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# Stuck Pipe Detection in Geothermal Operation with Support Vector Machine

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**Abstract**

One of the biggest problems during drilling operation is a stuck pipe in which the drill string would stick or freeze in the well. This challenge leads to a significant amount of remedial costs and time. Many researchers have investigated different factors regarding the stuck pipe. These factors include poor hole cleaning, improper mud design, key seating, balling up of bit, accumulation of cutting and caving, poor bottom hole assembly configuration, and differential pressure. Since geothermal drilling targets lost circulation zones at reservoir depth, the chance of getting stuck pipe events becomes higher. Many publications reported that lost circulation events that lead to stuck pipe events have become the top non-productive time (NPT) contributor to costs in many geothermal drilling projects. The consequences of a stuck pipe are very costly, that include lost time when releasing the pipe, time, and cost of fishing out the parted Bottom Hole Assembly (BHA), and efforts to abandon the tool(s) in the hole. Despite many observations that have been done to develop a system in avoiding stuck pipe incidents in oil and gas drilling operations using artificial intelligence (AI), few works have been developed for geothermal drilling operations. In this research, we propose a method to build an early warning system model for stuck pipe conditions based on a Support Vector Machine. Based on the experiment result Support Vector Machine Algorithm showed good performance with 89% accuracy and 81% recall for limited training dataset.

## INTRODUCTION

One of renewable energy source that we use is the geothermal energy, an energy to generate electricity obtained from geothermal reservoir that pumped steam out through a drilling well under high pressure. Geothermal drilling can be more expensive (in cost/depth) than onshore oil and gas drilling for two principal reasons (Sperber, Moeck, and Brandt 2010):

a. Technical challenge: Geothermal reservoirs may host highly corrosive fluids of high temperature in great depth, which mean that special tools and techniques are required for the harsh downhole conditions.
b. Large diameters: Because the produced fluid (hot water) is of intrinsically low value, large flow rates and thus large holes and casing are required.

The geological conditions of geothermal wells are generally harsher compared to standard shallower geothermal or oil and gas wells and might be similar to high pressure high temperature (HPHT) wells known from hydrocarbon (HC) drilling. HPHT wells are critical due to their small design margin, and well control is difficult to handle since it is often characterized by extreme pressures and temperatures coupled with small pore pressure-fracture gradient margins. Consequently, the casing design demands maintenance of high dimensional efficiency, and quantitative risk evaluation is necessary for more complex casing and

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tubing design (Geothermal communities 2021). This makes drilling stage as the most high-risk phase in geothermal development cycle (Sperber et al. 2010).

