (2021)
Natural biodegradable polymers	Polymer	Ismail et al. (2022)
Banana peels	Fibrous	Akmal et al. (2021)

Table 4 Summary of detection studies

Author	Objective of the study	Model	Inputs	Outputs	Performance
Yamaliev et al. (2009)	Identifying bit conditions	Neural networks	Spectrum, dispersion, entropy, and Jinny coefficient	Describe bit status	-
Lian et al. (2010)	Determining downhole conditions	Fuzzy reasoning	The data collected include total hydrocarbons, volume of the tank, temperature, conductivity, density and hook load	Detecting of various drilling problems	The application produced reliable and accurate results
Unrau and Torrione (2017)	Inspecting for false alarms	Support vector machine, regression models and other supervised ML models	Pit volume, flowing in and flowing out	Accurate alarm of fluid losses	The outcome was satisfactory
Zhao et al. (2017)	Identification of several drilling anomalies	Un-supervised ML	Well's geometrical properties, rheological and hole parameters	Pipe stuck, ECD change and fluid losses, etc	This method is used to notify the driller of any operational parameter changes that occur during drilling events
Jiang et al. (2018)	Identifying the loss of circulation and determining the depth and rate of loss	Using the unscented Kalman filter (UKF) to estimate transient pressure and temperature coupling	Physical properties of drilling fluids and formations, as well as well geometry	Pressure and outlet flow rate	The simulation result demonstrates the diagnosis method's superior performance

Conventional methods

Detecting fluid loss using a PWD tool

Real-time measurement of bottom-hole pressure using a pressure while drilling (PWD) tool is a more reliable way to detect fluid loss and kicks compared to surface measurements like SPP (Reitsma 2010). This method is not affected by borehole hydrostatic pressure, pressure loss from the bottom-hole assembly (BHA) or frictional forces (Nayeem et al. 2016). The PWD tool utilises a precise quartz pressure device to measure borehole pressures and temperatures, providing data for ECD measurement, pressure monitoring during tripping and reaming and mud weight inspection to identify fluid loss and influx (Amirov 2017). These capabilities enable quick decision-making to improve drilling efficiency.

Real-time monitoring of hydromechanical efficiency

Saihood and Samuel (2022) compared two wells in terms of fluid loss using real-time data. They calculated mechanical specific energy, hydraulic mechanical specific energy (HMSE) and unconfined compressive strength pressure (UCS) from log data to evaluate drilling efficiency. Loss circulation depths were categorized as [1] for no loss and [0] for loss events. An equation was developed to relate loss events to energy applied to loss zones, showing a significant difference between energy applied and excavation energy in the wells. Loss circulation severity was estimated from daily reports, and HMSE and UCS were used to predict severity. The study also quantified the impact of pressure differentials between zones in real-time. The workflow was validated on historical wells and compared to an analytical model.

Standpipe pressure and annular discharge pressure

Standpipe pressure (SPP) and annular discharge pressure (ADP) are critical parameters in drilling operations. SPP refers to the pressure in the standpipe, which is a key indicator of the drilling fluid's circulation system. ADP, on the other hand, is the pressure in the annular space between the drill string and the wellbore wall. Monitoring these pressures is essential for maintaining control over the well and ensuring safe drilling operations. The pressure difference between the SPP (inlet) and ADP (outlet) is used to detect abnormal flow conditions. A kick is identified by a simultaneous increase in both SPP and ADP, while a plugged drill string is indicated by an increase in SPP and a decrease in ADP. Maintaining steady-state flow with no pipe movement is crucial to prevent false alarms. Analysing delta-flow and pressure difference focuses on flow effects rather than direct comparisons. Le Blay et al. (2012) proposed comparing expected and measured flow rates to detect discrepancies, requiring continuous parameter monitoring under all flow conditions. This method relies on an accurate hydraulic model to reduce false alarms.

Delta flow

The difference between the inflow rate and outflow rate is known as delta-flow (Maus et al. 1979), providing a quick indication of any fluid loss or gain in the wellbore. A specialized system is used to monitor this parameter. Accurate measurement of both rates is crucial for reliable results (Schafer et al. 1992). Discrepancies in flow rates, whether due to operational factors or natural variations, can result in false alarms. Activities like mud pump operation, drill-string movement and heave motion of the floating vessel from slip-joint telescopic movement can trigger false alarms (Speers and Gehrig 1987).

Monitoring pit volume

Monitoring pit volume changes using mechanical devices like pit level indicators can help identify fluid loss or gain issues (Anfinsen and Rommetveit 1992). Comparing calculated and measured trip-tank volumes during tripping-in and tripping-out operations ensures the correct fluid volume is introduced into the well. However, interpreting changes in pit volume can be challenging when the inflow rate fluctuates or when mud pumps are turned on or off, as mud is stored in return flowlines of different equipment (Cayeux and Daireaux 2017). Detecting lost circulation issues can be difficult if the timing of mud pump activation and deactivation does not align with the reference data (Ali et al. 2013). Overcoming this difficulty involves detecting lost circulation issues by comparing five to ten flow rate patterns and mud pit level changes to establish a threshold for identifying lost circulation events (Brakel et al. 2015).

Survey tools for identifying loss circulation zones

Temperature survey

A temperature survey tool with platinum-based thermistors was used to measure formation temperatures at different depths in a wellbore. The tool converts sensor resistance into voltage and is capable of detecting temperature changes. The tool is first lowered into the well to establish a baseline temperature profile. Fresh mud is then introduced to create a temperature difference between the formation and the mud, and temperature changes are recorded during a second run. Analysis of the data shows that temperatures in the second run are lower above the loss circulation zone but increase significantly just below it due to drilling fluid seepage. This allows for the identification and accurate depth determination of the loss circulation zone based on temperature anomalies (Mitchell and Miska 2010).

