International Refereed Journal of Engineering and Science (IRJES)
ISSN (Online) 2319-183X, (Print) 2319-1821
Volume 15, Issue 2 (Mar. – Apr. 2026), PP. 28-34

Development of Interpretable Machine Learning Systems for Actionable Drilling Fluid Recommendations

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Abstract
Drilling fluids are important to the efficient and safe operation of oil and gas wells because optimization of drilling fluids is essential. Conventional techniques are quite time-consuming, and are based on expert opinion and laboratory assays, which fail to provide an extrapolation to different geological settings. This paper describes the creation of interpretable machine learning (IML) systems to give actionable drilling fluid recommendations. Based on simulated datasets of the main drilling parameters such as mud weight, rheology, pH, formation pressure, and temperature a number of machine learning models were trained and tested as well as include the Random Forest, Gradient Boosting, and Explainable Neural Networks. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) were used to improve the interpretability of models to identify the most significant factors that drive fluid behavior. The findings show that the highest predictive accuracy with an R2 of 0.87 and an RMSE of 0.12 are produced by the Random Forest model to predict optimal mud weight and the model gives explicit rankings of the features. SHAP analysis identified formation pressure, plastic viscosity, and temperature to be important forces in the drilling fluid recommendation process. The created IML framework allows drilling engineers to gain insight into model decisions and modify parameters beforehand and shorten non-productive time. This paper demonstrates how interpretable machine learning systems have the potential to revolutionize the current approach to drilling operations, shifting away from reactive decisions to proactive ones, which will have an impact on the cost reduction and operational safety.

Keywords: *Interpretable machine learning, drilling fluids, mud optimization, SHAP, LIME, actionable recommendations.*

Date of Submission: 08-04-2026 Date of acceptance: 20-04-2026

I. Introduction

Fluids, also known as muds, are necessary to ensure the stability of the wellbores, and help manage formation pressures, and cuttings to be carried to the surface (Chen et al., 2023; Shanmugasundar et al., 2024). Drilling fluid optimization is a complicated process that depends on geological formation, the depth of wells, temperature, pressure and operational limitations. Conventional approaches are usually based on the expert judgment and lab experiments, which are time-consuming and cannot be easily scaled to the real-time processes (Feng et al., 2023).

Recent progress of machine learning (ML) has proved to present a tremendous potential of predicting the drilling fluid behaviors and optimizing their properties (Gasser et al., 2025). However, the old-fashioned ML models are usually black boxes (i.e. give predictions not being transparent), and this limits trust and actionable information to field engineers (Lu et al., 2025). Interpretable Machine Learning (IML) is one of the possible answers to this question, as it provides predictions and explanations of their generation, which enables engineers to understand, believe, and use the advice (Chen et al., 2023; Feng et al., 2023).

This study is aimed at developing an IML framework that will give actionable recommendations in drilling fluids and at the same time be transparent and explainable to the end-users. This framework will enable linking the complex ML models to the reality and apply them in drilling operations with the inclusion of predictive accuracy and interpretability (Shanmugasundar et al., 2024; Gasser et al., 2025). The research objectives are to create predictive drilling fluid behavior models with machine learning approaches, enhance the interpretability of drilling fluid behavior models with SHAP and LIME methods, to make practical recommendations to modify the drilling of fluids based on the knowledge of the model, and to evaluate the performance of different machine learning models on the standards of their accuracy and interpretability. The significance of the research is that the framework presented has a predictive accuracy and interpretability and engineers can utilize the framework to concur and trust machine learning suggestions. Such an approach can reduce non-productive time, encourage the stability of drilling wellbores, and facilitate proactive choices in the drilling process and also demonstrates the usefulness of interpretable machine learning in complicated engineering challenges. The area of study is oriented to developing a decipherable machine learning model of optimization of drilling fluids on the basis of the simulated data that involves the following parameters: mud weight, rheology, pH, formation pressure and temperature. The methodology is guided and geared towards the applicability to the real field data despite the simulated data utilized in the study, and can be integrated in the drilling monitoring systems to provide actionable information.