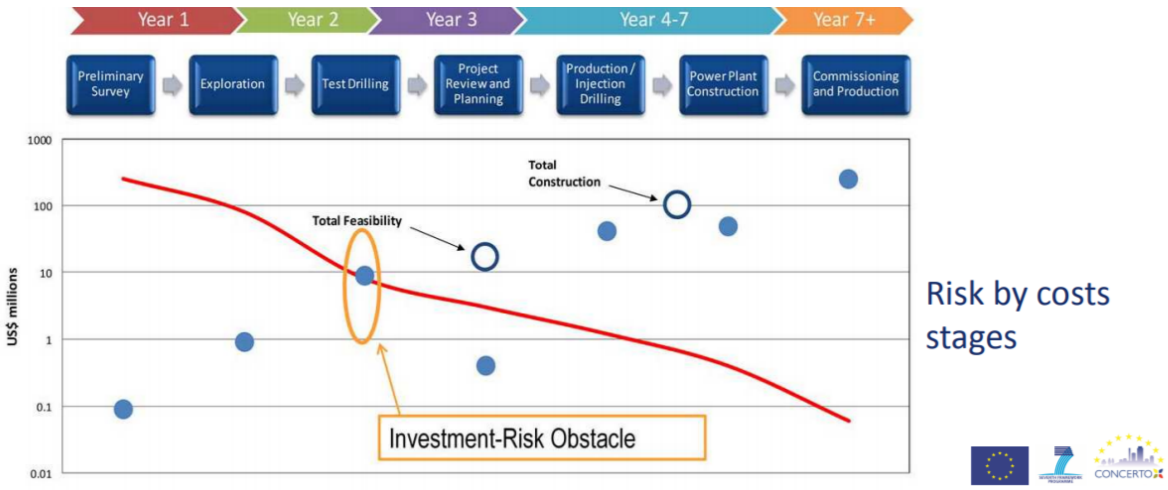


Figure 1. Geothermal Financial Risk by Stage (Geothermal communities 2021).

Many researchers attempt to identify the parameters and their corresponding effects to minimize the risk of stuck pipe (Salminen et al. 2017; Kirby et al. 2013; Purba et al. 2021; Zhu, Wang, and Huang 2019; Siruvuri et al. 2006; Murillo, Neuman, and Samuel 2009; Arnaout et al. 2012; Bradley et al. 1991). If a model or technique is proposed to identify and diagnose the stuck pipe early and prevent its occurrence, the costs and time would be reduced. In addition to these efforts, several studies published in literature in the area of stuck pipe mitigation suggest further solutions for stuck pipe avoidance, which are either of a drilling design approach or an automation approach (Chamkalani et al. 2013).

Since geothermal drilling targets lost circulation zones at reservoir depth, the chance of getting stuck pipe events becomes higher. Many publications reported that lost circulation events that lead to stuck pipe event have become top non-productive time (NPT) contributor to costs in many geothermal drilling projects. Figure 2 shows an example of three data from geothermal drilling projects in Indonesia. In field C, the total NPT of the 3-year drilling campaign reached 3,463 hrs., where the biggest contributor was the stuck pipe event. A similar phenomenon is also seen in drilling projects in field A and field B, two geothermal fields in Indonesia, that shows the stuck pipe event being the largest NPT contributor. Several authors have reported the same phenomenon in Kenya and Iceland where the main NPT contributor in geothermal drilling is stuck-pipe events (Purba et al. 2021).

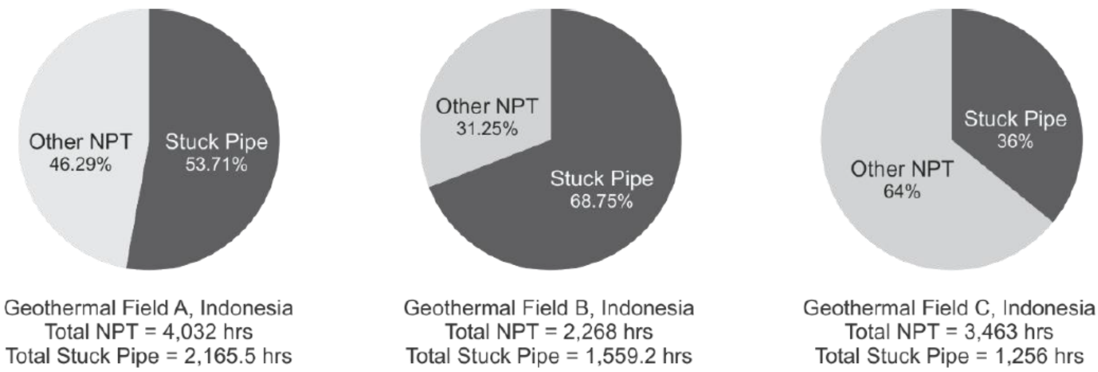


Figure 2. Geothermal Operation NPT (Purba et al. 2021).

