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Machine Learning Classifies Data for Early Warning of Stuck Pipe Detection in Geothermal Drilling

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***Abstract*— Stuck pipe is a common issue encountered during geothermal well drilling which often disrupts operations and potentially leads to the suspension of drilling activities. This issue commonly occurs in lost circulation conditions within the reservoir zone, which reduce the capacity to lift cuttings and destabilize the drill hole due to inadequate drilling fluid performance. Therefore, this study aimed to propose an early warning system for detecting stuck pipe anomalies in geothermal drilling using machine learning as an Artificial Intelligence (AI) technique to expedite detection and response times. Time-based mud logging unit sensor data was used in the study collected from the drilling of five wells in the MGL field, all of which experienced stuck pipe incidents. The analysis further analyzed significant drilling parameters such as gas rate (considered for the first time), weight on bit (WOB), rotations per minute (RPM), standpipe pressure, mud flow rate, torque, hook load, rate of penetration (ROP), return, and condition readings. The dataset was evaluated using Support Vector Machine (SVM) and Artificial Neural Network (ANN) models to predict and classify conditions as normal, pre-stuck, or stuck. The results showed that SVM provided accuracy, precision, and recall of 0.99, 0.98, and 0.97, respectively outperforming ANN scoring 0.99, 0.98, and 0.89. This implied that SVM could provide better prediction results than ANN, offering a fast and effective method for early detection by improving response times and accuracy in preventing stuck pipe incidents.**

***Keywords* — Stuck pipe; anomaly detection; geothermal drilling; machine learning.**

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I. Introduction

Geothermal energy is the heat naturally occurring within the Earth which combines two simple concepts namely "geo," meaning Earth, and "thermal," meaning heat. This Earth-sourced heat can be tapped and harnessed for various purposes from generating electricity to heating buildings. In essence, geothermal energy harnesses the Earth's internal heat to meet various human needs [1]. Indonesia, located within the Pacific Ring of Fire has significant geothermal energy capacity reaching approximately 23,765.5 Megawatts (MW) which represents around 40% of the world's total geothermal potential [2].

Indonesia is rapidly developing geothermal energy to meet the growing demand and required supply of geothermal capacity [3], as drilling programs are a core activity for any renewable energy geothermal operator, despite various challenges. These include the exploration, delineation, development, and well closure phases of geothermal well lifecycle management [4]. In addition to the well-known issues such as difficult formations, total loss of circulation, and high-temperature environments, optimizing drilling time has become a key economic factor [5]. These problems which impact the efficiency and productivity during geothermal well drilling are referred to as Non-Productive Time (NPT). Purba et al [6] further identified stuck pipes as a primary cause of NPT in Indonesia geothermal drilling.

A stuck pipe is a common drilling problem that causes significant NPT, occurring when the vertical or rotational movement of the drill string is suddenly impeded. Sticking can be classified into mechanical such as pack-off, bridging, wellbore geometry issues, or differential sticking [7]-[10]. Causes of stuck pipe incidents include uncontrolled mudflow, the accumulation of drill cuttings in the borehole, sand adhesion to the drill string and pipes, as well as rock collapses, such as sand and gravel near the drill bit formation. Schlumberger analysis showed that around 54% of stuck pipe incidents occur while pulling drill strings during activities such as changing drill bits (tripping) and backreaming. Furthermore, solid-induced pack-offs contribute to 64% of these occurrences, followed by pressure fluctuations at 21% and mechanical challenges or wellbore shape at 14% [11].

