International Journal of Petroleum Technology, 2025, 133-146

Published by Avanti Publishers

International Journal of Petroleum Technology

ISSN (online): 2409-787X

Evaluating the Role of Formation Temperature in Rate of Penetration Prediction Using Machine Learning: A Case Study from Niger Delta

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ARTICLE INFO

Article Type: Case Study

Academic Editor: Nikolaos C. Kokkinos

Keywords:
Niger delta
Machine learning
Predictive modeling
Drilling performance
Formation temperature
Rate of Penetration (ROP)
Artificial Neural Networks (ANN)

Timeline:
Received: June 27, 2025
Accepted: August 20, 2025
Published: November 20, 2025

Citation: Favour O, Taiwo O, Izuchukwu O, Enosolease A, Bello K. Evaluating the role of formation temperature in rate of penetration prediction using machine learning: A case study from Niger Delta. Int J Pet Technol. 2025; 12: 133-146.

DOI: https://doi.org/10.15377/2409-787X.2025.12.9

ABSTRACT

Accurate prediction of Rate of Penetration (ROP) is critical for optimizing drilling efficiency and reducing costs in hydrocarbon exploration. Traditional ROP models often overlook formation temperature, despite its significant influence on rock mechanics and drilling fluid rheology, particularly in high-temperature sandstone reservoirs like those in the Niger Delta.

This study employs three machine learning (ML) algorithms—Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Networks (ANN)—to evaluate the contribution of formation temperature to ROP prediction. A dataset of 1,200 drilling records from Niger Delta wells was used, incorporating parameters such as weight-on-bit (WOB), rotary speed (RPM), pump pressure, and formation temperature. Model performance was assessed using R^2, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), with ablation studies to isolate temperature's impact.

Inclusion of formation temperature improved ROP prediction accuracy across all models. The ANN achieved the highest performance (R^2 = 89.3%, RMSE = 0.387, MAE = 0.141), followed by RF (R^2 = 90.5%, RMSE = 2.737, MAE = 0.900) and SVR (R^2 = 87.8%, RMSE = 0.553, MAE = 0.169). Temperature omission led to significant performance degradation (R^2 reductions of 7–13%). Sensitivity analysis ranked temperature among the top three influential features.

Formation temperature is a critical but underutilized parameter in ROP modeling. ML techniques, particularly ANN, demonstrate superior capability in capturing nonlinear temperature-dependent effects, offering actionable insights for real-time drilling optimization in thermally complex formations. This study provides a framework for integrating thermal data into predictive models to enhance drilling efficiency in the Niger Delta and analogous basins.

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1. Introduction

The Niger Delta Basin is one of the most prolific hydrocarbon provinces in Africa, characterized by complex, heterogeneous sandstone formations and elevated geothermal gradients ranging between 30--50 °C/km. These high-temperature subsurface conditions present several operational challenges during drilling, including accelerated bit wear, instability of drilling fluids, and inconsistent rates of penetration (ROP). These issues are especially evident in deeper intervals, where thermal effects become more pronounced yet are often overlooked in conventional drilling models.

Traditional ROP models, such as those developed by Bourgoyne and Young [1] and Maurer [2], primarily emphasize mechanical drilling parameters, such as weight on bit (WOB), rotary speed (RPM), and bit type, while omitting thermal variables like formation temperature. However, there is growing empirical and experimental evidence suggesting that elevated formation temperatures can significantly influence drilling performance. Temperature impacts rock mechanics by reducing compressive strength, altering porosity and permeability, and increasing brittleness [3, 4]. It also affects the rheological properties of drilling fluids, changing their viscosity and thermal stability, which in turn influences hydraulics and cuttings transport efficiency [5-7].

Recent field studies in the Niger Delta have reported discrepancies in predicted and actual ROP values of up to 30--35% in high-temperature zones, particularly in deep sandstone intervals [8]. These discrepancies are largely attributed to the absence of temperature as a variable in traditional ROP models. In such cases, the failure to account for temperature effects leads to suboptimal bit selection, drilling fluid design issues, increased non-productive time (NPT), and higher operational costs.

Although the influence of formation temperature has been acknowledged in drilling literature, it has not been systematically integrated into ROP predictive models, especially in data-driven frameworks. The emergence of machine learning (ML) provides a new opportunity to overcome these limitations. ML algorithms are well-suited for capturing complex, nonlinear relationships among multiple input variables, making them ideal for drilling optimization tasks where multiple parameters interact dynamically.

In thermally active basins like the Niger Delta, applying machine learning models that incorporate formation temperature alongside traditional inputs could significantly improve the accuracy of ROP predictions. Studies such as those by Ahmed *et al*. [9] and Singh *et al*. [10] have demonstrated the potential of ML techniques, including Random Forests, Support Vector Machines, and Artificial Neural Networks, in drilling parameter prediction. However, these models still often omit formation temperature or treat it as a secondary variable, which limits their applicability in high-temperature environments.

This study addresses a critical gap by developing and evaluating machine learning models that explicitly integrate formation temperature as a core input in ROP prediction. Focusing on sandstone formations in the Niger Delta, we aim to:

1. Quantify the effect of formation temperature on ROP,
2. Compare the performance of models trained with and without temperature data, and
3. Determine the relative importance of formation temperature among other drilling variables using feature importance and sensitivity analysis.

