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Original article

Real-Time Prediction of Drill String Stuck Type and Probability using Machine Learning and Drilling Data on an Iranian Oil Field

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Abstract

Drill string stuck pipe remains a pervasive and costly Non-Productive Time (NPT) challenge in petroleum operations. While the previous studies have often focused on binary stuck/non-stuck prediction using low-resolution daily reports, this research introduces two key innovations: (1) the utilization of high-resolution Mud Logging data to capture subtle pre-failure signatures, and (2) a novel unsupervised labeling methodology using K-Means clustering to identify the specific stuck mechanisms (Wellbore Geometry, Differential Pressure, and Hole Packing), a critical step given the absence of physical labels in field data. Daily drilling reports from 28 wells were initially screened; however, the predictive models were developed using high-resolution mud logging data from 8 wells selected for data completeness, providing a methodological framework for real-time classification. For the binary early warning task, the Coarse Gaussian Support Vector Machine (SVM) demonstrated superior reliability, achieving the lowest count of critical False Negatives (FN=1) on the test set. For the multi-class mechanism identification task, the Linear SVM (while the Differential Pressure mechanism remained unresolved with the available surface data) proved optimal, achieving perfect classificationon the distinguishable classes on all distinguishable stuck types (Wellbore Geometry and Hole Packing) and an overall accuracy of 98 percent. This framework validates that the combination of high-resolution data with unsupervised labeling provides a computationally efficient and reliable foundation for deployment on the driller's panel, enabling proactive operational adjustments and significantly reducing NPT.

1. Introduction

Drill string stuck pipe represents one of the most critical and capital-intensive challenges in oil and gas drilling operations. It frequently results in significant project delays, the loss of high-value downhole equipment, and substantial economic penalties due to non-productive time (NPT). The prompt and accurate identification of the specific stuck mechanism is essential, as the effectiveness of remediation procedures such as jarring or spotting fluids drastically decreases over time. Historically, efforts to mitigate this problem began with fundamental analyses. Warren [1] provided early foundational work identifying drilling fluid properties and formation characteristics as primary contributors to stuck incidents. By the late 1980s, the industry moved towards statistical approaches; Hempkins et al. [2] utilized multivariate statistical analysis on 131 wells in the Gulf of Mexico to correlate drilling parameters with stuck probability. Similarly, Bradley et al. [3] analyzed 98 wells, attributing a significant portion of stuck events to mechanical factors and emphasizing the role of stationary pipe time. With the advent of computational intelligence, the focus shifted towards Machine Learning (ML) and Artificial Intelligence (AI) for predictive modeling. Siruvuri et al. [4] pioneered

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the use of Artificial Neural Networks (ANN) to predict stuck pipe, though their work was limited specifically to differential sticking. Poordad et al. [5] advanced this by employing Support Vector Machines (SVM) to classify drilling parameters into three categories: no stuck, differential sticking, and mechanical sticking, demonstrating the potential of kernel-based methods. More recently, the field has seen the adoption of ensemble methods and deep learning. Elmousalami and Elaskary [6] conducted a comparative study of twelve ML algorithms, highlighting the efficacy of Random Forests and Genetic Algorithms in feature selection. Kizayev [7] further demonstrated the superiority of Neural Networks and XGBoost over traditional statistical methods for prediction accuracy.

Despite these significant advancements, two critical gaps remain in the existing literature. First, the majority of predictive models rely heavily on Daily Drilling Reports (DDRs). As noted by Salminen et al. [8], the low temporal resolution and aggregated nature of DDR data are fundamentally inadequate for capturing the subtle, transient, and short-term trends that immediately precede a stuck event. This reliance leads to models that suffer from severe bias and delayed warnings. Second, a major hurdle for multi-class classification is the lack of reliable "ground truth" labels in historical data. Field reports often record a "stuck" event without specifying the exact physical mechanism (e.g., distinguishing between wellbore geometry and hole packing), making it difficult to train supervised models to predict the type of stuck pipe. To overcome these challenges, this research proposes a novel, data-driven framework for the real-time prediction of both the probability and type of stuck pipe. This study diverges from conventional approaches by utilizing high-resolution Mud Logging data, which offers the necessary granularity in operational parameters (such as Torque, WOB, and Flow Rate) to model pre-failure patterns effectively.