Considering that the target is within lost circulation in the reservoir depth zone, the risk of encountering a stuck pipe during geothermal drilling operations is high. Factors such as improper hole cleaning, poor well trajectory, incorrect drilling mud usage, and pressure differences are responsible for stuck pipe incidents. An anomaly that caused the formation to change parameters is further detected before the pipe could get any further [12]. Poor hole-cleaning conditions can be detected early on by looking for erratic torque where the drill string repeatedly gets stuck in cuttings or an unexplained rise in bottom hole pressure. This pressure increase could be connected to a tight spot with packings which causes flow restrictions higher up in the annulus. Additionally, an unexpected hook load potentially caused by the drill string resting on a tight packing can also indicate a problem [13]. The importance of preventing stuck pipes cannot be understated as it is more cost-effective to prevent than to rely on freeing procedures [14]. Early detection and prediction of the symptoms are also essential in avoiding stuck pipe incidents by enabling prompt preventive actions. By using a predictive model or technique to anticipate stuck pipes and prevent the occurrence, considerable savings in costs and time can be further realized [15].

Various researchers are actively investigating the symptoms and associated consequences to anticipate and prevent occurrences of stuck pipes. Despite existing results, there is currently no mathematical equation or analytical modelling tool available to accurately predict stuck pipe incidents based on drilling parameters. This has led certain articles to explore the use of Artificial Intelligence (AI) for this purpose [15]. Over the past two decades, a variety of data analytics methods including Machine Learning and AI have been explored with varying degrees of success [16]. For instance, W. K. Wong et.al [17] explored the use of machine learning to predict sonic wave travel time in oil and gas exploration helping to understand the composition and structure of underground rocks. Although travel-time data is not consistently available during drilling, Wong tested two machine learning methods namely Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN) using the Volve dataset. The results showed that ANN slightly outperformed MLR, suggesting the data had a non-linear nature. Therefore, this study aimed to bridge the gap between machine learning experts and oil & gas engineers, helping to make the technology more accessible and practical in the field. To continue the previous articles, W. K. Wong [18] focused on developing transparent mathematical models to predict compressional (P-wave) and shear (S-wave) wave travel times in oil and gas exploration, addressing the limitations of "black-box" machine learning models. The article further used a two-stage evolutionary modelling method and adopted tree-based genetic programming (GP) and adaptive differential evolution (ADE) to create these models. The results showed that the models provided reliable predictions with R^2 values of 0.90 for P-wave and 0.75 for S-wave, offering interpretability and analysis opportunities not available with traditional black-box models. The procedure marks the first attempt to apply a mathematical method to predict missing sonic readings in this context.

Abbas et al [19] showed how to detect stuck pipes using historical data such as Daily Drilling Reports, daily mud reports, final good reports, and master logs. The article further adopts the classification concept with two algorithms namely SVM and ANN with SVM outperforming ANN in predictive accuracy. Similarly, Do et al. [20] compared SVM and ANN for detecting stuck pipe incidents in oil and gas drilling using stuck and non-stuck labels with SVM showing superior performance. Kizayev et al [21] also used the XGBoost algorithm to develop a machine-learning model outlining flow rate, inclination, and penetration rate as the three most important parameters for stuck pipes in oil well drilling. Sarwono et.al [15] further modelled machine learning stuck pipe with ANN algorithm using data from time-based mud log in geothermal drilling with seven parameters including Torque, Hookload, Standpipe pressure, rotation per minute (RPM), weight on bit (WOB), flow rate, and rate of penetration (ROP). The parameters use the concept of classification of two classes namely stuck and non-stuck. Furthermore, Aseel et al. [22] developed a predictive model using ANN to classify pipe sticking due to wellbore uncleanliness in oil and gas drilling into two classes non-pipe sticking and pipe sticking showing high generalization ability and an average accuracy of 90%. Pradana et.al [12] updated the modelling stuck pipe machine learning in geothermal drilling using the concept of classification of three classes namely Normal, pre-stuck, and stuck with ANN algorithm adopting nine parameters namely WOB, ROP, RPM, torque, mudflow in, mudflow out, standpipe pressure, hook load, and condition (Reaming or Drilling).