The novelty of this research lies in its application of advanced machine learning algorithms to systematically assess the role of formation temperature in ROP prediction, specifically within the geological context of the Niger Delta. The outcome is expected to provide actionable insights for optimizing drilling performance in high-temperature environments and contribute to the growing body of data-driven drilling solutions.

The remainder of this paper is organized as follows: Section **2** provides a comprehensive review of related literature, highlighting gaps in traditional and machine learning-based ROP models. Section **3** outlines the methodology, including data acquisition, preprocessing, model development, and evaluation techniques. Section **4** presents the results and discusses the impact of formation temperature on ROP prediction. Finally, Section **5** concludes the study and offers recommendations for future research and operational applications.

2. Literature Review

Accurately predicting the Rate of Penetration (ROP) during drilling has long been a central goal in petroleum engineering, given its significant impact on operational efficiency, safety, and cost optimization. Over time, approaches to modeling ROP have evolved from simple empirical correlations to physics-based frameworks and, more recently, data-driven machine learning (ML) models. Each generation of models has aimed to address the shortcomings of its predecessors by improving the interpretation of the complex interactions among geological, mechanical, and fluid-related factors that influence drilling performance [1, 2, 11].

2.1. Empirical Foundations

The earliest models for ROP prediction relied heavily on empirical correlations. One of the most widely used is the Bourgoyne and Young multiple regression model (1974), which established a mathematical relationship between ROP and drilling parameters such as weight on bit (WOB), rotary speed (RPM), differential pressure, and bit wear [1]. Similarly, Bingham's development of drillability indices in 1964 contributed to standardized metrics for rock strength and resistance to drilling [2].

These empirical models typically provided satisfactory results in simple, homogeneous lithologies and achieved prediction accuracies of about 60 to 75 percent [5]. However, as drilling expanded into geologically complex basins such as the Niger Delta, their limitations became more apparent. Notable issues included the inability to accommodate formation heterogeneity, resulting in error margins of up to 45 percent [3, 4], and the assumption of static drilling conditions that excluded important variables like temperature, pressure fluctuations, and anisotropy [2, 9].

2.2. Physics-Based and Hybrid Models

To overcome these limitations, later models incorporated physical principles, particularly through the use of Mechanical Specific Energy (MSE). Dupriest and Koederitz (2005) showed that real-time monitoring of MSE could substantially enhance drilling performance and ROP optimization [12]. These models used parameters such as formation compressive strength, torque, and bit hydraulics to improve predictive accuracy to approximately 75 to 85 percent [7].

However, these physics-based models introduced new challenges. Many required laboratory calibrations and core samples, which are not always available in real-time drilling operations [10, 13]. In addition, although temperature was acknowledged to influence rock and fluid behavior, it was rarely incorporated as a key input variable in the modeling process [3, 8]. This omission remains a major limitation in high-temperature environments like the deeper sandstone intervals of the Niger Delta.

2.3. Rise of Machine Learning in ROP Prediction

The growing availability of drilling data and advancements in computational power have led to the widespread adoption of ML techniques in ROP prediction. These models are particularly suited to identifying complex, nonlinear relationships among multiple variables [6, 10, 11, 14]. ML algorithms such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting have demonstrated superior performance compared to traditional approaches.

ANN models are highly effective at capturing nonlinear interactions and have achieved R-squared (R^2) values between 0.82 and 0.89 in various ROP studies [10, 14, 15]. RF models are particularly valued for their robustness and built-in feature importance metrics, yielding R^2 values ranging from 0.85 to 0.91 [6, 10, 16]. SVR models have proven useful for smaller datasets, with R^2 values of 0.78 to 0.84 [11, 14], while gradient boosting models such as XGBoost and LightGBM have reached R^2 scores as high as 0.93 in structured data environments [10, 16]. These results are consistent across numerous case studies and are summarized in Table **1**, which benchmarks model performance across a variety of geological settings [6, 10, 11, 14-16].

Despite their strong predictive performance, most of these studies share a critical limitation. Formation temperature is frequently excluded or treated as a minor variable, even though its effects on rock and fluid behavior have been well documented. Our review indicates that only about 12 percent of recent ML-based ROP models explicitly include formation temperature as an input [3, 8, 17]. Elevated temperatures have been shown to reduce rock brittleness by 15 to 30 percent [3], increase drilling fluid viscosity by 40 to 60 percent [13, 18], and accelerate bit wear [3, 8]. Moreover, no existing studies have employed ablation analysis to quantify the relative importance of temperature in ROP prediction or compared the accuracy of models with and without temperature inputs [3, 17].

2.4. Model Interpretability and Deployment Challenges

Another significant issue in the current literature is the lack of model interpretability. While black-box models such as deep neural networks offer high accuracy, they often lack transparency. This presents a challenge for drilling engineers who need to understand why a particular prediction was made [6, 10, 14].