The core novelty of this work lies in two main contributions:

1. Unsupervised Stuck Type Identification: To resolve the critical issue of absent physical labels, the K-Means clustering algorithm was successfully applied to the features of stuck events. The clustering results were physically interpreted to create a reliable cluster-derived pseudo-labels for the three primary mechanisms (wellbore geometry, differential pressure, and hole packing), enabling the training of a multi-class predictor.
2. Minimization of Critical Errors: We employed a robust preprocessing and feature engineering pipeline to develop predictive models focused on minimizing False Negatives (missed alarms), ensuring the system is viable for safety-critical deployment on the driller's panel.

From an operational standpoint, the time-critical nature of stuck-pipe management is well documented in the literature. Alshaikh et al. [9] catalogued the early operational signs of the three primary sticking mechanisms (wellbore geometry, differential pressure, and hole packing) and outlined the pathway toward automated detection, and Jahanbakhshi et al. [10] compared SVM with conventional ANN for the intelligent prediction of differential pipe sticking in Iranian offshore fields. On the field-implementation side, Jardine et al. [11] proved an advanced early-detection system based on continuous torque and overpull monitoring, Mitchell [12] compiled field statistics showing that roughly half of stuck strings are freed within the first four hours whereas fewer than 10% recover beyond that window, Shadizadeh and Zoveidavianpoor [13] quantified the substantial annual economic burden of stuck pipe in Iranian oil fields and applied ANN for its prediction, and Yarim et al. [14] reported that more than half of stuck incidents occur during tripping and pipe-pulling operations, advocating proactive prevention. Collectively, these studies reinforce the necessity of continuous, real-time surveillance and early warning, which directly motivates the present work.

2. Materials and Methods

The methodology section comprehensively describes the transition from raw field data to a validated predictive model. The approach centered on leveraging high-resolution Mud Logging data over traditional low-frequency daily drilling reports to capture subtle pre-failure signatures. The core of the method involved transforming the continuous Mud Logging stream via an event windowing approach and applying random under sampling to mitigate the severe class imbalance inherent to stuck pipe events. Critically, the study integrated an unsupervised step: the K-Means clustering algorithm was successfully applied to stuck event features (K=3) to create reliable physical labels for the three primary sticking mechanisms (Wellbore Geometry, Differential Pressure, and Hole Packing), thereby overcoming a major limitation in field data. Finally, model validation relied exclusively on the in-depth analysis of the confusion matrix components (TP, FP, TN, FN). This ensured the selected model maximized the ability to issue reliable early warnings by prioritizing the minimization of the absolute count of False Negatives (FN).

2.1. Data Preprocessing and Feature Engineering

The initial dataset for this study comprised daily drilling reports (DDRs) from 28 oil and gas wells located in Southwest Iran (5,760 daily records). Because of the insufficient temporal resolution of DDRs, the final predictive models were developed exclusively on high-resolution mud logging data from 8 wells selected from the original 28 based on data completeness and recording consistency. A critical decision was to move beyond the traditional reliance on low-frequency Daily Drilling Reports (DDRs). Consequently, the core of the analysis was based on high-resolution Mud Logging data, which provides records of key operational parameters such as Weight on Bit (WOB), Torque (T), ROP, and Rotary Speed (RPM) at a much higher frequency, vital for an effective early warning system.

Initial Data Preparation and Standardization. The initial stages focused on validating and normalizing the raw input:

- Data Acquisition and Extraction: This involved gathering the raw Mud Logging data and performing Feature Extraction on key parameters.
- Data Cleaning: Rows containing missing values in any of the selected parameters were removed entirely from the dataset to avoid imputation bias. Outliers were subsequently identified using the Mahalanobis distance, which accounts for the covariance structure among variables, with the removal threshold set according to the chi-square distribution ($p < 0.001$) at degrees of freedom equal to the number of features. Outlier removal was applied only to the training subset after splitting (see below).
- Proportional Splitting: 70% training and 30% testing at the sample level (no separate validation set; 5-fold cross-validation was used on the training set). Sample-level splitting was adopted because the scarcity of stuck events (87 total) made well-level splitting statistically infeasible. Stuck Event Windowing and Balancing. To prepare the data for supervised learning, the following steps were taken:
- Stuck Point Labeling: An event windowing approach was implemented. A time window of 10 to 30 minutes immediately preceding each confirmed stuck event was extracted for the stuck class (positive class). This window is designed to capture the operational signature of the pipe becoming progressively stuck. The officially recorded stuck timestamp was used as anchor t=0; the 10–30 min window strictly precedes t=0, ensuring causal feature extraction and a prediction lead time of up to 30 minutes.
- Class Balancing: The resulting severely imbalanced dataset was mitigated using random under sampling to equalize the number of samples between the stuck and non-stuck classes. Random undersampling was applied exclusively to the training subset after the split; the test subset retained its natural imbalanced distribution. Synthetic oversampling (e.g., SMOTE) was avoided to prevent physically impossible drilling parameter combinations.
- Feature Normalization and Final Construction: Min-Max scaling was applied to map all features to the [0, 1] range; the scaling parameters (min and max) were computed exclusively from the training subset and then applied to the test subset to prevent information leakage. Normalization prior to multivariate outlier detection ensures that variables with large physical ranges (depth or hook load) do not dominate the covariance matrix used by the Mahalanobis criterion.