This study aimed to focus on early detection of stuck pipe incidents in geothermal drilling. The accurate predictions of these incidents can help identify potential stuck pipes before occurring which allows operators to conduct appropriate preventive measures. This not only reduces time and costs lost due to stuck pipes but also increases the efficiency and sustainability of drilling operations. Consequently, this study contributes directly to the safety, productivity, and overall effectiveness of geothermal projects. A common issue in geothermal drilling is lost circulation where drilling fluid is lost into the formation, leading to stuck pipe incidents.

A new parameter named the Gas Rate is introduced in this study which refers to the amount of gas injected during the aerated drilling process. Aerated drilling is a technique used to clean boreholes and is particularly effective for addressing total lost circulation. Furthermore, the amount of gas injected or the Gas Rate is a critical factor that significantly impacts the possibility of stuck pipes. The addition of the Gas Rate parameter provides a new perspective and potential solution for improving geothermal drilling operations. To further enhance predictive accuracy, this study uses advanced machine learning algorithms such as ANN and SVM, categorizing the data into three classes namely normal, pre-stuck, and stuck.

II. Materials and Method

The data used in this study was the actual field records from the geothermal field in West Java with a water-dominated fluid type. Records from a case of drilling five geothermal wells in the same field were also obtained. The wells selected as study objects were wells with the same problem characteristics in sections 12.25 "and 9.875" which included experiencing stuck pipe incidents and lost circulation conditions respectively. The data further comprised real-time drilling data from mud logging unit readings and Daily Drilling Reports. Furthermore, all the wells were drilled by the same operator prompting the assumption that the range of drilling parameters was equal in each well.

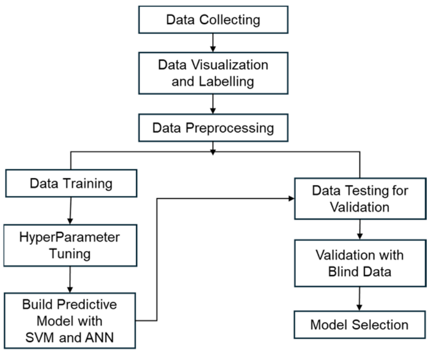


Fig. 1 Proposed system design

This study applied machine learning to predict drilling parameter conditions into normal, anomaly, and stuck conditions. Actual field data which totalled 2775 from four wells filtered data were used to construct a predictive model with 10 input variables such as WOB, ROP, RPM, Torque, MudFlowIn, MudFlowOut, StandPipe Pressure, Hookload, Condition (Reaming or Drilling), and gas rate. The output variable was classified into three classes namely 0 (normal), 1 (prestuck), and 2 (stuck). The prediction models of the two methods were further developed using the Python programming language where the datasets labelled were processed for data balancing to prevent the models from favoring the most frequent data. Furthermore, datasets were split into 80% allocated for training and 20% for testing purposes. Training data was further used to develop model prediction with SVM and ANN methods classifying drilling parameters into three conditions. Both algorithms possessed personal architecture to identify relationships among the variables. After the models were developed, validation would be conducted using actual data from a well not included in the dataset used to develop the models.

TABLE I
DATASET

Num	Scfm	WOB	ROPi	Trq	RPM	Hkld
1	0	5	22	14	143	146
2	0	5	10	14	143	146
..	..	..	..	..	..	..
55725	1204	0	0	0	155	233

Num	MFO	SPP	MFI	Condition	Class
1	33	935	706	1	0
2	33	935	706	1	0
..	..	..	..	..	..
55725	0	2175	847	0	0

This study further aimed to create a predictive model for stuck pipe detection in geothermal drilling using AI with 10 drilling parameters as input. From the available five well data A1, A2, B1, and B2 were used to train the model and A3 was used to validate how accurate the model was developed.

TABLE II
RAWS OF DATASET

No	Well Name	Total of Rows Data	Data Utilization
1	A1	267840	Training
2	A2	120960	Training
3	B1	77760	Training
4	B2	285120	Training
5	A3	250560	Validating

In Table 2, the data was collected during the drilling process in the reservoir Sections 12.25” and 9.785” in each well. Raw data processing was conducted by visualising the information using Python to identify the data to be used or deleted. Through the visualisation, the information in the Daily Drilling Report was validated for the process of screening unnecessary data to be done accurately. Removal of data not needed in this study included Non Productive time, Wait on Cement, Running Casing, Leak of Test, Sliding, and equipment repair.