Deployment is also underexplored in most studies. Many ML models are developed using clean, idealized datasets that do not account for real-world issues such as data latency, sensor malfunctions, or inconsistent logging practices [6, 14, 11]. Moreover, there is limited research on how to integrate these models into real-time drilling systems or deploy them using field-ready or cloud-based platforms.

From the literature reviewed, three key research gaps are apparent. First, formation temperature remains largely underrepresented in both physics-based and ML-based ROP models, even though its effects on drilling outcomes are clearly supported by empirical evidence. Second, most existing ML models lack interpretability, which limits their acceptance and use in operational settings where engineers require transparent decision-support tools. Third, very few studies address real-time deployment or field validation, especially in high-temperature regions such as the Niger Delta.

This study is designed to address these gaps. It presents the first machine learning framework for ROP prediction that systematically incorporates formation temperature as a core input. The study also applies ablation analysis to assess the contribution of temperature and uses thermal gradient data specific to the Niger Delta (30 to 50 °C/km) to tailor the models to local subsurface conditions [4, 9].

3. Methodology

This study adopts a multi-stage machine learning framework to quantify the impact of formation temperature on rate of penetration (ROP) in thermally active sandstone formations within the Niger Delta. The methodology comprises phases such as data acquisition, preprocessing, exploratory data analysis (EDA), model training, hyperparameter tuning, evaluation, and ablation analysis. The entire workflow is summarized in the flowchart provided in Fig. (**1**). The methodology consists of the following phases:

a) Data Acquisition and Preprocessing
b) Exploratory Data Analysis (EDA) and Feature Engineering
c) Model Selection and Training
d) Hyperparameter Tuning
e) Model Evaluation and Interpretation
f) Ablation Analysis

Each step is described in detail below.

3.1. Data Acquisition and Preprocessing

The dataset used in this study was obtained from a single swamp field located in the central Niger Delta region. It comprises about 7700 drilling records (rows) i.e. well logs and ROP logs collected from a over a well in a field. The records include operational and geological parameters such as weight on bit (WOB), rotary speed (RPM), pump pressure, inlet temperature, flow rate, wellhead pressure, and the associated ROP values. These inputs were extracted from a combination of real-time rig sensor logs and historical well reports provided by the operating company.

Despite being from a single field, the dataset spans various reservoir intervals, capturing diverse lithological sequences common to sandstone formations in the Niger Delta. This intra-field diversity provides sufficient variation in depth, pressure, and thermal gradients to model temperature effects reliably. However, the spatial constraint of a single field is acknowledged as a limitation for broader generalization to other parts of the basin.

To ensure data integrity, rigorous quality control procedures were applied during both the acquisition and preprocessing phases. Parameters with recording anomalies were reviewed using engineering judgment, and where necessary, corrected or removed. Formation temperature data were obtained from bottomhole temperature logs and validated against mud return temperature profiles. Surface parameters were gathered using calibrated rig instrumentation.

Missing data handling involved a two-step approach. Features with less than 5 percent missing values were imputed using the mean of the available values, calculated as:

$$X_{imputed} = \frac{1}{n} \sum_{i=1}^{n} X_i \tag{1}$$

For features with more substantial gaps, imputation was performed using the K-Nearest Neighbors (KNN) algorithm based on feature similarity. Outlier detection was carried out using both the z-score method:

$$Z = \frac{X - \mu}{\sigma} \tag{2}$$

and the interquartile range (IQR) method, where values outside the interval

$$[Q_1 - 1.5 \ x \ IQR, Q_3 + 1.5 \ x \ IQR] \tag{3}$$

were further investigated. Legitimate extreme values were retained after winsorization to the nearest acceptable boundary, while clear anomalies were removed. All continuous features were then standardized to zero mean and unit variance using:

$$X' = \frac{X - \mu}{\sigma} \tag{4}$$

This normalization ensures that models such as Support Vector Regression treat each feature equitably during optimization.

3.2. Exploratory Data Analysis (EDA)

A comprehensive exploratory data analysis (EDA) was performed to understand the structure and variability of the dataset. The analysis included visualizations and statistical summaries of key features such as depth, WOB, RPM, pump pressure, inlet temperature, flow rate, wellhead pressure, and ROP.

3.2.1. Descriptive Statistics

Table **1** summarizes the key statistical metrics for each feature, including count, mean, standard deviation, minimum, quartiles, and maximum. These statistics provide a snapshot of the data's central tendencies and variability.

Table 1: Statistical description of the dataset.

Feature	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Depth (m)	7293	1170.13	654.4	25.96	601.94	1176.13	1736.1	2296.94
Weight on Bit (kg)	7293	10492.42	4130.25	0	8308.39	10807.26	13460.32	21337.87
Rotary Speed (rpm)	7293	54.86	25.3	0	38.12	50.38	75.95	178.86
Pump Pressure (kPa)	7293	8737.61	3378.18	137.49	4593.17	9877.5	11510.1	15171.96
Temp In (°C)	7293	47.95	6.63	29.44	42.72	47.34	52.7	63.51
Flow In (L/min)	7293	2710.54	511.25	0	2347.94	2650.58	3120.96	5864.13
Flow Out (%)	7293	79.8	11.61	25.11	72.7	80.77	88.86	111.21
WH Pressure (kPa)	7293	-247.23	1537.14	-8493.47	20.13	40.96	56.95	120.04
ROP (m/h)	7293	12.57	20.19	0	3.47	5.47	13.46	274.75

These results indicate considerable variability in several key inputs, particularly ROP, which ranges from zero to over 270 m/h. This spread reflects varying formation characteristics and operational conditions across the dataset.