The consequences of a stuck pipe are very costly, that include lost time when releasing the pipe, time, and cost of fishing out the parted Bottom Hole Assembly (BHA), and efforts to abandon the tool(s) in the hole. Assuming the summation cost of all drilling equipment per hour is US $ 3,000, the total cost lost due to the stuck-pipe event on the field A, B and C (Figure 2) is US $ 4,980,000 on average, excluding the cost of downhole equipment lost in hole. This figure is a potential cost saving if the drilling organization involved successfully minimizes or eliminates the stuck pipe events. Unfortunately, based on authors' observations, many drilling organizations running geothermal drilling project in Indonesia are still reactive instead of proactive against the stuck-pipe risk, meaning that they only react when a stuck pipe has occurred and do not take active preventive actions from the early phase of the project.

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One of the biggest problems during drilling operation is stuck pipe in which the drill string would stick or frozen in the well. This challenge leads to significant amount of remedial costs and time. Since geothermal drilling targets lost circulation zones at reservoir depth, the chance of getting stuck pipe events becomes higher. Many publications reported that lost circulation events that lead to stuck pipe event have become top non-productive time (NPT) contributor to costs in many geothermal drilling projects. Based on the identification of existing problems, this research is limited by the following:

a. Geothermal drilling operation on North Sumatera Field by one operator.
b. Research on the feasibility of using machine learning to identify stuck pipe in geothermal drilling operation.

Despite many observations have been done to develop a system in avoiding stuck pipe incident in oil and gas drilling operation using artificial intelligence (AI), few works have been developed for geothermal drilling operation. Based on this fact, we propose research for stuck pipe prediction based on AI algorithm. The specific aim is to experiment if the agent model can give reliable output to help provide warning to drilling operator in mitigating stuck pipe.

## METHODS

In this research, we will do simulation of the trained agent model working with new data. Data acquired from one of Geothermal Drilling Operator in North Sumatera, mostly in the form of mud logging data (drilling parameter) which was measured in real-time during drilling operations. Data already QC by the mud logging company before submitted to company. Data used in this research are well data for pad T in North Sumatera field. Following are several important drilling parameters that will be used as input for this research (Xue 2020):

a. Torque (TRQ). Value of torque applied to the drillstring.
b. Hookload (HKLD). Value of drillstring weight
c. Standpipe pressure (SPP). Internal pressure inside the drillstring
d. Rotation per minute (RPM). Value of rotation applied to the drillstring.
e. Weight on Bit (WOB). Value applied to the drilling bit (i.e lowest part in drillstring that used to crush the formation)
f. Gallon per Minute (GPM). Value of fluid pumped into the drillstring.
g. Rate of Penetration (ROP). Drilling speed value of a well usually in meter per hour or feet per hour unit.

### Support Vector Machine

SVM overcomes the curse of dimensionality by first defining basis functions that are centered on the training data points and then selecting a subset of these during training. An important property of SVM is that the determination of model parameters corresponds to a convex optimization problem, and so any local solution is also a global optimum.

In support vector machines the decision boundary is chosen to be the one for which the margin is maximized (Russell and Norvig 2022). The margin is defined as the perpendicular distance between the decision boundary and the closest of the data points, as shown in the left of Figure 6. Maximizing the margin leads to a particular choice of the decision boundary, as shown on the right. The location of this boundary is determined by a subset of the data points, known as support vectors, which are indicated by the circles. SVM use kernel tricks to create the optimum solution in high dimensional problem (Figure 7). Taking into account the fact that the computational complexity strongly increases with the number of training data least squares support vector machines (LS-SVM's) can be efficiently estimated using iterative methods (Suykens, Lukas, and Vandewalle 2000).

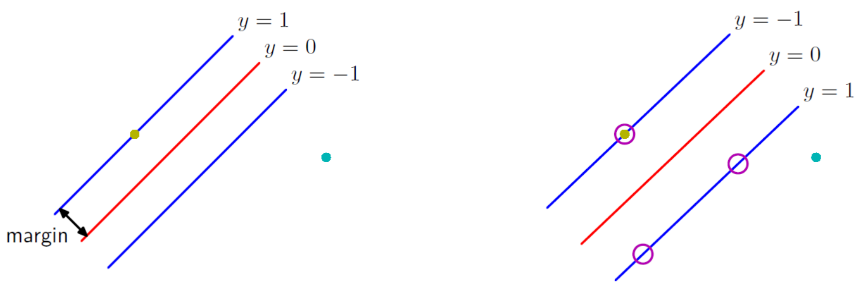



Figure 6. Margin in SVM (Bishop 2006)