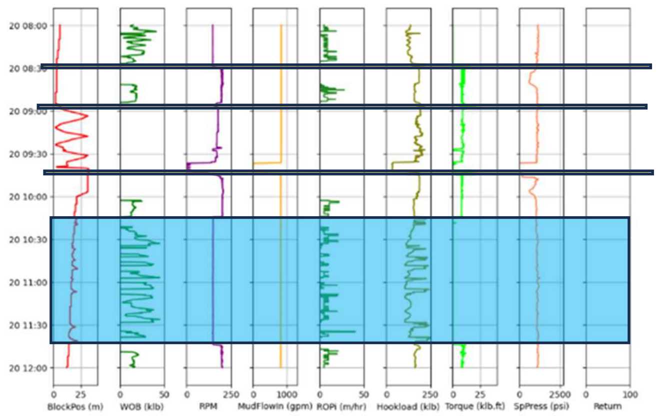


Fig. 2 Visualization of Raw data to screening Dataset

In this study, the type of machine learning used was supervised learning classification which was necessary to label each row of data in determining the category of the machine. For this labelling, the data was grouped into three classes namely label 0 (normal condition), label 1 (pre-stuck condition), and label 2 (stuck condition). Labelling the data was assisted by the visualisation conducted previously as well as the information included in the Daily Drilling Report. Additionally, an understanding of drilling engineering such as drilling parameters and problems was required to provide proper labelling prompting the Datasets to be labeled as shown in Table 2.

Tables 3 and 4 further showed the dataset before and after the balancing process where the data from the four wells exhibited an imbalance in the distribution of each class. Therefore, carrying out a data balancing process was necessary using the under-sampling method for the 925 rows of data with the selection through stratified random sampling to ensure data from each well was proportionally collected. The dataset after the balancing process was further provided in Table 3 where the Total data from the four wells was 2775 which was split into 2220 data trains and 555 data tests with the ratio 80:20.

TABLE III
DATASET AFTER SCREENING AND LABELING

Label	Well A1	Well A2	Well B1	Well B2	Well A3	Total
Normal	16328	24886	12118	19874	52743	125949
Prestuck	605	123	886	44	99	1757
Stuck	180	394	223	128	107	1032

TABLE IV
DATASET AFTER DATA BALANCING PROCESS

Label	Well A1	Well A2	Well B1	Well B2	Total
Normal	207	314	153	251	925
Prestuck	338	69	494	24	925
Stuck	180	394	223	128	925

A. *Performance Evaluation*

The prediction models were constructed based on the data of the four Wells which led to three distinct prediction models. Subsequently, the models were compared and the method that produced a highly accurate prediction was selected based on the testing data and test validation. The accuracy of the prediction was evaluated using confusion matrix [23]-[28] through equations (1), (2), and (3).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+TN} \times 100 \tag{1}$$

$$\text{Presicion} = \frac{TP}{TP+FP} \times 100 \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \times 100 \tag{3}$$

Accuracy was widely used in machine learning, describing the percentage of correctly classified instances [29]. Precision evaluated the relevance of retrieved instances and was calculated as the ratio of true positive predictions to the total number of positive predictions [30]. Recall on the other hand measured the proportion of true positives among actual positives, and was particularly important when minimizing false negatives against false positives. It was further calculated as the number of true positives divided by the total number of actual positives [24].