Finally, statistical descriptors (e.g., mean, standard deviation, and rate of change) for the operational parameters were calculated within these event windows, summarizing the behavioral trend of the drilling parameters within the critical pre-stuck period. The parameters listed below constitute the input parameters used in the machine learning models. The implementation of these models relies on accurate sequence or arrangement of these variables.

Table 1. Data inventory at each preparation stage.

Stage	Stuck (window samples)	Non-stuck (window samples)
Labeled stuck windows (8 wells)	125	1,218
Training subset (70%)	87	846
Testing subset (30%)	38	372
Training after undersampling (binary task)	87	87
Multi-class training (imbalanced)	87 (52 / 27 / 8 per cluster)	846
Multi-class testing (imbalanced)	38 (24 / 6 / 8 per class)	372
Binary testing (event level)	15 distinct stuck incidents	15 non-stuck events

The ten variables listed in Table 1 were selected because they were the only parameters consistently recorded at high resolution across all 8 wells and because they jointly span the mechanical domain (WOB, RPM, ROP, Torque, Hook Load), the hydraulic domain (Flow In, ECD, Mud Weight), and the thermal/depth context (Temperature, TVD) that govern stuck-pipe mechanics. A Pearson correlation analysis confirmed expected interdependencies (e.g., between WOB, ROP, and Torque); however, these variables were retained because (i) SVM and neural-network classifiers are not adversely affected by multicollinearity, and (ii) the physical interdependence among them (e.g., as embodied in Mechanical Specific Energy) carries essential diagnostic information for distinguishing stuck mechanisms.

Table 2. Input Variables for the Machine Learning Models

Variable	Description
TVD	True Vertical Depth
WOB	Weight on Bit
RPM	Revolutions per Minute
ROP	Rate of Penetration
TQ	Torque
MW	Mud Weight
HL	Hook Load
ECD	Equivalent Circulating Density
FI	Flow In
T	Temperature

2.2. Unsupervised Stuck Type Labeling using K-Means Clustering

A significant challenge in developing a multi-class prediction system is the lack of explicit labels in field data specifying why the pipe got stuck (differential pressure, hole packing, or wellbore geometry [9]). This study overcame this limitation by integrating an unsupervised learning method into the labeling process:

- Clustering Input: All ten variables of Table 1 were used as clustering inputs, after Min-Max normalization with parameters fitted on the training subset, so that no single variable could dominate the distance metric. The number of clusters was set to K = 3 on the basis of established drilling-engineering consensus that stuck incidents manifest through three primary macroscopic mechanisms (wellbore geometry, differential pressure, and hole packing); the choice was further confirmed post hoc by the physical interpretability of the centroids. To guard against initialization sensitivity, the K-Means++ seeding scheme was used together with multiple replicates, and the resulting cluster assignments were stable across runs.
- Physical Interpretation: The three resulting clusters (K=3) were analyzed based on the statistical center (centroid) of each cluster, revealing distinct operational signatures.

Table 3. Characteristics of the Cluster Centers Identified by the K-Means Algorithm.

Type No.	Stuck Type	Count	ROP(avg)	WOB(avg)	RPM(avg)
1	Wellbore Geometry	52	13.08	31.51	137.56
2	Differential	27	37.49	11.71	106.23
3	Hole Packing	8	15.03	12.80	171.11

Cluster 1 (n = 52) exhibits the highest average WOB (31.51 klb) combined with the lowest ROP (13.08 m/hr), the classic signature of mechanical restriction (wellbore geometry). Cluster 2 (n = 27) shows low WOB (11.71 klb) and low RPM (106.23), consistent with a stationary or slowly moving string under overbalance (differential pressure). Cluster 3 (n = 8) shows the highest RPM (171.11) with low ROP (15.03), indicating aggressive rotation struggling against annular friction (hole packing).