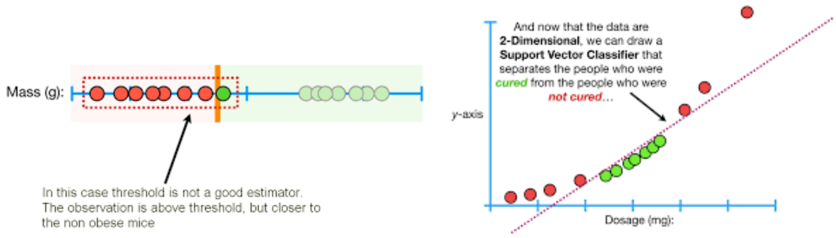



Figure 7. Kernel Trick Example (Starmer 2021)

Support Vector Machines (SVMs) are one of the advanced classification algorithms (Vapnik 2000), it was constructed to maximize the minimum distance between data that leads to an optimum hyperplane. One advantage of SVMs is that, although the training involves nonlinear optimization, the objective function is convex, and so the solution of the optimization problem is relatively straightforward. The number of basic functions in the resulting models is generally much smaller than the number of training points, although it is often still relatively large and typically increases with the size of the training set. An important property of support vector machines is that the determination of the model parameters corresponds to a convex optimization problem, and so any local solution is also a global optimum.

SVM has three attractive properties (Russell and Norvig 2022):

1. SVMs construct a maximum margin separator—a decision boundary with the largest possible distance to example points. This helps them generalize well and minimize overfitting.
2. SVMs create a linear separating hyperplane and use kernel-trick for high dimensional space.
3. SVMs combine the advantages of nonparametric and parametric models: they have the flexibility to represent complex functions, but they are resistant to overfitting.

The key insight of SVMs is that some examples are more important than others, and that paying attention to them can lead to better generalization.

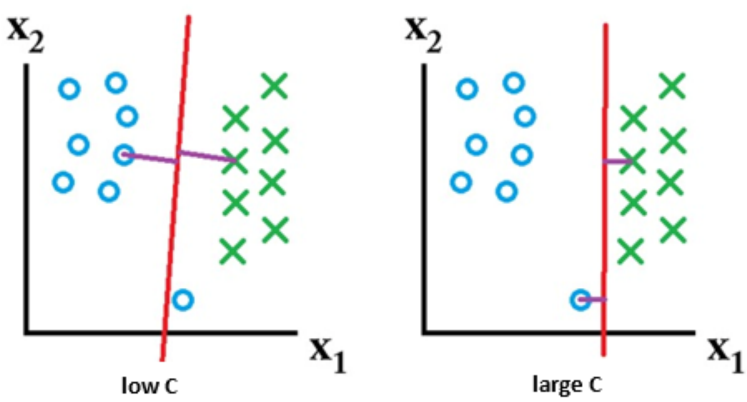
**Support Vector Machine with Python 3**

In Python to use SVM algorithm for classification SVC function is used, there are several kernel options when using SVM algorithm:

- Linear
- Radial Basis Function (RBF)
- Polynomial
- Sigmoid

C parameter is the regularization factor that will be used during training, also known as the penalty parameter (Anon 2021). Effect of C parameter in training:

- Small C, the algorithm will tend to choose a hyperplane that will give a bigger margin size which allows a greater number of misclassifications.
- Large C, the algorithm will tend to choose a hyperplane that will give a smaller margin size to minimize the number of misclassifications.