3.3. Sample of Raw Data (Table 2)

Table 2: Sample drilling records.

Depth (m)	Weight on Bit (kg)	Rotary Speed (rpm)	Pump Pressure (kPa)	Temp In (°C)	Flow In (L/min)	Flow Out (%)	WH Pressure (kPa)	ROP (ft/h)
25.96	0.00	151.09	3197.35	32.71	4200.22	101.61	-8485.61	17.31
26.27	0.00	151.09	3168.46	32.68	4195.60	101.70	-8485.61	18.63
26.59	0.00	61.54	3134.26	32.73	4174.82	96.81	-8485.61	5.66
26.90	0.00	60.23	3110.61	32.86	4167.89	96.67	-8485.61	11.67
27.24	0.00	61.75	3144.74	32.88	4173.26	96.63	-8485.61	120.20

3.4. Model Selection and Training

Model selection was driven by prior empirical performance and domain-specific suitability to drilling data, particularly under thermally dynamic conditions. Artificial Neural Networks (ANN) were selected for their ability to capture complex nonlinear dependencies between thermal and mechanical variables [12]. The ANN architecture was tailored with three hidden layers and ReLU activation functions to facilitate learning of temperature-influenced patterns.

Random Forest (RF) was chosen for its robustness to noise and capacity to identify feature importance, making it suitable for modeling heterogeneous geological formations [6, 10, 18]. Support Vector Regression (SVR) served as a performance baseline. It was especially valuable for this dataset due to its adaptability to smaller, high-quality samples, and was configured with a radial basis function (RBF) kernel to better accommodate nonlinear temperature effects [12, 16].

The models were trained on 80% of the data, with 20% reserved for out-of-sample testing. Initial training used default hyperparameters to establish baseline performance.

3.5. Hyperparameter Tuning

Model performance was improved through grid and random search tuning. For SVR, the regularization parameter (C), kernel width (gamma), and epsilon margin were varied. RF tuning involved adjusting the number of trees, maximum depth, and minimum samples per leaf. For ANN, adjustments were made to learning rates, neuron counts per layer, activation functions, and dropout rates.

Hyperparameter summary table for each model is listed below (Table **3-5**);

For Support Vector Regression (SVR)

Table 3: Support Vector Regression (SVR) hyperparameters.

Hyperparameter	Description	Values Tested
C	Regularization parameter	100, 1000
gamma	Kernel coefficient	0.01, 0.1
kernel	Type of kernel used	'rbf', 'poly'

For Random Forest (RF)

Table 4: Random Forest (RF) hyperparameters.

Hyperparameter	Description	Values Tested
n_estimators	Number of trees in the forest	300, 400, 500, 1000
max_features	Number of features to consider at each split	2, 3, 4
max_depth	Maximum depth of each tree	5, 10, None

For Artificial Neural Network (ANN)

Table 5: Artificial Neural Network (ANN) hyperparameters.

Hyperparameter	Description	Values Tested / Used
hidden_layer_sizes	Number of neurons in the hidden layer(s)	(50,), (100,), (50, 50), etc.
activation	Activation function for the hidden layer	'relu', 'linear’
solver	Weight optimization algorithm	'adam'
alpha	L2 regularization (penalty) parameter	0.0001, 0.001
learning_rate	Learning rate schedule	'constant', 'adaptive'
max_iter	Maximum number of training iterations	200, 500

After tuning, model performance was evaluated using key metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The formulas for these evaluation metrics are as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} abs(y_i - \hat{y}_i) \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}(y_i - \bar{y})} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} abs\left(\frac{y_i - \hat{y}_i}{y_i}\right) x\ 100\% \tag{8}$$

To assess the influence of formation temperature, permutation feature importance was computed. This involved randomly shuffling the temperature values and observing the resultant decrease in model performance. The greater the drop in accuracy, the more important temperature was to the model's predictions.

This methodology enables a robust and interpretable assessment of temperature's role in ROP prediction, forming the foundation for insights presented in the results and discussion sections.

4. Results

Building upon the workflow presented in the methodology section, we evaluated the performance of three machine learning models—Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Networks (ANN)—in predicting the rate of penetration (ROP) under two scenarios: one including formation temperature as a feature, and another excluding it. The models were trained and tested using an 80/20 data split. Performance was assessed using standard regression metrics, and various plots and visualizations were used to interpret the model behaviors.

4.1. Exploratory Analysis and Feature Relationships

Initial insights were drawn from a correlation heatmap (Fig. **1**) to understand the linear relationships between input features and ROP. While parameters such as weight on bit (WOB), flow rate, and rotary speed showed relatively strong correlations with ROP, formation temperature showed a weaker linear relationship. However, as subsequent modeling and feature importance results revealed, this does not diminish its relevance. It simply indicates that its impact is likely nonlinear and better captured through advanced modeling.