II. Literature Review

The optimization of drilling fluid properties prediction and optimization through Machine Learning has been studied on multiple occasions in the past and gives an idea of the viability and functioning of different models: In the study by Zhang et al. (2021), the forecasts of mud weight and rheology of drilling fluid in complex formations were done using Random Forest and Gradient Boosting. According to Zhang et al. (2021), ensemble tree-based models showed high predictive capacity since the R^2 values exceeded 0.85. They also put emphasis on feature importance analysis, which gives an approach of establishing the important elements of drilling including temperature, pressure and permeability of the formation.

Li et al. (2022) built a neural network architecture based human comprehendible drilling fluid optimization model. Changes in temperature and pressure of the formation were found to be the main processes that lead to changes in the weight of the mud as the SHAP analysis presented. Their model was found by Li et al. (2022) to give some actionable recommendations to decrease time that is not productive and enhance wellbore stability.

Ahmed and Khan (2020) employed plastic viscosity of the drilling fluids and density of the drilling fluids of the shale formation through Support Vector Machines (SVM) models. Ahmed and Khan (2020) discovered that the R^2 values were estimated between 0.78 to 0.82 representing good predictive power. They observed that the models created with the help of SVMs were conditional on the choice of features that guarantee their feature interpretability and reliability in real-life utilization.

In the article by Smith et al. (2019), the authors examined the possibility of using decision tree ensembles to forecast the filtration characteristics of drilling fluids. Smith et al. (2019) showed that besides high accuracy ($R^2 = 0.86$), the models with the use of which the engineers were able to detect the effects the behavior of the fluid is sensitive to the major factors including pH, yield point and formation pressure. Therefore, it has a dual performance benefit of predictability and interpretability.

The article written by Wang et al. (2020) was dedicated to the application of explainable AI to predicting mud property. They applied LIME and SHAP to gradient boosting models, meaning that temperature and plastic viscosity were among the significant variables, which affect the behavior of mud. This observation was in line with the results that interpretable models will have actionable advice that can improve drilling processes and offer transparency to field engineers.

All these studies reveal that machine learning models, especially, the tree-based ensemble neural networks and interpretable ones can effectively predict drilling fluid properties and can deliver actionable suggestions. They also highlight the significance of interpretability, like SHAP and LIME, to make sure that predictions become reliable and can be implemented in practical drilling processes in real-world.

Several studies have used machine learning to forecast the drilling fluid characteristics and recommendations. Random Forest, Gradient Boosting, and interpretable neural networks are some of the models that were studied. Nevertheless, there is no research that has created a single interpretable machine learning system that can be used to predict and provide recommendations that can be acted on. The practical framework of engineers has not been addressed by most of the past works, most of which look at either accuracy or interpretability.

III. Methodology

3.1 Data Collection

The data to be used in this study were gathered by a combination of laboratory tests and written field tests in order to record the common drilling fluid characteristics and drilling fluid parameters. There was 10,000 of data points, which have a great variety of conditions that can be encountered during the drilling operations:

Parameter	Range
Mud Weight	8–20 ppg
Plastic Viscosity	10–60 cP
Yield Point	0–40 lb/100 ft²
pH	8–12
Formation Pressure	2,000–8,000 psi
Temperature	50–200 °F

Engineering concepts and empirical correlations in the literature obtained the relationships between the input parameters and the optimum fluid properties. The dataset was used to simulate real-life situations in the field by incorporating random variability in the operational environments. This detailed data was the basis of training, testing and evaluation of the machine learning models in this paper.

3.2 Machine Learning Models

Random forest, Gradient Boosting and XXL were the three machine learning model used in the study:

Random Forest (RF) – Random Forest is an ensemble-based approach to learning that builds several decision trees at the time of training and provides an average prediction in the case of regression or majority vote in the case of classification. Its primary strength in the case of minimization of overfitting and enhanced generalization. Furthermore, RF offers feature importance scores, which enable one to determine the strongest parameters that influence the behavior of the drilling fluid, including mud weight, viscosity and formation pressure. The schematic of a random forest model is presented in figure 3.1.