B. *Support Vector Machine*

Support Vector Machine (SVM) was a supervised learning technique with a corresponding algorithm that examined data to identify patterns in the input/output outcomes [31]. To effectively separate observations, SVM models developed hyperplanes that maximized the distance between the upper and lower margins from the data. By applying an optimal separation rule and a nonlinear mapping technique to convert input prototypes into a high-dimensional feature space, the SVM classification model found the best-separating hyperplane and further maximized the distance between linearly separable classes [32]-[33]. Furthermore, SVM methods were used across various important fields which surpassed ANNs in certain scenarios [34].

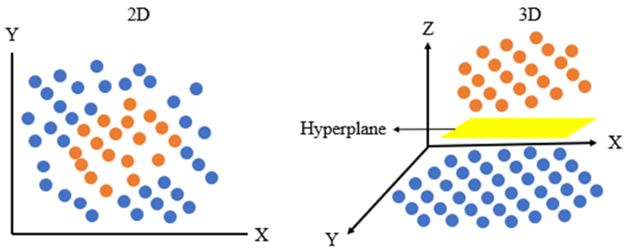


Fig. 3 SVM working principle

In Figure 3, the SVM transformed the nonlinear inputs using the mappings such as polynomial or Radial Basis Functions into a high-dimensional space [35]. This transformation enabled the inputs to be linearly separated by a hyperplane. The primary objective of SVM was to classify data into two groups with the largest margin between the separating boundaries separating the information. Additionally, the points where the decision lines intervene were called support vectors [35].

C. *Artificial Neural Network*

Figure 4 showed a type of ANN referred to as Multilayer perceptrons. An ANN served as an information processing system with performance characteristics, performing inherently the same as biological neural networks [36]-[37]. Neural networks with input layers possessed one or more hidden layers with an output which were trained by assigning a specific number of neurons [38]. Furthermore, the most popular type of ANN was the multilayer perceptron [34]

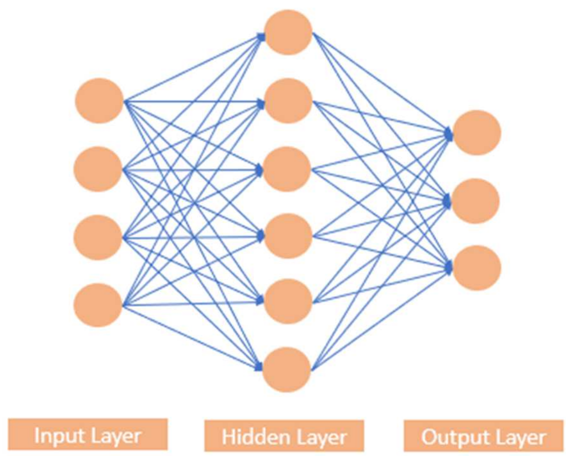


Fig. 4 ANN working principle with three layers (manual)

III. RESULTS AND DISCUSSION

This study aimed to develop a predictive model for stuck pipe detection in geothermal drilling using AI with 10 drilling parameters as input. From the available five well data, four were used to train the model and one to validate how accurately the model was developed. Furthermore, the trend of data was gathered after observing the scatter plot in Figure 5.