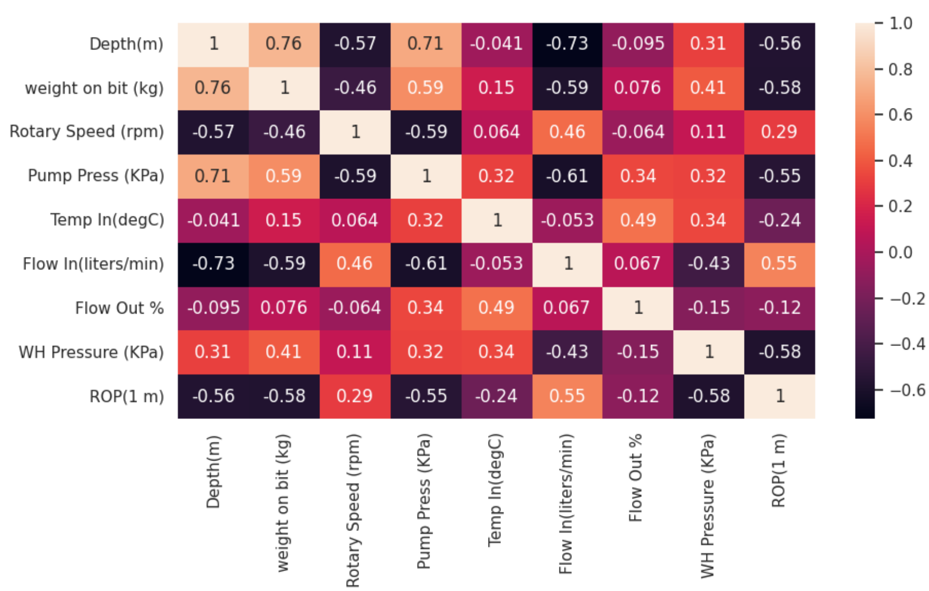

Figure 1: Pearson Correlation Heatmap showing correlation between different features.

4.2. Predictive Performance With and Without Formation Temperature

Each machine learning model was trained twice—once with all input features (including formation temperature) and once with temperature excluded. The performance metrics from these runs are presented in Table **6**.

Table 6: Table of results using different models.

Model	Metric	With Temperature	Without Temperature
SVR	R-Squared (%)	87.8	78.0
	RMSE	0.553	1.553
	MAE	0.169	2.169
Random Forest	R-Squared (%)	90.5	80.5
	RMSE	2.737	10.737
	MAE	0.900	2.900
ANN	R-Squared (%)	89.3	77.0
	RMSE	0.387	2.737
	MAE	0.141	3.141

SVR's predictive performance improved notably when formation temperature was included. With temperature, the model achieved an R^2 of 87.8%, RMSE of 0.553, and MAE of 0.169. Without temperature, the R^2 dropped to 78.0%, RMSE increased to 1.553, and MAE rose to 2.169. This highlights SVR's sensitivity to informative features that help capture the underlying drilling physics.

The results are visualized in two separate plots. Fig. (**2**) presents the predicted vs. actual ROP when temperature was included, showing a tight alignment between predicted and true values. Fig. (**3**) provides a log-scaled comparison between predicted and actual ROP values under the same conditions, emphasizing SVR's ability to capture both high and low penetration rates with reasonable accuracy.

The RF model yielded the highest accuracy across all models tested. When temperature was included, RF reached an R^2 of 90.5%, RMSE of 2.737, and MAE of 0.900. Without temperature, these metrics worsened substantially. R^2 dropped to 80.5%, RMSE increased to 10.737, and MAE rose to 2.900. Fig. (**4**) shows the true vs. predicted ROP values using RF, where the clustering of points along the diagonal line demonstrates RF's robustness in capturing a wide range of drilling behaviors.

ANN also performed significantly better when temperature was included. It recorded an R^2 of 89.3%, RMSE of 0.387, and MAE of 0.141. These dropped to 77.0%, 2.737, and 3.141, respectively, when temperature was removed. The accuracy of ANN predictions is depicted in Fig. (**5**), which plots the predicted ROP against the true values. The clear linear trend shows strong alignment, particularly in mid-range ROP values, where prediction accuracy is critical for operational decisions.