Hot wire survey

The hot wire survey is a method used to monitor temperature changes in wellbore fluid. It involves using a resistance wire to transfer heat to the fluid. The rate of heat transfer is affected by the temperature difference between the fluid and the wire, as well as the fluid velocity (McDonald et al. 1981). By measuring the rate of heat loss, the fluid velocity can be determined. The tool is placed in the desired location, and a temperature change indicates that the tool is above the thief zone, while no change suggests it is below the thief zone (Mitchell and Miska 2010). This survey can be conducted in any mud system but requires a significant amount of mud for accurate results.

Spinner survey

Spinner flowmeters are commonly used to measure fluid velocity by monitoring the rotation of spinner blades in rounds per second (RPS). A small spinner attached to a wire is placed at suspected thief zones to detect fluid loss. The RPS data recorded on film helps determine the severity of the thief zone by calculating fluid loss rate. This survey method, similar to hot wire surveys, requires a significant amount of mud for accurate results (Shad et al. 2015; Whittaker 2013; Mitchell and Miska 2010).

Radioactive-tracer survey

Radioactive-tracer surveys are a common method used to detect and locate loss circulation zones during drilling operations. A gamma-ray log tool, equipped with radioactive tracer material such as carnotite, is employed with detectors positioned at the top and bottom of the tool. The tool is maneuvered up and down the wellbore to establish a base log, after which the tracer material is mixed with the fluid (McKinsley and Carlson 2007). By comparing the second gamma-ray log data with the base log, areas of fluid loss can be pinpointed accurately. While this method offers precise detection of fluid loss, it necessitates specialized equipment and incurs significant costs (Mitchell and Miska 2010).

Detecting fluid loss using geostatistics-based methods

Geostatistics-based detection modelling is a valuable tool for characterizing reservoir heterogeneity at small scales. Abdideh (2014) used geostatistical methods, particularly kriging, to accurately predict mud loss volume and analyse variable reservoir parameters. Willersrud et al. (2015a, b) developed a fault diagnosis system (FDS) that employs a multivariate statistical detection algorithm with the generalized likelihood ratio test (GLRT) to detect operational anomalies like lost circulation during drilling. The FDS monitors changes in parameters and flow rates to identify and isolate faults, focusing on frictional pressure and flow rates to detect fluid loss effectively. Garrouch and Lababidi (2001) introduced the Lost Circulation Index (*LCI*) to assess the risk of lost circulation during drilling. The *LCI* considers factors such as permeability, porosity, fractures and vugs in the reservoir, assigning index values based on severity. The *LCI* is calculated as the product of the likelihood of these events occurring, using a maximum permeability of 4000 md and porosity of 40%. Guidelines for interpreting outcomes based on the *LCI* are as follows:

- *LCI* greater than 5% indicates severe lost circulation.
- *LCI* less than 0.1% suggests no issues.
- *LCI* between 0.1 and 5% indicates potential for some loss.

Analysis of wellbore temperature (analytical and numerical methods) under lost circulation

In well engineering, temperature field research in a wellbore is typically conducted using analytical or numerical methods. Various models have been developed to analyse heat transfer processes in drilling operations. Holmes and Swift (1970) introduced an analytical model for steady-state heat transfer between the fluid in the drill string and the annulus fluid. Raymond (1969) developed a one-dimensional numerical model to study temperature distribution in vertical wells. Keller expanded on this model to include inner heat sources and created a two-dimensional transient heat transfer model considering factors like drill string rotation and friction resistance of drilling fluid. Romero studied the impact of circulation time, displacement and seawater temperature on wellbore temperature during deep-water drilling. Mou et al. (2013) developed a radial grid model for drilling fluid temperature distribution. Li et al (2015) examined heat sources during horizontal well drilling and their impact on temperature distribution. Li et al. (2015) established a transient heat transfer model for wellbore-formation interactions during drilling fluid circulation and well shut-in. Yang et al. (2019) developed a transient heat transfer model for deepwater multigradient drilling, emphasising numerical methods for comprehensive analysis of factors influencing wellbore temperature distribution. Research on wellbore heat transfer of drilling fluid under no-loss circulation conditions is well-established. However, there is a lack of studies on variable mass heat transfer of annulus fluid under loss circulation. Chen et al. (2017) developed the first variable mass heat transfer model for wellbore under loss circulation conditions and proposed a method to identify the loss zone based on temperature gradient curves. This model had limitations in considering heat sources generated during drilling and the impact of casing programs on wellbore temperature distribution, leading to errors in deep and ultradeep well drilling processes. Wang et al. (2020) expanded on the Chen model by incorporating internal heat sources from drilling and casing programs to predict wellbore temperature profiles under loss circulation. Zhang et al. (2020) proposed a two-dimensional wellbore temperature distribution model based on regional loss, highlighting the significant impact of two-dimensional loss on annulus temperature profiles but lacking the ability to pinpoint the loss zone. Building on these models, Ao (2022) established a coupling model of wellbore temperature and pressure fields under loss circulation, considering the mutual effect of physical parameters of drilling fluid, wellbore temperature and pressure. The study found that under loss circulation, the density and viscosity of drilling fluid initially decrease and then increase with increasing well depth. Loss circulation reduces volume flow, annulus pressure loss and convective heat transfer coefficient, leading to a significant decrease in annulus temperature near the loss zone. Additionally, when loss occurs in the upper open-hole section, the temperature difference curve shows an inflection point near the loss zone, aiding in identifying the location of the loss zone.