By interpreting the centroid features, the three clusters were mapped to the three known stuck mechanisms, thus providing the cluster-derived pseudo-labels required for the multi-class supervised learning task.

2.3. Evaluation Metrics

Given the high-stakes, safety-critical nature of stuck pipe prediction, model performance was evaluated based exclusively on the detailed analysis of the confusion matrix for each classifier. In addition to the standard metrics (accuracy, precision, recall, F1-score, specificity and balanced accuracy), which are now reported numerically in Section 3, model selection for this safety-critical application prioritized minimizing the absolute count of False Negatives (FN), since an FN represents a missed alarm with potentially catastrophic operational consequences.

2.4. Model Implementation and Hyperparameter Settings

All models were trained in the MATLAB Classification Learner environment using its documented preset configurations; no manual hyperparameter tuning was performed. The exact settings are reported in Tables 4 and 5 to ensure reproducibility. The training and testing subsets were saved as separate files and are available from the corresponding author upon reasonable request .

Table 4. SVM hyperparameters as implemented.

Model	Kernel Function	Kernel Scale
Linear SVM	Linear	Auto
Quadratic SVM	Polynomial (order 2)	Auto
Cubic SVM	Polynomial (order 3)	Auto
Fine Gaussian SVM	Gaussian (RBF)	0.87
Medium Gaussian SVM	Gaussian (RBF)	3.5
Coarse Gaussian SVM	Gaussian (RBF)	14

The Gaussian kernel scales follow the software's automatic heuristic ($\sigma \approx 3.5$), with the Fine and Coarse presets adopting $\sigma/4$ and 4σ, respectively.

Table 5. Neural-network architectures as implemented.

Preset	Fully Connected Layers	Layer Sizes
Narrow NN	1	[10]
Medium NN	1	[25]
Wide NN	1	[100]
Bilayered NN	2	[10, 10]
Trilayered NN	3	[10, 10, 10]

The architectures span the width (10→25→100 neurons) and depth (1→3 layers) dimensions to probe the capacity–generalization trade-off. Networks were trained with the default limited-memory BFGS solver and terminated at the 1,000-iteration limit (no early stopping); with Lambda = 0 no explicit penalty was applied, and overfitting was monitored through 5-fold cross-validation on the training set.

3. Results and Discussion

3.1. Binary Classification Results (Stuck vs. Non-Stuck)

The performance of all classification models for the binary task (stuck vs. non-stuck) was evaluated. The primary objective for this early warning system is to minimize False Negatives (FN), as an FN represents a missed alarm-the most critical error type for this safety-critical application. The analysis of the Decision Tree family showed moderate performance. As shown in Figure 1 Both the Fine Tree and Medium Tree models yielded identical results, registering 4 False Negatives (FN=4). The Coarse Tree model reduced this critical error count to 2 False Negatives (FN=2) and correctly identified 13 stuck events (TP=13).

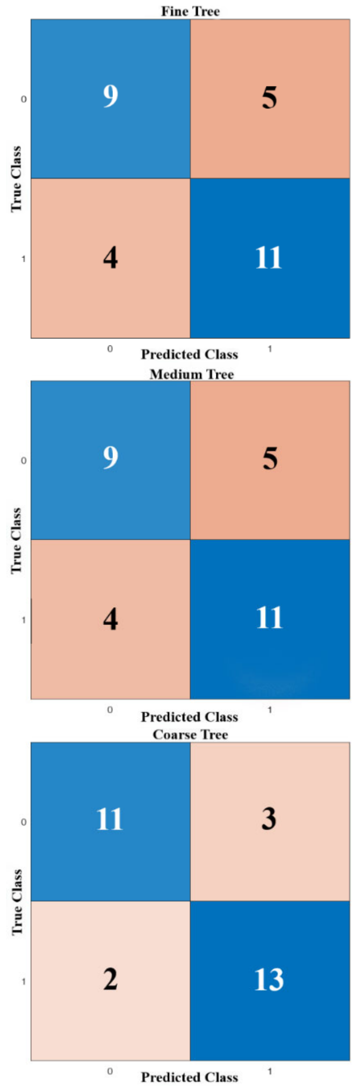
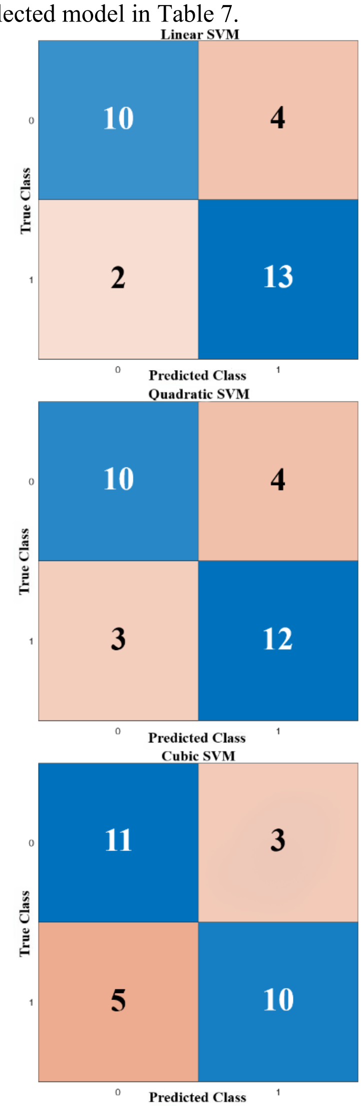