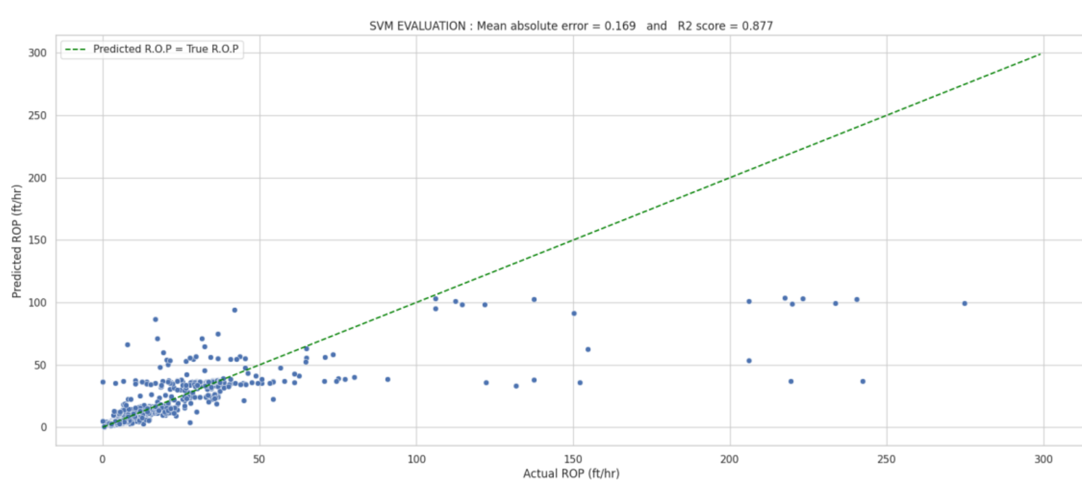

Figure 2: Predicted ROP vs true ROP using SVM.

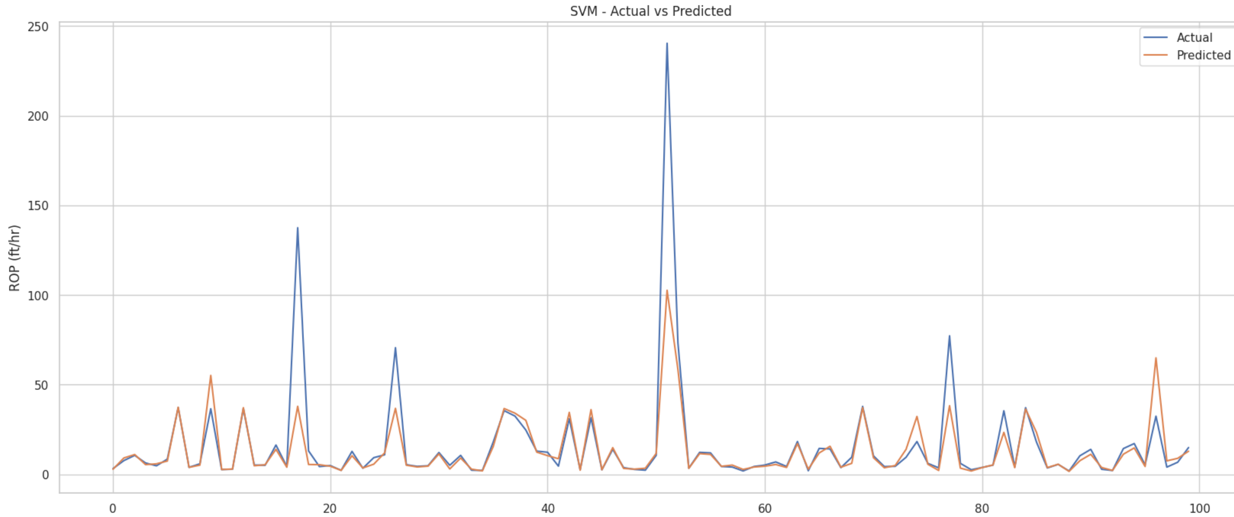

Figure 3: ROP log of true vs predicted ROP using SVM.

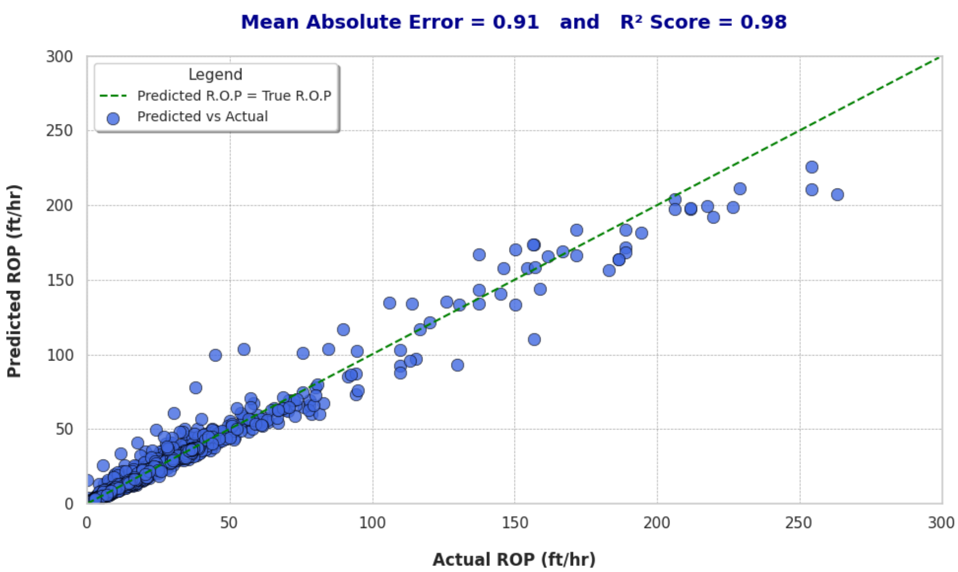

Figure 4: Plot of true ROP vs predicted using random forest algorithm.