Lost circulation prediction using machine learning

A high level of flexibility in classification, selection, prediction and optimization has enabled machine learning and artificial intelligence to flourish in petroleum operations. Therefore, ML is a powerful method for learning from drilled well data and predicting the outcomes of new wells based on complex non-linear relationships between input parameters and output results. ML (Fig. 2) is a subset of AI that

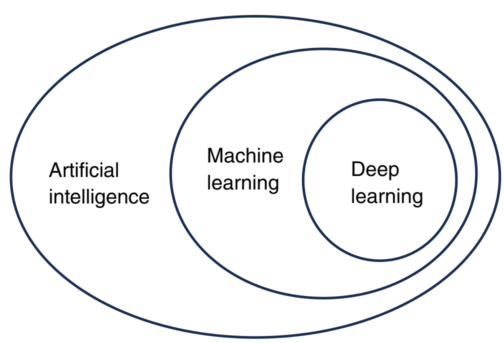

Fig. 2 AI, ML, and DL

enables computers to learn without explicit programming (Samuel 1959). A traditional programming model runs both the data and the program on the computer to compute the output, whereas ML runs both the data and the programme simultaneously to develop the programme (Brownlee 2015). Figure 3 presents this concept. A machine learning (ML) method, as described by Mitchell (1997), uses a combination of data and knowledge to automate a specific task. In other words, ML predicts the future by identifying patterns.

ML algorithms

ML algorithms are mathematical models used to perform tasks like regression, classification and clustering. Many fields, including natural language processing, and medical diagnostics, have recently benefited from ML (Schmidhuber 2015). Machine learning algorithms work by transforming a set of data into a model that identifies patterns or makes predictions based on new data. The ML algorithm is made up of three key components:

- Representation: the algorithm for representing knowledge of data patterns Regressors, classifiers, decision trees, SVMs, model ensembles and other algorithms are examples.
- Evaluation: how to determine whether the selected algorithms are effective. Examples include mean squared error, accuracy, precision, recall, etc.
- Optimization: modifying the model's hyperparameters to improve model performance.

All ML algorithms are made up of these three elements, which can be considered a framework for understanding all algorithms.

Types of learning algorithms

According to Brownlee (2019), ML algorithms can be divided into four types. Supervised ML algorithms are programmes that learn while being supervised. The algorithm can learn from a labelled training data set created by subject-matter experts. The algorithms then apply what they have learned to unseen data. Without any training, the algorithm randomly searches through the data for patterns and commonalities. This is referred to as unsupervised learning. Compared to unsupervised and supervised learning, semisupervised learning falls somewhere between them. Unlabelled data points are labelled by using knowledge from labelled data points, using a mix of labels and unlabelled examples. In order to organise data and make predictions, the model must learn the structures. Reinforcement is a method of learning. It works like this: there is an agent and an environment. As a result, the agent would be able to reward or punish the environment. For more than half a century, ML has been developed, and there are now numerous algorithms. ANNs are the most frequently employed ML technique in drilling operations (Hassoun 1995). The complex interactions between preferred objective functions and input parameters are identified and approximated using ANN. It is a flexible and easy-to-implement algorithm that can be used for both supervised and unsupervised ML challenges. The SVM is an advanced machine learning model that provides regression, classification and outlier detection capabilities (Cortes and Vapnik 1995). Drilling practitioners have used SVMs in ML applications especially effective at classifying complex small- to medium-sized data sets (Geron 2017). Linear regression and logistic regression (LR) are a few of the regression algorithm variations used in drilling publications (Cox 1958). In the papers examined in this research, the DT algorithms were used due to their simplicity and interpretability. In terms of flexibility, Decision trees and random forests (RF) (Breiman 2001) are similar to SVMs because they are ML algorithms that can perform regression, classification and multioutput functions. They are highly efficient algorithms that excel at fitting complex data sets. DT is also a key component of RF, one of the most efficient ML algorithms currently available (Geron 2017). The advantages and disadvantages of a few of these algorithms are shown in Table 5 (Geron 2017; Shoombuatong et al. 2018).

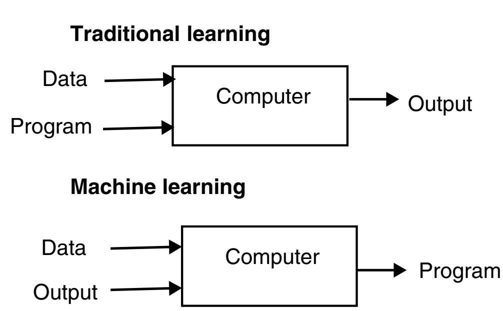

Fig. 3 Traditional programming and ML (Adopted from Brownlee 2015)

ML project

Figure 4 illustrates a typical workflow of a ML project.

Data gathering Various data sets from different wells should be collected. Each data array should contain a well event as well as various features relating to the final resolution of lost circulation. Mud parameters, drilling parameters and geological parameters are the three types of data most frequently used in ML studies of lost circulation prediction. In drilling operations, records of drilling data may vary according to the service provider and the facility. Drilling data