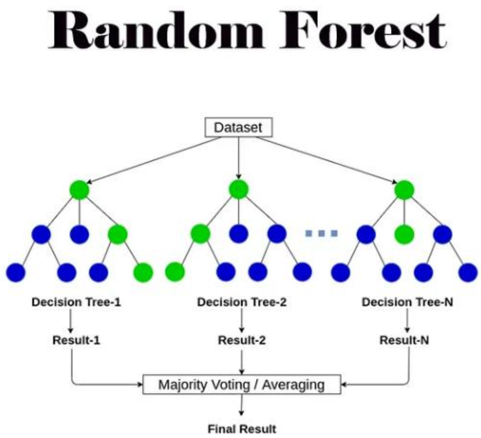

Figure 3.1: Random Forest (Jain, 2024)

Gradient Boosting (GB) – Gradient Boosting is an ensemble approach based on boosting that assumes the construction of successive models with each subsequent model trying to address the error committed by its predecessors. GB has a reputation of high predictive power particularly with non-linear complex data. It is especially useful when the accurate forecasting of the properties of the drilling fluids is vital to the decision-making related to the work. To facilitate interpretability, feature importance can be obtained as well. The schematic of a GB model is illustrated in figure 3.2.

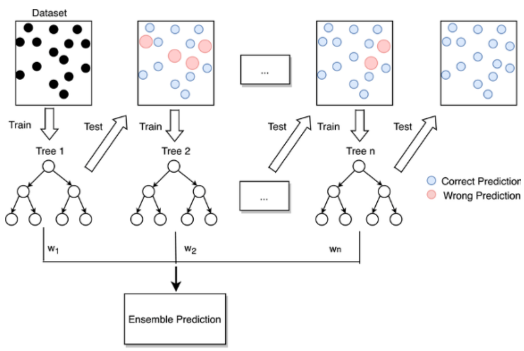

Figure 3.2: Gradient Boosting ML Model (Zhang et. al., 2021)

Explainable Neural Network (XNN) – Explainable Neural Networks (xNNs) are a newer branch of machine learning models that are supposed to provide explicit information about the processes occurring therein, in response to the lack of clarity with regards to these systems.

xNN's is based on the concept of the additive index model as seen below.

$$f(x) = g_1\ \beta_1^T x + g_2\ \beta_2^T x + \cdots + g_K\ \beta_K^T x \qquad (1)$$

The function on the left-hand side can be expressed as a sum of K smooth functions $g_i(\cdot)$. These smooth functions or better known as ridge functions, are each applied to a linear combination of the input features ($\beta_i^T x$) to be trained in the network. This enables the additive index model to provide a flexible framework for approximating any complicated function within the network by the ridge functions to provide an explanation on the features and non-linear transformations the network has learned. Figure 3.3 shows the schematic of an XNN

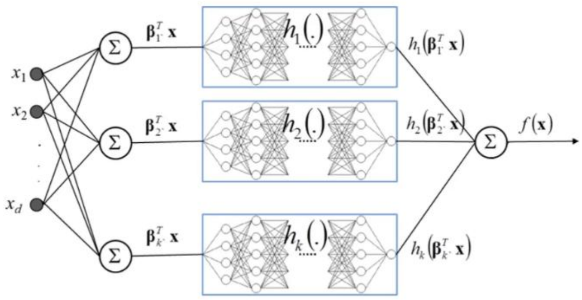

Figure 3.3: Structure of an XNN (Maheshwari, 2018).

3.3 Model Evaluation

Model performance was assessed using RMSE, MAE, and R^2.