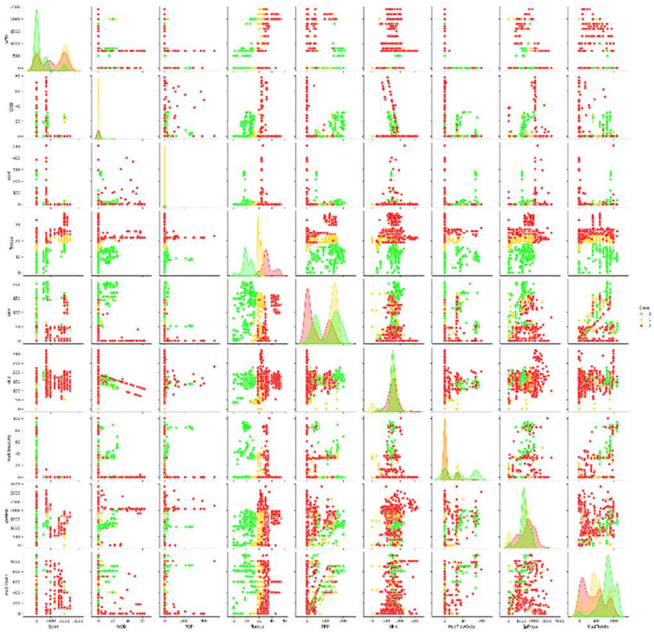


Fig. 5 Trend of Data Description using Scatter Plot

A. Prediction Model

The study resulted in two different algorithms to develop the prediction models. Both models were developed using Python and hyperparameter tuning features to obtain a combination of algorithmic architectures that best suited the dataset. The SVM model was further created with a combination of parameters such as C = (20, 30, 40), gamma = (auto, scaled), and kernel trick = (rbf, linear, poly).

TABLE V
SVM HYPERPARAMETER TUNING RESULTS

rank_test_score	Param_C	param_ga mma	param_ke rnel	*mean_test_score*
1	30	scale	rbf	0.986486
2	40	scale	poly	0.986036
3	40	scale	rbf	0.985586
4	30	scale	poly	0.984234
5	20	scale	poly	0.983333
6	40	scale	linear	0.982883
6	40	auto	linear	0.982883
8	20	scale	rbf	0.981532
9	20	scale	linear	0.98018
10	20	auto	linear	0.98018
11	30	scale	linear	0.97973
12	30	auto	linear	0.97973
13	40	auto	rbf	0.97973
14	30	auto	rbf	0.978829
15	20	auto	rbf	0.972973
16	40	auto	poly	0.917117
17	30	auto	poly	0.908559
18	20	auto	poly	0.898649

Based on result in Table 5, the combination of architecture to create the SVM model included C = 30, gamma = auto, and kernel = rbf. This combination of parameters produced the highest score when tested with a five-fold cross-validation. The ANN model was developed with a combination of parameters such as hidden layers (100, 100), (30,20,10), (8,8,8,8), activation (relu, tanh), and solver (lbfgs, adam).

TABLE VI
ANN HYPERPARAMETER TUNING RESULTS

rank_test_score	param_activation	param_hidden_*layer*_sizes	param_solver	*mean_test_score*
1	tanh	(30, 20, 10)	lbfgs	0.981522
2	tanh	(8, 8, 8, 8)	lbfgs	0.981522
3	tanh	(100, 100)	lbfgs	0.981026
4	relu	(30, 20, 10)	lbfgs	0.981022
5	relu	(100, 100)	lbfgs	0.980524
6	relu	(30, 20, 10)	adam	0.971039
7	relu	(8, 8, 8, 8)	lbfgs	0.969545
8	relu	(100, 100)	adam	0.967545
9	tanh	(30, 20, 10)	adam	0.96455
10	tanh	(100, 100)	adam	0.964044
11	tanh	(8, 8, 8, 8)	adam	0.963554

The combination of architecture to develop ANN model was Hidden layer size (30,20,10), activation = tanh, and solver = lbfgs. This model achieved the highest score when tested using five-fold cross-validation. The results for every combination of parameters are presented in Table 6.

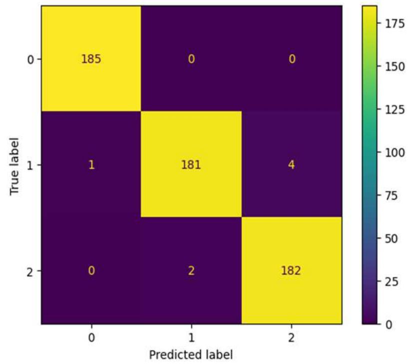
Hyperparameter tuning which includes finding the best combination of settings for a machine learning model was conducted to achieve optimal performance. In this study, the neural network model was configured with three key hyperparameters namely hidden layers, activation functions, and solvers. The hidden layers had three different configurations such as (100, 100), (30, 20, 10), and (8, 8, 8, 8), each representing a unique network architecture with varying numbers of neurons. The activation functions tested were relu and tanh while the solvers used were lbfgs and adam.