Figure 1. Decision Tree binary classification results

The Support Vector Machine (SVM) family showed the widest performance variation but also contained the best-performing models (Figure 2). The Cubic and Fine Gaussian models were non-optimal, with 5 False Negatives. The Quadratic and Medium Gaussian models offered intermediate performance (FN=3). The Linear SVM successfully matched the performance of the best Decision Tree model, with 2 False Negatives. Critically, the Coarse Gaussian SVM demonstrated superior performance, achieving the lowest error rate of all models with only 1 False Negative (FN=1) and correctly identifying 14 of the 15 stuck events. The 15 stuck events in the binary test set correspond to 15 distinct, temporally independent incident windows drawn from the 8 wells; the remaining non-stuck test events were used to quantify false alarms. The numerical detection counts for all binary models are given in Table 6, and the standard metrics for the selected model in Table 7.



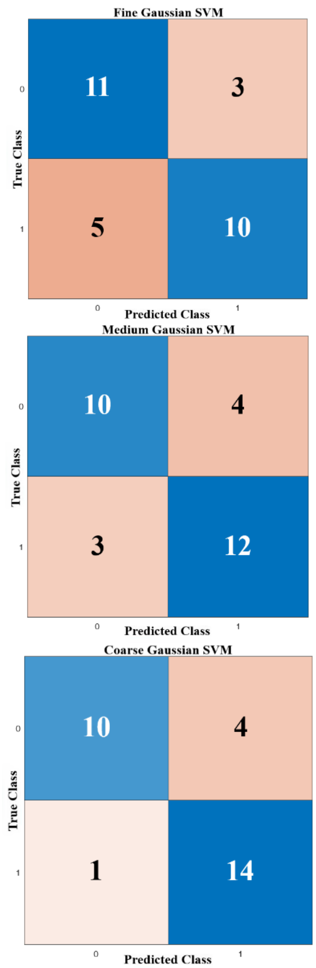
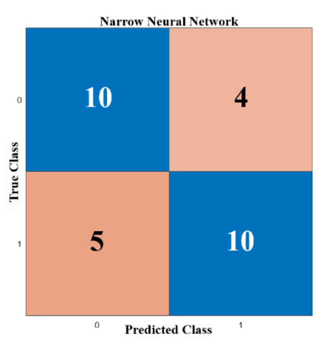


Figure 2. Support Vector Machine binary classification results

Conversely, In Figure 3, the Neural Network family generally demonstrated the weakest performance in managing critical errors.