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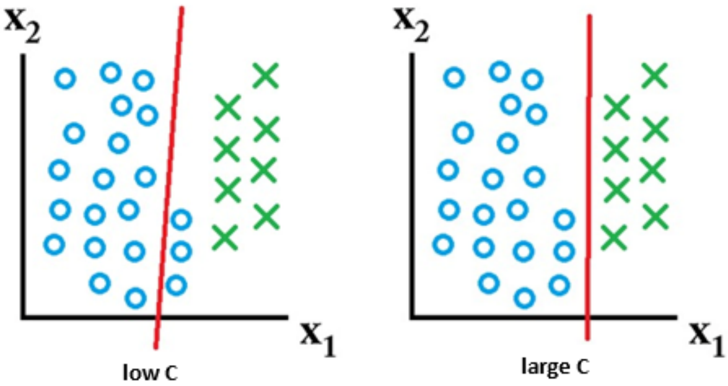


Figure 8. C parameter effect in training (Anon 2021)

One of the commonly used kernel functions is the radial basis function (RBF). The Gamma parameter of RBF controls the distance of influence of a single training point. Low values of gamma indicate a large similarity radius which results in more points being grouped together. For high values of gamma, the points need to be very close to each other in order to be considered in the same group (or class). Therefore, models with very large gamma values tend to overfit (Yildirim 2021).

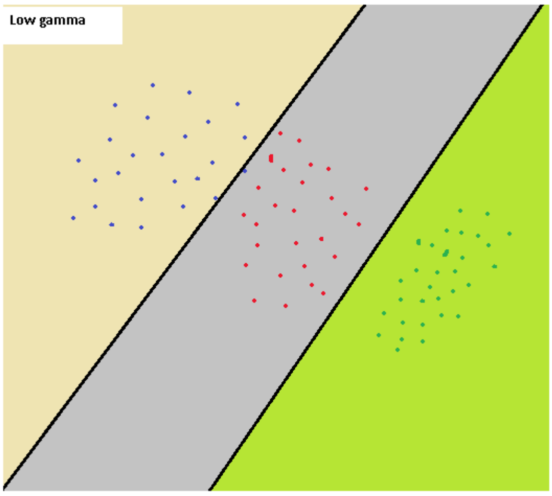


Figure 9. Low Gamma Illustration (Yildirim 2021)

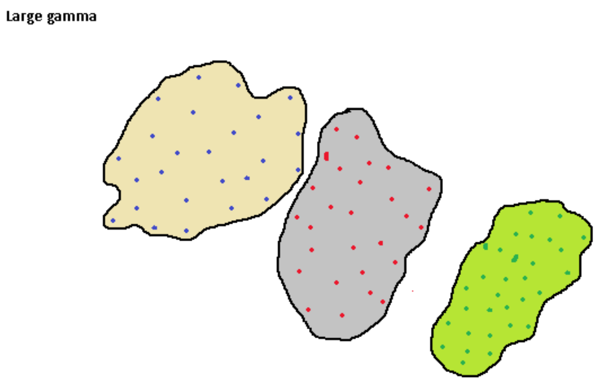


Figure 10. Large Gamma Illustration (Yildirim 2021)

Figure 9 represents the case with a low gamma value. The similarity radius is large so all the points in the colored regions are considered to be in the same class. For instance, a point on the right bottom corner is classified as a “green” class. On the other hand, Figure 10 is the case with large gamma. For data points to be grouped in the same class, they must fall in the tight bounded area. Thus, a small noise may cause a data point to fall out of a class. Large gamma values are likely to end up in overfitting.

As the gamma decreases, the regions separating different classes get more generalized. Very large gamma values result in too specific class regions (overfitting).

**Research and Development**

Research begins with reviewing the literature on several papers that discuss Geothermal operation and Stuck pipe problems in drilling operation.

The experiment will use the data from a Geothermal drilling operation in Indonesia, that was collected using sensors during the drilling operation and will be processed accordingly prior to use as training and testing data.