All 12 possible combinations of these hyperparameters were explored to identify the optimal model setup using Grid Search, a systematic approach that evaluated every combination by training and testing the model. To ensure reliable results, Cross-Validation was used, splitting the data into multiple parts and evaluating the model across different subsets. The process identified the best combination of hidden layers, activation function, and solver that delivered the highest performance on the validation data. Once the optimal configuration was determined, the final model was trained on the complete training dataset. This ensured that the model was prepared to make accurate predictions on new data. The systematic method of hyperparameter tuning and model evaluation helped ensure that the resulting neural network was both effective and reliable.

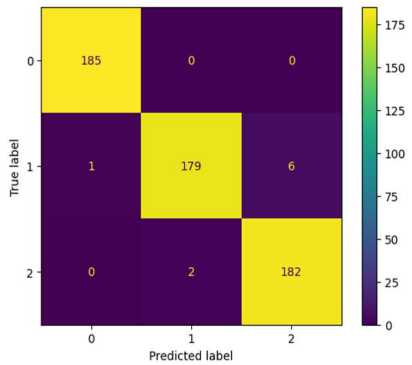
B. Model selection

The predictive models generated using SVM and ANN algorithms were compared. The comparison results were obtained from testing and validating the models with blind data. The performance of the two classification models was measured using a confusion matrix, evaluating metrics such as precision, accuracy, and recall. A value closer to 1 indicated better model performance.

The prediction results for the SVM and ANN models were summarized in Figure 6. In general, the SVM algorithm outperformed the ANN in terms of prediction accuracy. Both models successfully predicted all 185 incidents under normal conditions. For anomalies/pre-stuck states, the ANN model accurately identified 179 out of 186 cases while the SVM model correctly predicted 181 cases, making five errors. In stuck conditions, both models correctly predicted 182 out of 184 instances with each making two mistakes. When tested with new data, the SVM algorithm showed superior overall prediction performance compared to the ANN. The results of the confusion matrix for both algorithms were presented in Tables 7 and 8.



(a)



(b)

Fig. 6 Prediction results on data test (a) SVM and (b) ANN

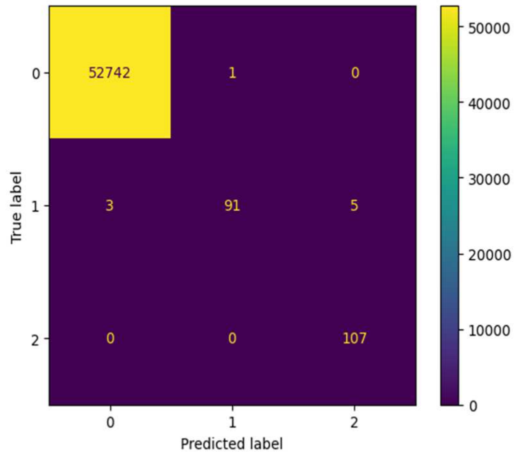
TABLE VII
SVM CONFUSION MATRIX ON DATA TEST

class	*Support Vector Machine*		
	precision	*recall*	*accuracy*
Normal	0.99	1.00	
Prestuck	0.99	0.96	0.98
Stuck	0.97	0.99	

TABLE VIII
ANN CONFUSION MATRIX ON DATA TEST

class	*Artificial Neural Network*		
	precision	*recall*	*accuracy*
Normal	0.99	1.00	
Prestuck	0.99	0.96	0.98
Stuck	0.97	0.99	

To further evaluate model performance, a validation test was conducted using blind data which referred to new data not introduced to the model at any stage of the training process. This test helped assess how well the model could predict previously unseen data accurately.