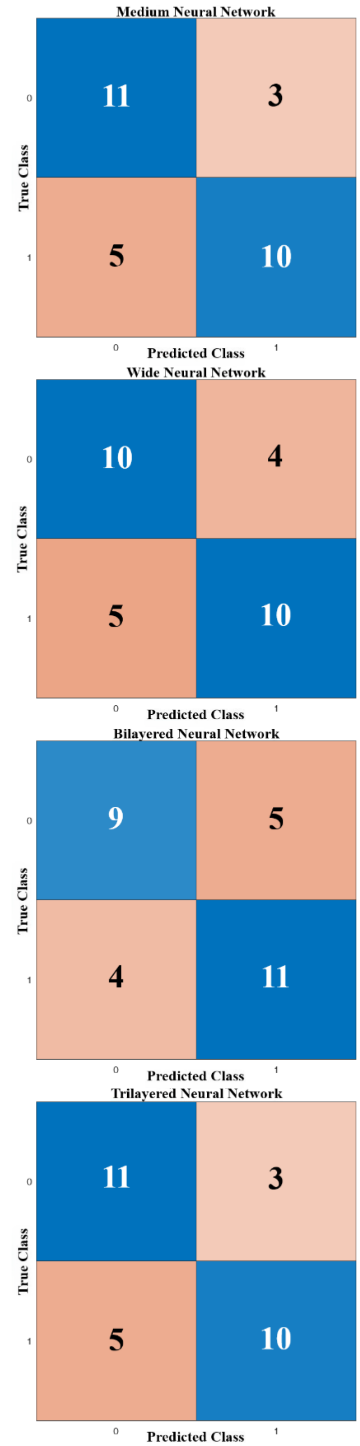


Figure 3. Neural Networks binary classification results

Table 6. Numerical binary detection counts on the test set (15 stuck / 15 non-stuck events).

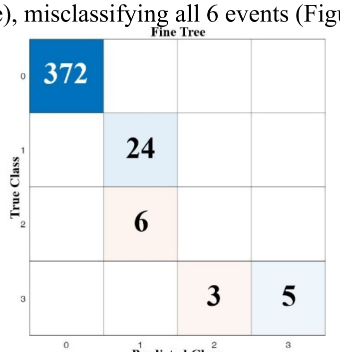
Model	TP	FN	Recall (stuck)
Fine Tree / Medium Tree	11	4	0.733
Coarse Tree	13	2	0.867
Linear SVM	13	2	0.867
Quadratic / Medium Gaussian SVM	12	3	0.800
Cubic / Fine Gaussian SVM	10	5	0.667
Coarse Gaussian SVM	14	1	0.933

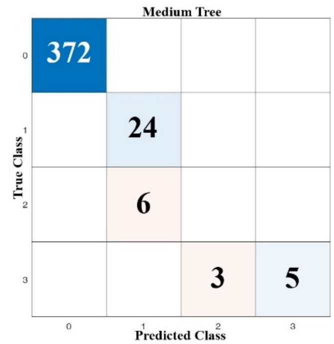
Table 7. Standard performance metrics of the deployed models.

Task / Model	**Accuracy**	**Precision**	**Recall**	**F1**	**Balanced acc.**
Binary – Coarse Gaussian SVM	0.900	0.875	0.933	0.903	0.900
Multi-class – Linear SVM	0.985	0.700	0.750	0.722	0.750

3.2. Multi-Class Classification Results (Stuck Type Prediction)

Following the binary analysis, the models were evaluated on the more complex multi-class task. The objective was to correctly classify the specific stuck pipe mechanism (Class 1: Wellbore Geometry, Class 2: Differential Pressure, Class 3: Hole Packing) in addition to the non-stuck state (Class 0). The Decision Tree models performed perfectly on the majority Class 0 (Non-Stuck) and on Class 1 (Wellbore Geometry), but failed to identify any instance of Class 2 (Differential Pressure), misclassifying all 6 events (Figure 4).





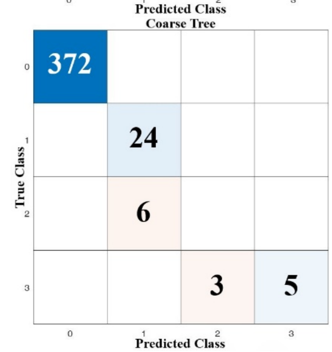
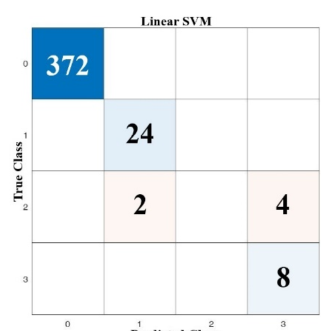


Figure 4. Decision Tree multi-class classification results

As shown in Figure 5, the SVM family showed significant performance variation. The Gaussian-based models performed poorly, while the Linear SVM demonstrated exceptional performance. It achieved 100% recall for Class 0 and Class 1, and crucially, it was the only model in the entire study to achieve 100% recall for Class 3 (Hole Packing), identifying all 8 instances correctly. Given that only eight Hole Packing events exist in the entire dataset, this result should be interpreted with caution and is not statistically robust; it is reported as an encouraging but preliminary indication rather than proof of generalization for this class. Notably, all SVM models completely failed to identify any instance of Class 2.