Table 5 Common ML models' strengths and weaknesses

Algorithm	Strengths	Weaknesses	Authors
LR Logistic regression	• Robust to noise • No scaling or tuning required • Parameters are interpretable • Simple and easy to interpret • Computationally inexpensive	• Data preparation is required • It only works with linear decision boundaries • Predictive performance is often poor	Dreiseitl and Ohno-Machado (2002)
SVM Support vector machine	• Effective in complex domains • Capable of handling high dimensional issues • Able to model non-linear decision boundaries • Effective with outliers	• Require the preparation of data • Complicated to tune • Picking a kernel can be challenging • If the dataset is large and noisy, poor performance and prolonged computation time will result	Bottou and Lin (2007), Soofi and Awan (2017)
ANN Artificial neural network	• Resistant to noise and missing values • The architectures are adaptable to various issues • Effective performance on a few tasks, such as text and image recognition • Can address non-linear relationships • Predict situation with unknown relationship types between the input and output parameters	• Interpretability issues • Requires a lot of data • Expensive to compute • The architecture and hyper-parameter tuning take time	Anderson and McNeill (1992), Dreiseitl and Ohno-Machado (2002)
RF Random forest	• No effort required for data preparation • Able to rank feature importance • Functions well in high-dimensional spaces • Handles a large number of features • Evaluates the contribution of each feature • Requires less training time	• There is a lack of interpretability when the number of trees is large • May overfit if the data is noisy • It takes a lot of memory to store datasets as large as trees	Soofi and Awan (2017)
DT Decision tree	• Easy to comprehend and interpret • Able to learn non-linear relationships • No prerequisite data normalization or scaling	• Frequently inaccurate • It has moderate to high variance • Model instability can be caused by even a small change in the data • Long training time	Dietterich and Kong (1995), Ghosh et al. (2017)
GA Genetic algorithm	• Global optimization • Efficiency and ease of implementation • Parallel processing • Flexibility and ease of modification for different problems	• Computationally expensive, i.e. time-consuming	Sankar et al. (2023)
KNN k-Nearest neighbours	• Susceptible to noisy training data • It is possible to approximate the target function locally due to slow learning (training data generalization is delayed until a query is made) • Simple and easy to interpret	• Sensitive to outliers • The number of nearest neighbours must be specified • Memory-intensive • As the number of data points increases, model speed decreases	Guo et al. (2003), Soofi and Awan (2017)

usually needs to be carefully examined for quality due to the noise in the top drive. Logging and standard wireline logging can provide comprehensive rock data. Despite the fact that advanced drilling logging and measurement provide real-time measurements, their costs make them unaffordable. Smoothing is a common approach in well logging and can be applied to both drilling and log data. The Savitzky-Golay (SG) filter is another method for noise reduction. Originally, it was used to smooth data from chemical spectrum analysers. The concept of a fixed impulse can be used to fit polynomials to various criteria and investigate the outcomes to estimate a data interval (Savitzky and Golay 1964). The number of data points at such intervals should be odd. It is also recommended that they are less than the order number of the polynomial. The algorithm's data smoothing effects can be enhanced by eliminating more initial noisy data,

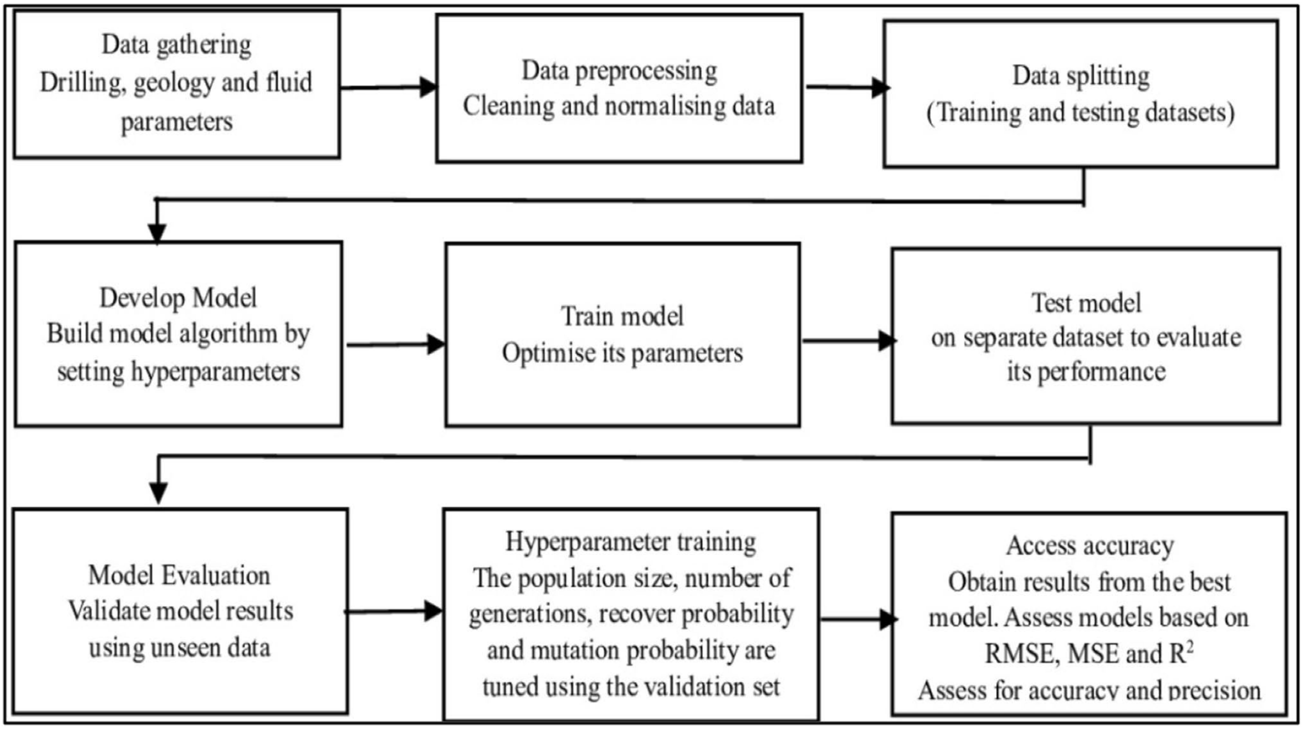

Fig. 4 Flowchart of a ML project

making these conditions essential. As a result, identifying these two influencing variables is essential for effective noise reduction. Using various SG filter designs, analyse and process data variables from daily drilling reports (DDRs), daily mud reports (DMRs), end-of-well reports (EWRs) and well geological settings across the field. Once the data has been smoothed, all non-numeric values (such as −999.25 in logs) and outliers need to be removed. Drilling data measurements are subject to uncertainty, the majority of which is due to human error and/or equipment failure. This has always been a major challenge. Data from these sources should be examined and validated to remove data that appears to be incorrect (also known as outliers). During the training and prediction phases, outliers can have a significant impact on ML performance.