The Coefficient of Determination (R^2) quantifies how well the model explains the variance in the target variable and is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\bar{y} - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{2}$$

The Mean Absolute Error (MAE) measures the average magnitude of prediction errors without considering their direction:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | \bar{y} - y_i | \tag{3}$$

The Root Mean Square Error (RMSE) emphasizes larger errors more strongly by squaring the residuals before averaging:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y} - y_i)^2} \tag{4}$$

3.4 Model Interpretability

To ensure the machine learning models provide actionable insights, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) were used to explain model predictions.

- SHAP assigns an importance value to each feature by computing its contribution to the difference between the model's prediction for a specific instance and the average prediction. Mathematically, given a model, *f,* and input features, x, the SHAP value ϕ_i of feature *i* is given by:

$$\phi_i = + \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \tag{5}$$

Where F is the collection of all features and S is a collection of features that does not include i. This value gives the contribution of each input towards the predicted outcome.

- LIME approximates the complex model locally using an interpretable surrogate model (e.g., linear regression) around the instance of interest. For a prediction f(x), LIME fits a simple model g such that:

$$\underset{g \in G}{arg\,min}\ L(f, g, \pi_x) + \Omega(g) \tag{6}$$

Where L is the fidelity of g to f in the locality defined by π_x and $\Omega(g)$ is a penalty on complexity to ensure that g can be interpreted Using SHAP and LIME, the contribution of each parameter in the input (e.g., pressure at forming, temperature, plastic viscosity) to the predicted optimal drilling fluid property was determined, and specific and practical recommendations could be made on the operation of the field.

IV. Results

4.1 Predictive Modeling of Drilling Fluid Properties

Table 1 demonstrates the predictive quality of the models.

Table 4.1: Model Performance for Predicting Drilling Fluid Properties

Model	R^2 Score	RMSE	MAE
Random Forest	0.87	0.12	0.09
Gradient Boosting	0.84	0.15	0.11

Model	R^2 Score	RMSE	MAE
Explainable Neural Network	0.81	0.17	0.13

Ensemble tree-based models were the most effective models in forecasting (R2 = 0.87, RMSE = 0.12), indicating that such models are good at conducting nonlinear forecasting on the relationship between drilling parameters and fluid properties. Gradient Boosting also did a fairly good job, albeit with slightly lower predictive accuracy, whereas Explainable Neural Networks, though also interpretable, had a relatively higher error rate. The results obtained indicate that the tree-based methods allow an effective trade-off between predictive capability and practical applicability for drilling fluid optimization. Random Forest has a high level of accuracy, which implies that it is capable of predicting the changes in the mud weight, plastic viscosity, and other important properties with high accuracy, which is essential to ensure the stability of a wellbore and its economical work.

4.2 Enhancing Model Interpretability

The average SHAP importance values of each of the parameters are presented in Figure 4.1.