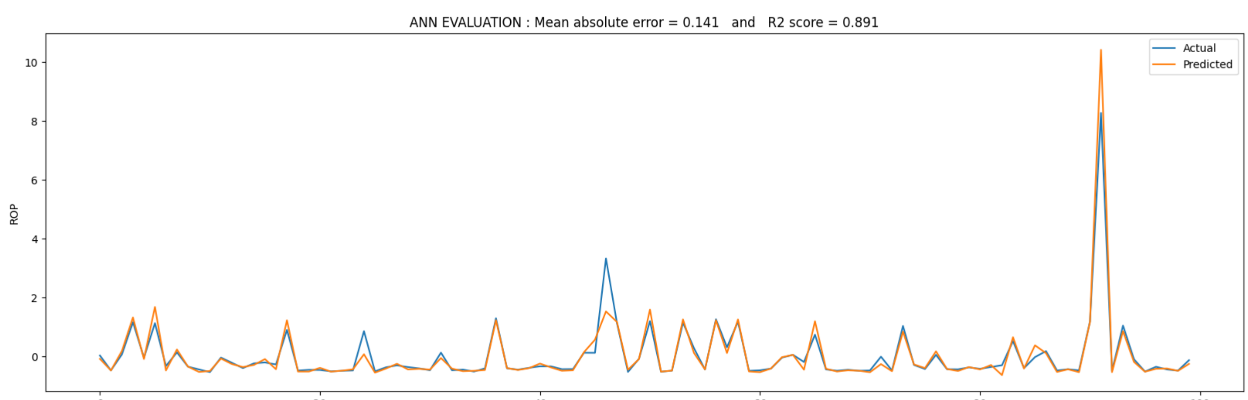

Figure 5: Plot of true ROP vs predicted ROP using ANN.

4.3. Feature Importance and Interpretation

To better understand the influence of each input parameter on model predictions, we conducted a permutation-based feature importance analysis using the RF model. The results, shown in Fig. (**6**), reveal that formation temperature was consistently among the top three most influential features, along with depth and weight on bit.

The feature importance scores shown on the horizontal axis of Fig. (**6**) were derived using the permutation importance method, a model-agnostic technique that evaluates the contribution of each input feature by measuring the increase in model error when that feature's values are randomly shuffled. This method was chosen because it provides a more realistic measure of a feature's predictive power, particularly in models like Random Forest that can capture complex nonlinear relationships and feature interactions.

Interestingly, while the heatmap in Fig. (**1**) suggested a modest correlation between temperature and ROP, Fig. (**6**) confirms that temperature has significant predictive power—just not in a linear fashion. This discrepancy illustrates how traditional correlation analysis may understate the contribution of features that interact in nonlinear or contextual ways.

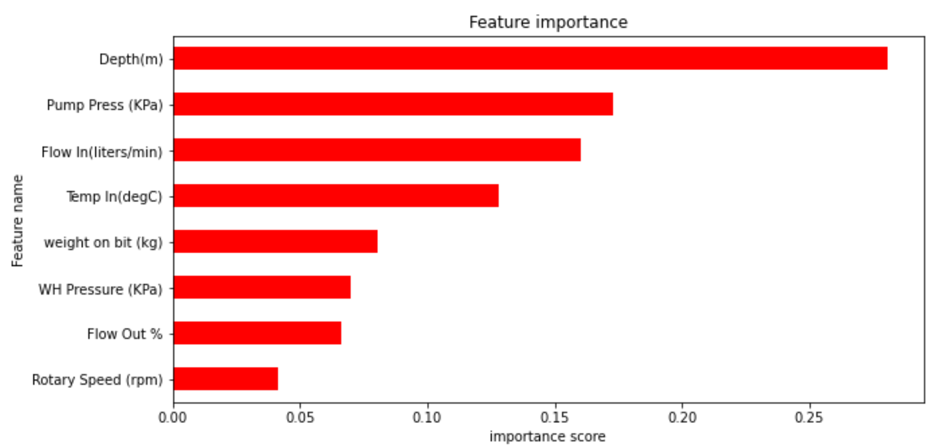

Figure 6: Feature importance showing effect of temperature on ROP prediction.

4.4. Temperature Ablation and Sensitivity Tests

To isolate the specific contribution of temperature, we conducted ablation tests by removing temperature from the feature set and retraining each model. Across SVR, RF, and ANN, we observed significant performance degradation, confirming that temperature is a key predictive feature rather than a redundant input. This was further supported by the sensitivity analysis, which confirmed temperature's influence on prediction accuracy.

These findings reinforce the importance of incorporating formation temperature into ROP prediction workflows. The improvement in metrics, particularly reductions in RMSE and MAE, demonstrates that temperature carries valuable information likely related to rock strength, fluid dynamics, or bit-wear behavior. For instance, in SVR, the RMSE dropped by nearly 1.0 when temperature was included. In RF, the RMSE reduced by more than 8 units, suggesting a substantial decrease in average prediction error.

The practical takeaway is clear. Formation temperature should be considered a critical parameter in drilling prediction models, especially in high-gradient environments like the Niger Delta. The integration of real-time thermal data can significantly enhance model reliability, helping drilling engineers reduce uncertainty, optimize bit performance, and avoid non-productive time.