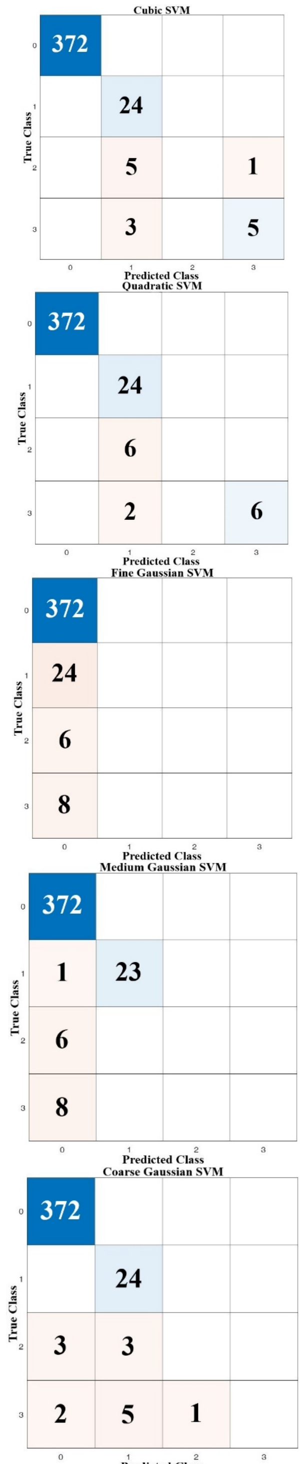
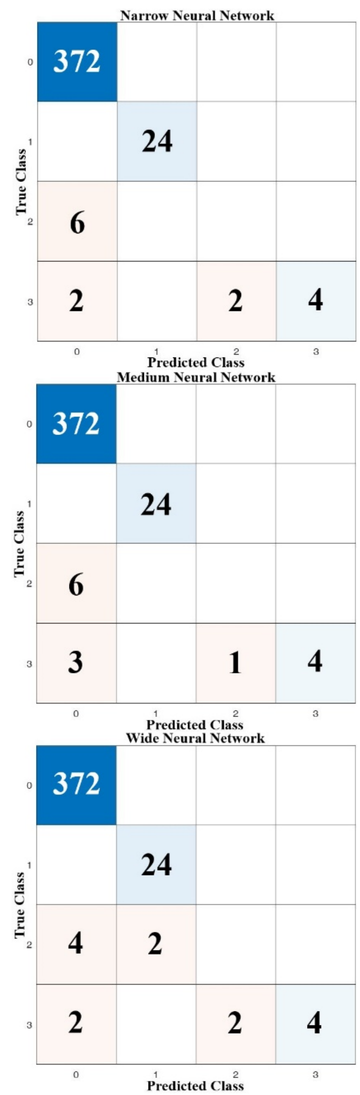


Figure 5. Support Vector Machine multi-class classification results

A detailed analysis reveals several key insights: All models (except the Bilayered Neural Network) achieved perfect classification on the distinguishable classes for the majority non-stuck class. The critical failure on Class 2 (Differential Pressure) across nearly all models strongly suggests that the input features from mud logging data are insufficient to distinguish this specific mechanism. The Linear SVM is identified as the single best-performing model, demonstrating the highest capability to accurately distinguish between the actionable stuck types represented in the dataset.



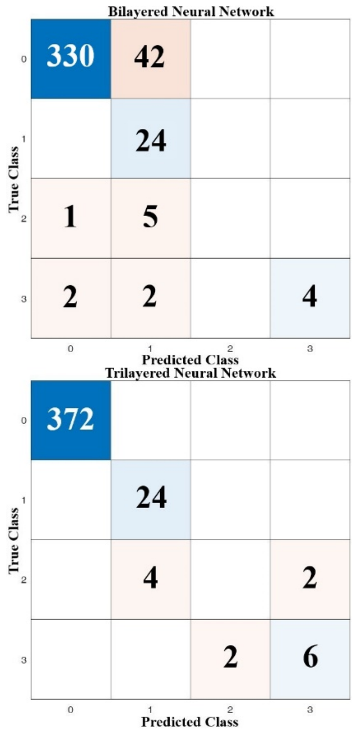


Figure 6. Neural Networks multi-class classification results

3.3. Model Selection, Limitations, and Generalizability

The selection of the Coarse Gaussian SVM as the superior binary classifier was driven by the operational necessity for promising generalization rather than overfitting to training noise. The systemic inability of all tested classifiers to identify the "Differential Pressure" stuck mechanism (Class 2) strongly suggests that the limitation lies in the input data source. Standard Mud Logging data lacks real-time measurements of formation pore pressure, permeability, or detailed filter cake properties [10]. While the specific predictive weights derived in this study are tuned to the geomechanical characteristics of the studied Iranian oil field, the methodology of employing K-Means clustering to derive pseudo-labels from historical data addresses a global industry challenge and is methodologically transferable; however, the trained model weights remain field-specific and require recalibration before deployment in other fields.