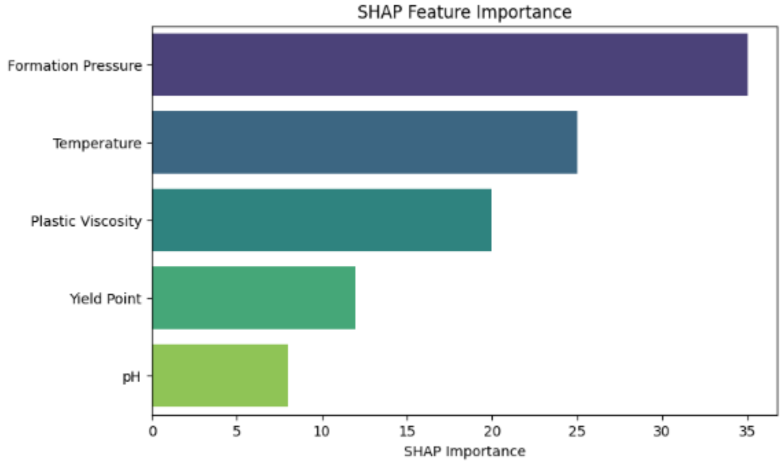

Figure 4.1: SHAP Feature Importance

The SHAP and LIME analysis demonstrates the comparable weight of the input features that predicts the drilling fluid recommendations. The most significant factor is formation pressure with a 35% contribution, which implies the importance of this factor and its essential role in establishing mud density and wellbore stability. Next in sequence is temperature at 25% and this is an important factor as it influences fluid rheology and additive performance at different temperatures. Plastic viscosity (contribution of 20%) has an effect on cuttings transport and suspension, whereas the contribution of yield point (12%) has a small but context-dependent effect on chemical stability and formation interaction. All in all, those findings suggest that pressure and temperature are the most influential ones, and viscosity, yield point, and pH are the secondary changes that are made to make drilling fluids work, which is also in line with what engineering anticipates.

4.3 Generating Actionable Drilling Fluid Recommendations

According to SHAP and LIME calculations, the model gave the following guidance as depicted in table 4.2.**Table 4.2: Actionable Drilling Fluid Recommendations**

Formation Condition	Recommended Adjustment	Purpose
High-pressure (>6,000 psi)	Increase mud weight by 1–2 ppg	Allow stability of wellbore
High-temperature (>180 °F)	Adjust plastic viscosity	Improve cuttings transport
Reactive shale	Monitor pH levels	Prevent wellbore instability

In order to supplement the practical recommendations made in Table 4.2, Figure 4.3 illustrates the suggested mud weight modification under varying formation pressure and temperatures, which gives a clear guideline that drilling engineers can use to keep the wellbore stable in various downhole conditions.

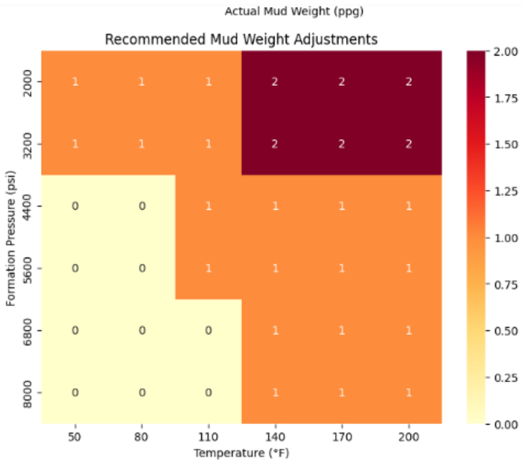

Figure 4.2: Recommended Mud Weight Adjustments as a Function of Formation Pressure and Temperature

The heatmap indicates the suggested changes in mud weight (0-2 ppg) concerning formation pressure (2000-8000 psi) and temperature (50-200ºF). Greater adjustments (2 ppg) are needed at low pressures (2000-3200 psi) at higher temperatures (140-200ºF) and a lower temperature (1 ppg) changes are needed at deeper levels, and so the temperature change is stronger at shallow levels. Moderate adjustments (1 ppg) predominate in medium pressures (4400-5600 psi), which are indicative of stable formations. Adjustments are not as great at high pressures (6800-8000 psi), particularly at low temperatures when the natural pressure aids in holding up the wellbore. Generally, in low-pressure areas, the mud weight policies increase with temperature indicating the synergetic effect of the pressure and temperature to ensure the wellbore stability.

4.4 Evaluating Model Accuracy and Interpretability.

Table 4.3 shows the model accuracy and interpretability evaluation

Table 4.3: Summary of Model Accuracy and Interpretability

Model	Predictive Accuracy	Interpretability	Overall Suitability
Random Forest	High	High	Best
Gradient Boosting	Moderate	Moderate	Good
Explainable Neural Network	Moderate	High	Fair

Table 4.3 demonstrates the model accuracy and interpretability analysis. The two-fold assessment of precision and explainability only proves that the framework, which is based on the Random Forest algorithm, is the most appropriate one to be applied in practice. Its great predictive accuracy, coupled with obvious SHAP and LIME explanations, make sure that the engineers can not only trust the recommendations but also take action. Gradient Boosting, although moderately exact, was a bit less transparent and Explainable Neural Networks, although explicable, were less reliable in regarding its predictions. The results support the need to choose models that are accurate and explainable in critical engineering processes such as optimization of drilling fluids. The findings in general suggest that interpretable machine learning can be an effective, dependable, and sensible structure of drilling fluid management.