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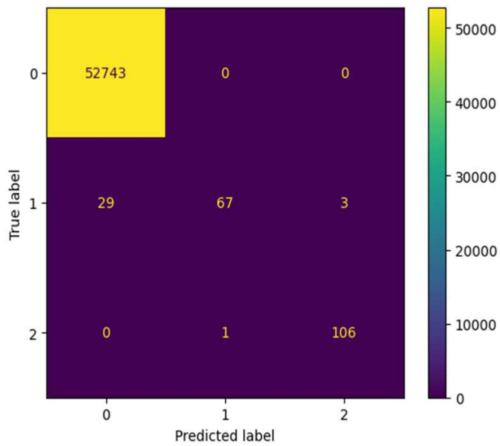

(b)

Fig. 7 Prediction results on validation test (a) SVM and (b) ANN

Figure 7 showed the prediction results of the two models when tested using data not seen or introduced previously in the training process. For normal condition predictions, the SVM model provided highly accurate results by correctly predicting 52,741 out of 52,742 instances with only one incorrect prediction but the ANN model predicted all instances correctly. For pre-stuck or anomaly conditions, the SVM model accurately predicted 91 out of 99 instances making eight errors while the ANN model correctly predicted 67 out of 99 instances with 33 errors. For stuck/stall conditions, the SVM model achieved perfect accuracy by correctly predicting all instances while the ANN model correctly predicted 106 out of 107 instances with one error. These results clearly showed that the SVM algorithm outperformed the ANN in predicting stuck pipe conditions. Furthermore, Tables 9 and 10 provided detailed performance metrics for the SVM and ANN models during the validation test.

TABLE IX
SVM CONFUSION MATRIX ON VALIDATION TEST

class	*Support Vector Machine*		
	precision	*recall*	*accuracy*
Normal	1.00	1.00	
Prestuck	0.99	0.92	0.99
Stuck	0.96	1.00	

TABLE X
ANN CONFUSION MATRIX ON VALIDATION TEST

class	*Artificial Neural Network*		
	precision	*recall*	*accuracy*
Normal	1.00	1.00	
Prestuck	0.99	0.68	0.99
Stuck	0.97	0.99	

The method not only optimized model performance but also surpassed the results of previous articles. By implementing a more comprehensive and targeted hyperparameter search, this study delivered an accurate, reliable, and resilient model when compared to earlier efforts.

IV. CONCLUSION

In conclusion, this study showed the effectiveness of machine learning techniques, particularly SVM in developing predictive models for the early detection of stuck pipe conditions in geothermal drilling operations. By incorporating a comprehensive dataset that included a numerical parameter, the Gas Rate parameter, and traditional drilling metrics, the authors adopted a holistic method to addressing the critical challenge of stuck pipe incidents.

The results of this study showed that the SVM model outperformed the ANN model with outstanding accuracy, precision, and recall scores of 0.99, 0.98, and 0.97, respectively. The superior performance of the SVM model was further validated using blind data where it accurately predicted 52,741 out of 52,742 instances for normal conditions, 91 out of 99 instances for pre-stuck conditions, and 107 out of 107 instances for stuck conditions. These results suggested that the SVM-based predictive model offered a fast and effective solution for the early detection of stuck pipe anomalies in geothermal drilling. By enabling early identification of potential stuck pipe situations, drilling teams could proactively implement preventive measures to enhance the efficiency, cost-effectiveness, and overall productivity of geothermal drilling operations.

The incorporation of the Gas rate parameter which was a unique aspect of this study underscored the importance of considering all relevant drilling parameters to improve the accuracy and reliability of predictive models. This holistic method further served as a valuable reference for future articles and the development of advanced drilling optimization strategies in the geothermal industry.

Overall, this study represented a significant contribution to the field of geothermal drilling by providing a strong and practical solution for the early detection and prevention of stuck pipe incidents. The successful implementation of the SVM-based predictive model held the potential to transform the method the geothermal industry addressed the critical challenge by enhancing the overall viability and sustainability of geothermal energy development. Future articles could use more advanced methods and develop an application to identify drilling parameter conditions in real-time during geothermal well drilling operations.

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