While the proposed framework demonstrates strong potential for real-time stuck pipe early warning, several methodological boundaries, operational implications, and statistical limitations must be acknowledged to properly contextualize the current findings and guide future field deployments. Specifically, the following considerations define the scope, constraints, and practical applicability of the developed models:

- Operational cost asymmetry and tiered alarm logic: In drilling operations, the economic penalty of a False Negative (missed alarm) is orders of magnitude higher than that of a False Positive, as the former can lead to catastrophic immobilization of the drill string and the probability of successful freeing declines sharply with elapsed time [12]. Consequently, the decision-support logic is designed as a tiered system: the binary early-warning alarm (which achieved FN = 1) serves as the primary safety trigger, while the multi-class mechanism output is treated as an advisory diagnostic tool.
- Statistical and validation constraints: Due to the inherent rarity of stuck events, the test set comprises a limited number of independent incidents. Therefore, advanced statistical validations such as bootstrap analysis, confidence intervals, and leave-one-well-out (LOWO) cross-validation were not feasible in this proof-of-concept study. Sample-level splitting was adopted out of necessity, and well-level validation remains a mandatory standard for future, larger-scale datasets.
- Methodological extensions: While the current study establishes a foundational framework, future work must incorporate sensitivity analyses across alternative prediction horizons (e.g., 5, 15, and 45 minutes), evaluate advanced ensemble baselines (e.g., XGBoost, LightGBM), and implement systematic hyperparameter optimization to further refine decision boundaries.
- Computational feasibility for edge deployment: The deployed models operate on a highly reduced feature space of only ten statistical descriptors per window. Consequently, the inference time is computationally trivial (sub-millisecond on standard industrial hardware), which is negligible compared to the typical 1–10 second telemetry update rates of mud logging systems, confirming its viability for real-time panel deployment without dedicated GPUs.
- Evidence for high-resolution data necessity:

The transition from Daily Drilling Reports (DDRs) to Mud Logging (ML) data was driven by empirical evidence; preliminary baseline models trained on the 28-well DDR dataset failed to capture transient pre-failure signatures and yielded unacceptably high False Negative rates, quantitatively proving that temporal resolution is the dominant performance driver.

- Position relative to prior work: Compared to recent field-scale studies reporting stuck-event sensitivities in the range of 75–85%, the proposed binary Coarse Gaussian SVM achieves a recall of 93.3% on the held-out test events, while simultaneously extending prior binary-only frameworks to multi-class mechanism identification via unsupervised pseudo-labeling.
- Aggregated training configuration: Rather than training isolated per-well models—which would suffer from severe overfitting due to insufficient local event counts—a single global model was trained on the aggregated, preprocessed data of the 8 selected wells. While this captures generalized pre-failure physical signatures, it implies that the learned weights are field-specific and require recalibration or transfer learning before deployment in new geological settings.

4. Conclusions

This research developed a data-driven framework for the real-time classification of both the occurrence and the specific type of drill string stuck, based on high-resolution operational data from an Iranian oil field. The key findings are as follows:

1. Necessity of high-resolution data: Low-frequency daily drilling reports are inadequate; high-resolution mud logging data is essential for capturing pre-failure signatures.
2. Novelty in stuck-type labeling: Unsupervised K-Means clustering, validated through physical interpretation of the centroids, generated cluster-derived pseudo-labels for the primary stuck mechanisms, resolving a critical data limitation.
3. Superior performance for early warning: The Coarse Gaussian SVM was the most reliable binary classifier, achieving the lowest count of critical False Negatives (FN = 1).
4. Stuck-type prediction: The Linear SVM achieved 100% recall on the distinguishable classes (Wellbore Geometry and Hole Packing), while the Differential Pressure mechanism remained unresolved with surface data alone, indicating the need for downhole or geomechanical inputs.
5. Operational impact: The framework is designed for real-time deployment on the driller's panel under a tiered alarm logic that prioritizes missed-alarm minimization.
6. Limitations and future work: Field-specific model weights, the limited test-set size, sample-level splitting, and the absence of ensemble baselines and horizon sensitivity analysis define the boundary of the present conclusions and the agenda for subsequent studies.

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