Data pre-processing Analytics is defined as the collection, processing and analysis of data (Bravo et al. 2014a). The transformations performed on the data prior to feeding it to the algorithm are referred to as data pre-processing (i.e. cleaning the data to achieve homogeneity). Dealing with missing values, outliers, biased data and other issues is part of this (Bravo et al. 2014b). Data preparation is one of the most challenging stages in any ML project. This is due to the fact that each dataset is unique to the project (Brownlee 2020). The following reasons prevent raw data from being directly used in ML models:

- ML algorithms require numerical data.
- Some ML algorithms set constraints on the data. The collected data must be corrected for errors and statistical noise.
- It may be difficult to obtain data for complex non-linear relationships.

Data cleaning appears to happen after data collection to check for errors and remove or fix data as needed. Remove all duplicate values from the dataset. Considering that each feature has a different relevance to the output, it was necessary to carefully review all of the collected data in order to assess its importance and eliminate features that were not relevant (Holdaway 2014).

Missing values

Real-world data frequently contains missing values. Observations that are not recorded or data that have been corrupted can result in missing data values. Many ML algorithms do not handle missing values, so handling them is crucial. An effective strategy should be in place for dealing with missing values. Missing values in research data can result from a number of issues, such as insufficient data, inaccurate data or mistakes during data entry. Missing values can be ignored by data mining (DM) methods; relevant records can be excluded; a variable mean can be used instead; or missing values can be inferred from existing values. The methods for replacing missing values are listed below:

- Using domain knowledge, manually fill in any missing values.
- Disregard the records that lack values.
- Use a universal constant (like "?") to fill in any missing values.
- If a variable is categorical or numerical, replace missing data with the most frequent or the mean value, respectively.
- Apply modelling strategies.

Based on subject-matter expertise, categorical imputation was used to replace the missing values in the dataset with other comparable values.

Detecting outliers

As the term implies, a significant difference exists between a particular data point and the rest of the set. An outlier can create issues with statistical analysis. Outliers can occur in any distribution by chance. Outliers may indicate missing data or faulty procedures. However, fewer outliers are to be expected in large data samples, and this is not due to a faulty condition.

Feature engineering

Feature engineering involves extracting attributes from unprocessed data by incorporating domain knowledge. It is desirable to enhance the efficiency of ML algorithms in order to reduce the computation cost of modelling and, in some cases, improve model performance. The effectiveness of ML algorithms could be increased by utilizing these features. Two or more features can be combined to form a single feature, aiding in reducing dimensionality and enhancing model performance. Two of the most popular feature engineering methods are categorical encoding and feature scaling. Any structured dataset that uses categorical encoding contains a variety of columns that combine numerical and categorical features. In Fig. 5 (Alakh 2020), each text category is encoded into numbers before it can be processed by model algorithms. Categories are transformed into numbers through categorical encoding. Label encoding and one-hot encoding are the two strategies that are most frequently used. Each text label is assigned a unique integer as part of label encoding, taking alphabetical order into account. There is a high likelihood that the model in this type of encoding captures false relationships between features. One-hot encoding, which generates dummy variables for each data feature, is an option. It is necessary to transform textual or symbolic data into numeric form before ML methodologies can use it for variables like type of formation. Numerous techniques, including binary encoding, unary encoding, and numbering classes, can be used to accomplish this.

Feature scaling

A key technique used to normalise the variety of data features is feature scaling. It is also referred to as data normalization and is typically used during the data preprocessing step. A number of ML algorithms require normalization of raw data when there are diverse sources of raw data. "Min–max scaling," also known as "min–max normalization," is the most straightforward technique for feature normalization and scaling. The following equation (Eq. (1)) provides the general formula for a min–max of [0, 1].

Normalization of input and output data is one of the most important steps in improving model accuracy. Each variable should be linearly scaled to the same range in order to prevent biases brought on by variable magnitudes. This will speed up training and significantly decrease overall computational times for each model. In Deosarkar and Sathe (2012), the difference between the highest and lowest values of each variable (xi) is divided by the sum of those values

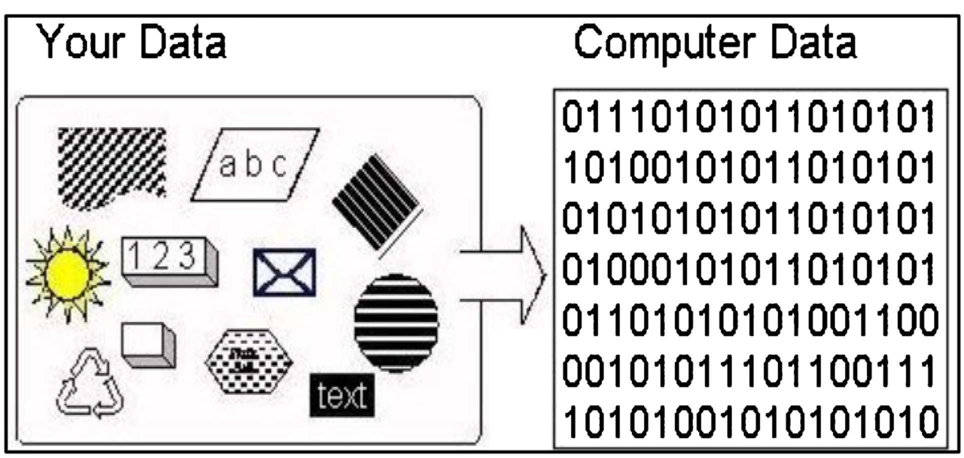

Fig. 5 Data processing (adopted after Alakh 2020)

to normalize each variable. Equation (1) is a mathematical representation of this formula.

$$x_i^n = 2 \times \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} - 1 \quad (1)$$

where x_i^n = the normalized value. x_i = the actual value.