Support Vector Machine algorithm that previously tested by other researchers on oil industry data will be implemented to the data from Geothermal operation, then compare the performance with the oil and gas research performance. Further study can be conducted to improve the system performance in order to provide a reliable early warning system for Geothermal drilling operation (i.e., if any improvement is needed from the oil industry method). Figure 11 shows the sequence of our research steps.

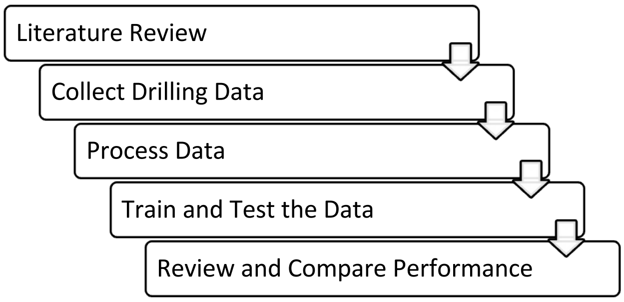


Figure 11. Research Steps

**Data Preprocessing**

There are six wells drilled in pad T, from these wells nine parameters will be used as input to predict the stuck pipe status, target column of "stuck pipe status" was added based on the Daily Drilling Report. Afterward, data cleaning was conducted by deleting rows with missing parameter data to prevent contamination during model training. Initial data balancing was done by cutting the data to be around the time when the stuck pipe incident happens (six hours before and one hour after). Dataset was split 4 wells was used for training and 2 wells for validation, furthermore the training data split into train-test data (80% and 20% respectively). Then sensitivity analysis was conducted to choose the optimum parameter and/or hyperparameter to train the model. When training the model using Python (Campesato 2020), below data processing was conducted:

- Data Normalization (Feature scaling) (Anon 2021)
  Feature scaling is a process to normalize all data & features so all have the same interval to prevent any feature affecting the model more than other features. This process also helps to conduct statistical analysis of the data
- Data Balancing
  In general, most of the data gathered in observation is not balanced which could affect the training process of the classifier model, thus data processing is needed to balance the class in the training data. The main purpose of data balancing is to increase the frequency of the minority class or reduce the frequency of the majority class so all classes will have a similar frequency of data
- Feature Selection (2021)
  Feature selection is used to rank the features that will be used to train a model. The aim is to reduce the number of features for the model based on the rank, this will reduce the dimension of the model thus reducing the resources requirements.

**Confusion Matrix and Model Performance**

A confusion matrix is one of the tools used to measure the performance of the model. There are four values in the confusion matrix (Figure 9) True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) (Afifah 2021; Mohajon 2021).

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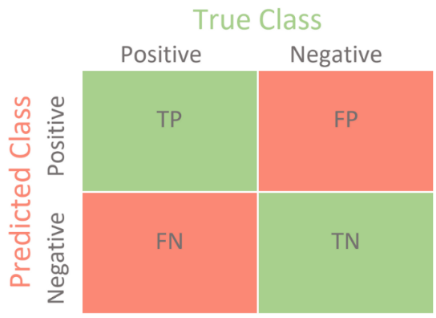


Figure 12. Confusion Matrix (Afifah 2021)

- True Positive (TP): number of predictions where the classifier correctly predicts the positive class as positive.
- True Negative (TN): number of predictions where the classifier correctly predicts the negative class as negative.
- False Positive (FP): number of predictions where the classifier incorrectly predicts the negative class as positive.
- False Negative (FN): number of predictions where the classifier incorrectly predicts the positive class as negative.

The aim of this research is to get the best recall and accuracy percentage to minimize miss identification of stuck pipe, where a false-positive condition is preferable to a false-negative condition.

## RESULTS AND DISCUSSION

### Sensitivity Analysis

During training the model, sensitivity analysis was done that concerns hyperparameter and kernel type in order to be aware of the optimum values of those parameters. Following is the discussion of the sensitivity analysis.