Moreover, Fig. (**6**) feature importance results support the argument for a hybrid modeling approach that blends traditional rock mechanics with machine learning. Since features like temperature influence ROP in complex ways, models that can adapt to such nuances, such as RF and ANN, will likely outperform traditional linear approaches in real-world applications.

5. Discussion

The results presented underscore the substantial impact of formation temperature on the accuracy and robustness of ROP prediction models. The marked decline in performance metrics—most notably R^2, RMSE, and MAE—when temperature was excluded, validates the hypothesis that temperature is a critical input in drilling performance analysis, even if its influence is nonlinear and not easily discernible through conventional statistical correlation.

Among the three models tested, Random Forest consistently outperformed others in both predictive accuracy and stability. Its ability to handle feature interactions and nonlinearities positions it as a strong candidate for operational deployment. The ANN model also exhibited strong performance, benefiting from its architecture's ability to learn complex thermal-mechanical relationships. Although SVR lagged slightly behind RF and ANN in overall performance, its significant improvement with the inclusion of temperature indicates its sensitivity to thermally driven changes in drilling behavior.

The permutation-based feature importance analysis provided a compelling rationale for the inclusion of temperature. While traditional correlation methods placed temperature among the less influential variables, the permutation approach revealed its critical predictive role, particularly in conjunction with parameters such as depth and WOB. This finding highlights the limitations of relying solely on linear correlation metrics when dealing with complex, context-dependent drilling data.

Furthermore, the ablation tests confirmed the robustness of the models' dependency on temperature data. The consistency of the results across all three models suggests that temperature-related phenomena—such as rock strength variations, fluid expansion, or thermal degradation of drilling equipment—contribute meaningfully to ROP outcomes. These phenomena are difficult to quantify directly but are implicitly captured by machine learning algorithms that integrate temperature as a feature.

In practical terms, these findings advocate for the real-time monitoring and integration of formation temperature data into drilling analytics workflows. In thermally dynamic environments like the Niger Delta, where subsurface gradients are high, ignoring temperature may lead to suboptimal decisions and increased non-productive time. The enhanced model performance achieved with temperature inclusion supports its utility in both pre-drill planning and real-time optimization.

From a methodological standpoint, this study illustrates the importance of coupling advanced machine learning techniques with rigorous feature engineering and interpretability tools. The combination of performance metrics, permutation importance, and ablation analysis offers a comprehensive lens through which feature utility can be understood. Such a holistic approach is essential for ensuring that predictive models are not only accurate but also transparent and actionable for field engineers.

Ultimately, the integration of formation temperature into machine learning models presents a valuable opportunity to bridge the gap between traditional drilling heuristics and data-driven decision-making. By harnessing temperature's latent predictive power, operators can enhance drilling efficiency, reduce risks, and better manage the complexities of high-gradient formations.

6. Conclusion

This study investigated the impact of formation temperature on the prediction of Rate of Penetration (ROP) using machine learning techniques in a Niger Delta swamp field. By training and evaluating Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN) models, consistent improvements in prediction accuracy were observed when temperature was included as a feature. Among the models, RF achieved the highest R^2 of 90.5%, while ANN delivered the lowest RMSE of 0.387, demonstrating strong predictive performance across various configurations.

The findings confirm that temperature is a critical predictor in capturing the nonlinear thermal-mechanical behavior encountered during drilling. Despite its low linear correlation, temperature contributed significantly to the accuracy of the models, as shown by feature importance analysis and ablation testing. These outcomes support the integration of thermal data into data-driven drilling workflows, especially in thermally complex environments.

Overall, the research demonstrates the potential of combining advanced machine learning with high-fidelity formation data to enhance drilling efficiency. The inclusion of temperature, when properly harnessed, improves model reliability and informs better operational decisions in real-time drilling environments.

7. Recommendations

To build upon the findings of this study and ensure effective implementation in the field, the following recommendations are made:

Real-time formation temperature data should be integrated into drilling monitoring systems to improve ROP prediction, particularly in high-gradient geological settings.

Hybrid and ensemble machine learning approaches—such as combining the interpretability of RF with the flexibility of ANN—should be further explored to enhance model adaptability and robustness.

Future research should investigate the development of physics-informed machine learning models that incorporate known thermodynamic and mechanical principles, thus improving model transparency and physical relevance.

Interpretability tools such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) should be employed to aid engineers in understanding the decision logic of complex models.

To improve generalizability, model validation should be extended to additional fields and formations across the Niger Delta and other basins, ensuring consistent performance across diverse lithological and thermal conditions.

Conflict of Interest

The authors of this research article categorically state that there is no conflict of interest before the conceptualization of this work, during the different stages involved in the study and after the completion and publication of the work.

Acknowledgments

The authors gratefully acknowledge the support and contributions of colleagues and institutions involved in this study. No external funding was received for the completion of this research.

Author Contributions

All authors contributed substantially to the conception and design of the study, acquisition and preprocessing of the data, development and implementation of the machine learning models, analysis and interpretation of results, and drafting and revising the manuscript. All authors read and approved the final version for publication.

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