Input parameters selection (feature ranking)

Once the data has been preprocessed (outliers identified), select the key parameters that will determine the model's outcome. Feature selection involves retaining only useful features and removing redundant ones. Use domain knowledge to determine if any features should be removed. If domain knowledge is lacking, utilize feature selection techniques such as filter-based, wrapper-based and hybrid. Expert opinions, statistical analysis, simulation, experimental tests, sensitivity analysis and other factors can all be used to select relevant inputs. ML applications have evolved from using fewer than ten features to hundreds in some cases. Removing irrelevant and redundant variables enhances prediction accuracy and computational efficiency. Many ML applications face inefficiencies due to these variables. According to Jain and Zongker (1997), "feature selection" involves determining which features (variables) will provide the most accurate predictions. This decision is often NP-hard (non-deterministic polynomial) as it requires evaluating all possible combinations of available variables after numerous iterations (Chandrashekar and Sahin 2014). Feature selection is crucial not only for preventing overfitting but also for extending analysis, processing data faster, and developing more accurate, streamlined models. The choice of predictive model directly impacts how variables are ranked in terms of their significance. Therefore, selecting a reliable model for feature selection is essential.

Algorithm selection and training

There are many algorithms in the field of machine learning, some of which can be used easily and others which require a higher level of understanding (Khan et al. 2020). A predictive model is created from historical data to make predictions based on new data for which we have no previous knowledge. Solving a mathematical problem requires an approximate mapping function (*f*) between input variables (*x*) and output variables (*y*). ML algorithms cannot learn some parameters; these parameters must be set prior to learning. These variables are referred to as hyperparameters. Model predictability can be increased (with a smaller loss or greater accuracy) by tuning hyperparameters. Once the time-consuming preprocessing is completed, the preprocessed data can be divided into training data and test data. To avoid model overtraining and ensure models perform as expected with unseen samples, a proper data split technique is required. An 80%/20% ratio is commonly used to divide training and test data. Classification tasks may require the use of data manipulation techniques if the data is unbalanced. The distribution of data in those classes is unbalanced when a majority class has more samples than a minority class. Using undersampling or oversampling methods for the majority and minority classes, respectively, will improve model performance. Then, ML algorithms can be fed the training data. It is advisable to test out various algorithms before choosing the best one. Cross-validation, grid search and hyperparameter tuning are methods for optimizing ML models with validation data. To apply the predictive model(s) to test data, the preferred predictive model(s) must first be generated. After applying the predictive models to the test data, the comparison between predicted and actual results is performed. To analyse the performance of ML models, a variety of evaluation metrics can be used. Tree-based ML algorithms allow for determining the significance of inputs. Therefore, if designers are knowledgeable about which inputs are more crucial than others, they can pay particular attention to them during data collection and processing, possibly enhancing model performance.

ML selection models

The performance of various ML algorithms depends on the complexity of the classification problem and the size of the data. Due to the complex non-linear relationships among the dataset variables, determining the best-performing model without empirical experimentation is extremely difficult. Previous research has shown that simpler and faster linear models solve simple classification problems better, while more complex non-linear models fit more complex problems better (Magana-Mora and Bajic 2017). Pedregosa et al. (2011) conducted an evaluation of the performance of various models in Python, along with ANN, RF and DT from the Scikit-learn ML library. An extensive empirical study revealed that RF and ANN were the most effective algorithms in the UCI machine-learning repository (Alshahrani et al. 2017). The reliability of these specific ML algorithms has also been demonstrated in several studies pertaining to drilling hazard prediction (Magana-Mora et al. 2020; Alshaikh et al. 2019). Finally, due to the model's clarity and interpretability, DT was taken into consideration.

LR (Cox 1958) is a common categorical variable classification algorithm. In logistic regression, features are correlated with outcomes to find out which is more likely to occur. The term "Logistic" refers to this classification technique, which is derived from the Logit function.

SVM (Cortes and Vapnik 1995) is a common non-probability supervised ML algorithm that is used for classification, regression and outlier detection. It excels at complex classification problems with small or medium data sets. The structural risk minimization (SRM) principle underpins the SVM. It reduces the expected error, which can aid in the reduction of over-fitting issues. The quadratic programming technique with a linear constraint is used in the SVM learning approach. SVM's mechanism is to identify the decision boundary with the "widest margin" that separates different classes. To perform tasks in high-dimensional feature spaces, SVM employs various kernels (e.g. linear kernel and polynomial kernel).

ANN (Hassoun 1995) In solving complex problems involving non-linear relationships, artificial neural networks (ANNs) are remarkably powerful tools based on the neural networks in animal brains. The neural network is made up of nodes known as artificial neurons to model a biological brain. In a deep neural network, there are multiple nodes on each layer (an input layer, many hidden layers and one output layer). The ANN performs mathematical computations between neurons in the input and output layers. For classification problems, ANN, like the LR, returns the probability of a class.

RF (Breiman 2001), due to variance, a single decision tree's prediction may be incorrect. Averaging predictions from hundreds or thousands of trees can solve this problem. During the model-building process, data are mapped to outputs using decision trees, the fundamental components of a random forest. The random forest's decision trees each generate an estimate by posing a series of queries that help them eliminate possibilities until they are certain they can make a prediction.

Despite being a supervised learning algorithm, decision tree (DT) is most commonly used for classification problems, though it can also be used for regression problems. As a tree, its internal nodes stand in for dataset features, its branches represent decision-making, and its leaves represent the results. A leaf or terminal node in a decision tree classifies an example, organizing examples in the tree from the root to the leaf or terminal node.

A summary of ML studies used to predict lost circulation is shown in Table 6.