Based on sensitivity analysis on the hyperparameter and kernel type, the below hyperparameter is showing the optimum result as shown in Table 1:

- Polynomial Kernel
- C = 1000
- Oversampling method

Table 1. Polynomial Kernel Sensitivity Oversampling

| Polynomial Kernel (C) | No Feature Selection, Over Sample | | | | | |
|---|---|---|---|---|---|---|
| | Accuracy | | Recall | | | |
| | | | Stuck | | Normal | |
| | Train | Test | Train | Test | Train | Test |
| 10 | 0.98 | 0.16 | 1 | 0.98 | 0.95 | 0.13 |
| 100 | 0.99 | 0.65 | 1 | 0.93 | 0.99 | 0.64 |
| 1000 | 1 | 0.89 | 1 | 0.81 | 0.99 | 0.89 |
| 10000 | 1 | 0.83 | 1 | 0.75 | 0.99 | 0.91 |
| 100000 | 1 | 0.83 | 1 | 0.75 | 0.99 | 0.91 |
| 1000000 | 1 | 0.83 | 1 | 0.75 | 0.99 | 0.91 |

### Feature Selection

Feature selection was done to reduce the dimension of features using filter and wrapper method. After reviewed the model performance (Table 2), it was decided that the best option is to keep all 9 features, since any reduction will reduce the model performance significantly.

Table 2. SVM Feature Selection (Kernel=Polynomial, C=1000, Over sampling)

| Feature Selection | k | Polynomial Kernel, C=1000, Over Sample | | | | | |
|---|---|---|---|---|---|---|---|
| | | Accuracy | | Recall | | | |
| | | | | Stuck | | Normal | |
| | | Train | Test | Train | Test | Train | Test |
| Filter | 9 | 1 | 0,89 | 1 | 0,79 | 0,99 | 0,9 |
| Filter | 8 | 1 | 0,9 | 1 | 0,71 | 0,99 | 0,91 |
| Filter | 7 | 1 | 0,93 | 1 | 0,72 | 0,99 | 0,94 |
| Filter | 6 | 1 | 0,93 | 1 | 0,7 | 0,99 | 0,94 |
| Filter | 5 | 1 | 0,67 | 1 | 0,85 | 0,99 | 0,66 |
| Filter | 4 | 0,99 | 0,26 | 0,99 | 0,53 | 1 | 0,25 |
| Filter | 3 | 0,98 | 0,67 | 1 | 0,68 | 0,95 | 0,67 |
| Wrapper | 9 | 1 | 0,9 | 1 | 0,78 | 0,99 | 0,9 |
| Wrapper | 8 | 1 | 0,94 | 1 | 0,78 | 0,99 | 0,94 |
| Wrapper | 7 | 1 | 0,65 | 1 | 0,9 | 0,99 | 0,64 |
| Wrapper | 6 | 1 | 0,67 | 1 | 0,85 | 0,99 | 0,66 |
| Wrapper | 5 | 0,99 | 0,31 | 1 | 0,71 | 0,99 | 0,29 |
| Wrapper | 4 | 0,97 | 0,18 | 0,97 | 0,89 | 0,98 | 0,15 |
| Wrapper | 3 | 0,91 | 0,52 | 0,96 | 0,93 | 0,86 | 0,5 |

## Discussion

SVM showed promising performance on the model training, this is aligned with its superiority when training data is limited (only pad T of the whole area), with relatively small training dataset SVM was able to develop a model that give good performance to predict stuck pipe event using drilling parameters values. SVM also shown good generalization when it was tested with new data set, this is also aligned with its superiority in generalization compared to other algorithms.

From the experiment conducted for under sampler balancing linear kernel showed best result while for over sampler balancing polynomial kernel showed best result. As seen in Figure 13, using C = 1000, for Linear Kernel we will have accuracy 81% with recall 63%, after C = 1000 accuracy significantly drop which means the model is experiencing overfitting.