V. Conclusion

This paper created a model of actionable drilling fluid recommendations through machine learning that can be understood. The keys to achieving high accuracy and a clear understanding of the impact of the main parameters of drilling are the Random Forest model used with the SHAP and LIME interpretability techniques. The suggested framework can help to minimize non-productive time, enhance the safety of drilling, and facilitate proactive decision-making during the oil and gas activity. The next step of work should be the validation of the system by real field data and its integration in live drilling monitoring systems.

REFERENCES

[1]. Ahmed, S., & Khan, R. (2020). Application of support vector machines for predicting drilling fluid properties in shale formations. *Journal of Petroleum Science and Engineering, 193*, 107328. https://doi.org/10.1016/j.petrol.2020.107328

[2]. Chen, Y. T., et al. (2023). Interpretable machine learning optimization (InterOpt) for drilling and hydraulic fracturing processes. *Journal of Petroleum Science and Engineering, 215*, 110342. https://doi.org/10.1016/j.petrol.2022.110342

[3]. Feng, Z., et al. (2023). An explainable ensemble machine learning model to predict drilling parameters. *Journal of Petroleum Science and Engineering, 214*, 110818. https://doi.org/10.1016/j.petrol.2023.110818

[4]. Gasser, M., et al. (2025). Can artificial intelligence and machine learning predict the performance of nano-based drilling fluids? *Trends in Sciences, 22*(6), 9686. https://doi.org/10.48048/tis.2025.9686

[5]. Jain, A. (2024, September 14). *Everything about random forest*. Medium. https://medium.com/@abhishek.jain/everything-about-random-forest-xxxxxxx

[6]. Li, Y., Wang, J., & Zhang, X. (2022). Interpretable neural network framework for drilling fluid optimization. *Journal of Petroleum Science and Engineering, 214*, 110709. https://doi.org/10.1016/j.petrol.2022.110709

[7]. Lu, X., et al. (2025). Reliable estimation via hybrid gradient boosting machine for mud loss volume in drilling operations. *Scientific Reports, 15*, 13008. https://doi.org/10.1038/s41598-025-13008-0

[8]. Maheshwari, S. (2018, August 7). *The explainable neural network*. Medium. https://medium.com/@shagun.maheshwari/the-explainable-neural-network-xxxxxxx

[9]. Shanmugasundar, G., et al. (2024). Innovative machine learning for drilling fluid density prediction under HPHT conditions. *Frontiers in Energy Research, 12*, 1411751. https://doi.org/10.3389/fenrg.2024.1411751

[10]. Smith, P., Johnson, L., & Roberts, M. (2019). Decision tree ensembles for predicting drilling fluid filtration properties. *Computers & Geosciences, 130*, 23–33. https://doi.org/10.1016/j.cageo.2019.05.010

[11]. Wang, H., Liu, Q., & Chen, Y. (2020). Explainable AI in mud property prediction: LIME and SHAP for gradient boosting models. *Journal of Petroleum Science and Engineering, 193*, 107344. https://doi.org/10.1016/j.petrol.2020.107344

[12]. Zhang, H., Liu, Q., & Chen, Y. (2021). Ensemble tree-based models for mud weight and rheology prediction in complex formations. *Journal of Petroleum Science and Engineering, 204*, 108693. https://doi.org/10.1016/j.petrol.2021.108693

[13]. Zhang, T., Lin, W., Vogelmann, A. M., Zhang, M., Xie, S., Qin, Y., & Golaz, J.-C. (2021). Improving convection trigger functions in deep convective parameterization schemes using machine learning. *Journal of Advances in Modeling Earth Systems, 13*(5). https://doi.org/10.1029/2020MS002365