Evaluation metrics

Almost all engineering problems are regression-based since they aim to predict a property value (for example, viscosity, density and pressure). Evaluation metrics measure the difference between predicted and actual values for regression problems. There are several regression metrics, including correlation coefficient r (or R), coefficient of determination R^2, mean absolute error (MAE), and root mean square error ($RMSE$). Higher r and R^2 values indicate better results. Lower MAE and $RMSE$ values, on the other hand, indicate better performance. If the model's performance is lacking, adjust the hyperparameters or fitness function. The equations for these metrics are as follows:

Mean square error (MSE) expressed in Eq. (2)

$$MAE = 1/n \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{2}$$

where n = the total number of data points. y_i = the true value. $\hat{y}_i$ = the predicted value.

The lower the value of the MSE, the better the model's prediction (Agwu et al.2021).

Root mean square error ($RMSE$) is expressed in Eq. (3)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2} \tag{3}$$

where n = the total number of data points. y_i = the true value. $\hat{y}_i$ = the predicted value.

Coefficient of determination (R^2) expressed in Eq. (4)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (f(x_i) - y_i)^2}{\sum_{i=1}^{n} f(x_i)^2 - \frac{\sum_{i=1}^{n} (y_i)^2}{n}} \tag{4}$$

where n = number of observations in the dataset. $f(x_i)$ = the predicted value. $\hat{y}_i$ = the actual value.

Challenges and future prospects of LCMs, conventional and intelligent modelling

Despite their usefulness, LCMs encounter challenges when it comes to sealing large fractures, especially in fractured-vuggy formations. They also face difficulties in high-pressure, high-temperature conditions found in deep and ultra-deep wells. To address these challenges, further research and development are needed to enhance the intelligence of LCMs and their associated equipment. While most studies have been conducted in laboratory settings, field-scale testing is crucial for real-world application. Additionally, nanotechnology research plays a vital role in improving LCM outcomes and will be instrumental in the future success of the oil and gas industry. Survey tools like radioactive-tracer surveys, temperature surveys and spinner surveys can identify loss circulation thief zones, but they are costly and time-consuming. Conventional tools for predicting loss circulation events have limitations. A sensor-based tool integrated into the drillstring could provide real-time forecasting by monitoring parameters such as bottom-hole differential pressure, downhole density, mud rheology and temperature. This

Table 6 A summary of ML studies used to predict lost circulation

Authors	Prediction method	No. of input variables	Sample size/field	Input parameters	Performance
Moazzeni et al. (2012)	ANN	18	589 Marun	Well depth, trajectory, drilling time, open hole length, formation top, hole size, flow rate, mud pump pressure, density of mud, solid content, filtrate volume, mud volume lost, formation type, porosity, permeability and minimum horizontal stress profile are all important factors to consider when drilling a well. Additionally, the Fan300 and Fan600 should be taken into account	0.76
Moazzeni et al. (2010)	ANN	15	32 wells Marun	DG, DSL, drilling time, formation top, well coordinates (easting and northing), hole diameter, mud flow rate, mud pump pressure, mud density, solid content, Fan 300, Fan 600, filtrate and mud volume lost	0.82
Sabah et al. (2019)	ANN, ANN with GA and DT	19	1900 Marun	Drilling length, north, east, hole diameter, WOB, flow rate, mud pump pressure, Fvisc, Fan300, Fan600, gel 10 m, drilling time, depth, solid content, string rotational speed, drilling meterage, FPP, FFP and mud density	DT 0.93
Agin et al. (2020)	Data Mining; ANFIS	18	42,948 Marun	Drilling-meterage, drilling-time, mud velocity, hole diameter, WOB, mud flow rate, mud pump pressure, Fvisc, FAan300, FAN 600, GS10 min, solid content, RPM, FPP and FFP, mud pressure, formation type and fluid loss severity	
Sabah et al. (2021)	MLP, MLP-GA, MLP-PSO, MLP-COA, LSSVM, LSSVM-GA, LSSVM-PSO and LSSVM-COA	10	2820 Marun	North, east, formation type, hole diameter, FPP and FFP, mud pump pressure, Fan300, Fan600, gel 10 m/gel 10 s, RPM	0.93
Jafarizadeh et al. (2023)	LSSVM; CNN; COA-MELM; PSO-MELM; GA-MELM; COA-LSSVM; PSO-LSSVM and GA-LSSVM	9	2783 Marun	Pump pressure, mud density, formation fracture pressure, formation pore pressure, well depth, gel 10 m/gel 10 s, Fan600/Fan300, flow rate and formation type	0.95
Jahanbakhshi et al. (2013)	ANN	20	260 Southern Iranian oilfield	Well depth, formation porosity, formation permeability, differential pressure, SSP, ECD, PV, YP, initial and 10 min gel-strength, Fvisc, mud solid content, temperature. Tensile strength, uniaxial strength, horizontal stress, E-modulus, average pump pressure, mud filtrate and ROP	0.94

Table 6 (continued)