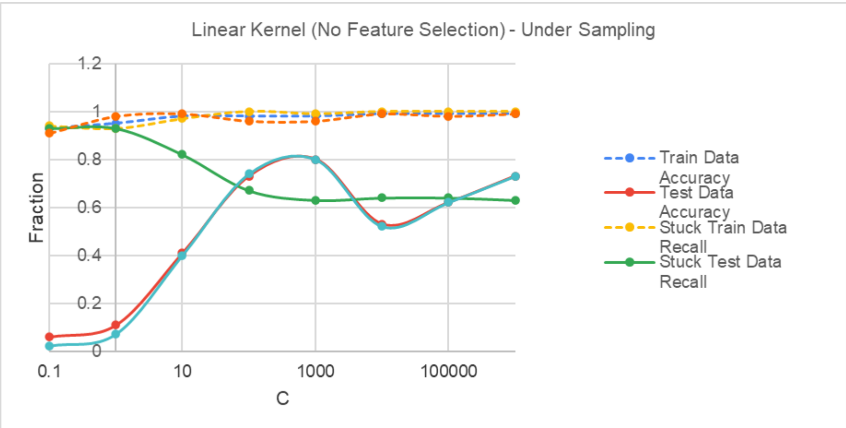


Figure 13. SVM Under Sampler

As for the Polynomial Kernel (Figure 14), the model achieves the best performance on C = 1000 with accuracy 89% and recall 81%. For C bigger than 1000 the model experience slight drop on the recall results, thus decided C = 1000 would be best parameter since increasing C have potential risk of overfitting.

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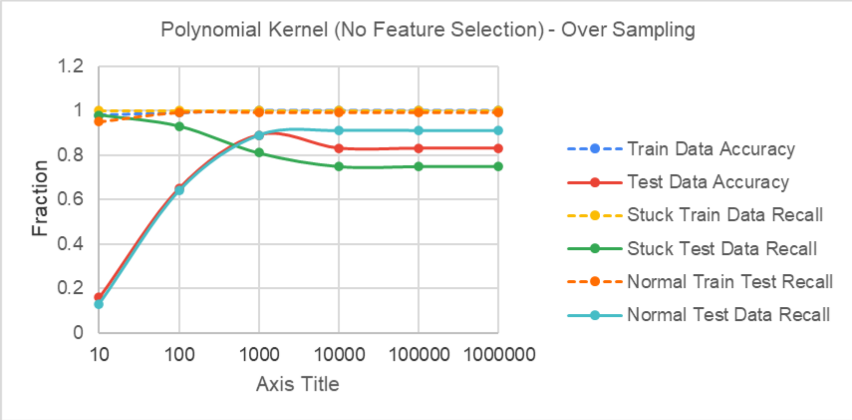


Figure 14. SVM Over Sampler

**Experiment Result**

Based on the sensistivity analysis using the optimum hyperparameter, the optimum result in this research is 89% accuracy and 81% recall (Table 3).

Table 3. SVM Results

| Algorithm | Accuracy (%) | Recall (%) |
|---|---|---|
| Support Vector Machine | 89 | 81 |

**CONCLUSION AND FUTURE WORKS**

Experiments result and model performance show that machine learning algorithm can be used in predicting stuck pipe incident in geothermal operation. As we can see in Table 3 the SVM algorithm performance shows good results (above 80%). It showed sufficient performance (more than 80%) and high potential to be used in the geothermal operation, thus further studies are recommended to improve the model performance and continue to pilot project in geothermal operation.

Using the model created during this research several future works that can enhance the model:

1. Run the research on another pad to improve model generalization thus will be applicable for all drilling pads. (Another feature may be relevant and worth trying)
2. Run another algorithm to train the model (e.g., ANN) to compare its performance.
3. To enhance the robustness and detect physically identified trends in the drilling parameters in real-time, future work would consider a detailed review with several geothermal experts to understand what can be improved in the model to make it feasible to be implemented.
4. Model interface to develop a simple and meaningful display as a warning system to the drilling team.
5. Offline test with new well data to confirm its performance and generalization.
6. A pilot project to implement this model to the real-time drilling parameter data.

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