Authors	Prediction method	No. of input variables	Sample size/field	Input parameters	Performance
Toreifi et al. (2014)	ANN and PSO	16	1630 Marun	Geographic coordinates, depth, formation type, formation top, SSP, flow pump rate, ROP, mud pump pressure, filtrate viscosity, mud solid content, PV, initial and 10 min gel strength, annulus volume and YP	0.96
Far and Hosseini (2017)	ANN with GA	4	3 wells Iraq UBD	Mwt, pump pressure, drilling depth and flow rate	0/95
Al-Hameedi et al. (2018)	MLR	9	500 wells Iraq	Drilling-parameters (ROP, WOB, pump flow rate, RPM and SPM), nozzles TFA, ECD and mud-properties (MW, PV and YP)	0.83
Li et al. (2018)	ANN, SVM and RF	12	6976 Iraq	Depth, lithology, pore pressure, geostress, mud-properties (mud weight, PV, YP, gel-strength and filtration), drilling-parameters (ROP, mud pump pressure and mud flow in)	46.6% (ANN), 55% (SVM) and 56% (RF)
Abbas et al. (2019)	ANN and SVM	19	744 Iraq	Mud-properties (MW, PV, YP, etc.), drilling-parameters (ROP, WOB, pump flow rate, RPM, etc.), lithology, wellbore trajectory, etc	ANN 0.81; SVM 0.91
Alkinani et al. (2019)	ANN	8	10,000 Worldwide	Mud-properties (MW, ECD, PV and YP), RPM, WOB, pump flow rate and nozzles total flow area	0.925
Geng et al. (2019)	Ensemble method (LR, RF and SVM	5	218,400 Iraq	Seismic attributes (variance, attenuation, sweetness, amplitude, intensity and time)	0.81
Ahmed et al. (2020)	ANN and SVM	9	> 5000 Anonymous Middle East	Depth, Torque, WOB, HKHT, HKL, FPWPMP, ROP, RPM and SPP	ANN 0.981; SVM 0.997
Alkinani et al. (2020)	ANN, DT, LR, SVM and Ensemble method	4	> 3000 wells Worldwide Multiple Sources	Reason, treatment number, type of loss and well type	NA
Hou et Al. (2020)	ANN	14	50 wells South China Sea	Drilling-parameters (WOB, RPM, SPP, FR, TFA and MD), mud-properties MW, YP, PV, solid content, formation properties (lithology, FFP, FPP, UCS, etc.)	0.93
Pang et al. (2022)	MDN	16	120 wells Iraq	Temperature in and out, mud density in and out, conductivity out, ECD, total gas, pit volume total, MD, TVD, ROP, HKL, mud pump pressure, SPM and flow in and out	NA

offers a cost-effective and efficient solution for monitoring fluid loss incidents.

Literature suggests that artificial intelligence techniques can accurately predict and detect loss circulation with a reasonable level of uncertainty. The Multi-Gene Genetic Programming approach has shown effectiveness in various applications. Implementing this method could help forecast fluid loss and reduce risks to well integrity and operational costs. It is important to validate predictive results by comparing them with outcomes from other established AI techniques. Field data quality is a significant concern, as drilling measurements can be inaccurate due to human error or equipment failure caused by harsh environmental conditions (i.e. temperature changes and mechanical shocks). Establishing a regular equipment calibration cycle is crucial to prevent misinterpretation of data by the drilling team.

Datasets are collected at different frequencies from various rigs using different acquisition systems. It is recommended that future wells be equipped with a digital system to gather essential surface parameters and mud system characteristics consistently. This system can provide solutions and accurately predict the onset of circulation problems based on its findings.

Conclusion

A sensor-based tool integrated into the drill string can predict and detect loss circulation in real-time, offering a significant advancement in the oil and gas industry. Artificial intelligence and machine learning have significantly contributed to petroleum operations by saving computation time, reducing associated expenses and providing effective solutions. The main differences between existing models are the type of model used, the input parameters selected and the accuracy of loss circulation prediction. A review of these models shows that they produce satisfactory results. However, it may be possible to improve them for more precise systems by incorporating AI techniques such as genetic algorithms. This requires reducing the amount of data and investigating compatibility between these tools and the company's current software platform. The Multi-Gene Genetic Programming technique has been used in various fields and applications but has not yet been used to predict fluid loss. Industrial operations are replacing harmful LCMs with environmentally friendly materials that are safer for people, the environment and marine life. A machine learning workflow for fluid loss prediction has been presented, and collaboration between academic researchers and industry will benefit the entire drilling industry. This has the potential to significantly reduce operational costs and minimise risks to people and the environment.

Symbols and abbreviations AI: Artificial intelligence; ANFIS: Adaptive neuro-fuzzy inference system; ANN: Artificial neural networks; bbl/h: Barrels per hour; CBR: Case-based reasoning; CNN: Convolutional neural network; COA: Cuckoo optimization algorithm; DDRs: Daily drilling reports; DMRs: Daily mud reports; DT: Decision trees; EWRs: End-of-well reports; FR: Flow rate; ft: Feet; GA: Genetic algorithm; CNN: Convolutional neural network; GP: Genetic programming; HPHT: High-pressure high temperature; LCM: Loss circulation materials; MGGP: Multi-gene Genetic Programming; min: Minutes; ML: Machine learning; MLP: Multi-layer perceptron; GA-MLP: Genetic algorithm-multi-layer perceptron; TFA: Total flow area; MW: Mud weight; SSP: Standpipe pressure; ADP: Annular discharge pressure; HKL: Hook load; PP: Formation pore pressure; FFP: Formation fracture pressure; BHA: Bottom-hole assembly; UCS: Unconfined compressive strength; RMS: Root mean square; NPT: Non-productive time; OBMs: Oil-based muds; psi: Pounds per square inch; PSO: Particle swarm optimization; PSO-MNN: Particle swarm optimization–modular neural network; R^2: Coefficient of determination/regression coefficient; *RMSE*: Root mean square error; *ROP*: Rate of penetration; RPM: String rotary speed per minute; SQRT: Square root; SVM: Support vector machines; USD: United States dollars; WBMs: Water-based muds; OBMs: Oil-based muds; WOB: Weight on bit; m^3/day: Cubic meter per day; m^3/h: Cubic meter per hour; *MAE*: Mean absolute error; MELM: Multilayer extreme learning machine; MFVIS: Marsh funnel viscosity; LSSVM: Least-squares support vector machines; MNN: Modular neural network; ECD: Equivalent circulation density; PV: Plastic viscosity; YP: Yield point; HKHT: Hook height; DG: Drilled depth from ground; DSL: Drilled depth from sea level; PWD: Pressure while drilling; HMSE: Hydraulic mechanical specific energy; LCI: Lost circulation index

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Author contribution All the authors have sufficiently contributed to the study and agreed with the results and conclusions. MA: conceptualization, methodology, formal analysis, investigation and writing—original draft preparation; MK: writing, review and editing.

Declarations

Competing interests The authors declare no competing interests.

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