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Lithological Classification from Well Logs using Machine Learning Algorithms

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Abstract

Well logging is a widely used geophysical method to gather information from subsurface rocks and establish lithological classification. However, the criteria of lithological classification are loosely defined and human error can significantly contribute to the uncertainty of the interpretation. This study uses machine learning approaches to classify rock types from well logs of the Snake River Plain (SRP) in Idaho. To achieve the comprehensive results, three machine learning algorithms, K-nearest neighbour (K-nn), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB) are employed on fifteen types of well logs from four geothermal wells in the SRP under three experimental conditions. In the first experiment, the classifiers are trained and tested with data from the same well in the train:test ratio of 7:3. The second scenario assigns data from three wells as a training subset and the remaining well as test subset. The third experiment uses the largest amount of data as a training subset, which combines data from three wells and 70% of the data from the remaining well. Hyperparameters in all classifiers are optimized to enhance model performance. Results suggest that SVM and K-nn exhibit comparable performance in all experiments, resulting in 89.68% (s = 10.40) and 88.84% (s = 9.92) of average accuracy, respectively. XGB shows the highest prediction accuracy in this study with average prediction accuracy at 90.67% (s = 8.21). This is largely because XGB partitions data into subgroups based on available features iteratively until every class is clearly separated from each other. In addition, XGB can recognize missing values in well logs and does not use these values for classification. XGB further indicates that gamma ray, neutron, and temperature are the top three important features that are used to improve the prediction accuracy.

Keywords: Machine learning, Well logging, Snake River Plain, Geothermal exploration

1. Introduction

Well logging is a widely used geophysical method to gather information from subsurface rocks. The main advantages of well logging include high vertical resolution, good continuity, and convenient data acquisition (Xie et al., 2018). Compared to other geophysical methods such as resistivity, gravity, and magnetic surveys, well logs has a significantly higher resolution, and is collected every 30 - 50 cm (Soltani et al., 2016). Data are continuously collected along exploration wells, and well logging can gather information both while drilling and after drilling. After a massive amount of subsurface information is gathered, it is interpreted to gain insights into the lithology and physical properties of the rock formation. However, the criteria of lithological classification are loosely defined, and human error can significantly contribute to the uncertainty of the interpretation. Previously there have been many mathematical methods such as deconvolution, noise filter, and signal stacking applied to well logging data to reduce the error of interpretation (Dubois et al., 2007). Recently, machine learning algorithms have been introduced to solve problems in pervasive fields such as regression, feature extraction, and classification (Tsangaratos and Ilia, 2016). Machine learning algorithms use statistical techniques to train models. Without being explicitly programmed, they can compute quickly and accurately for many tasks, including when the data is very noisy, and the task is non-linear, or requires no explicit knowledge (Devak et al., 2015).

Many machine learning algorithms have been developed for various data types such as text, picture, and video (Wu and Zhao, 2018). Each algorithm uses different theories being appropriate for the disparate dataset. This study aims to compare the ability of three machine learning approaches in rock classification in order to ascertain the applicable algorithm for

well logging data. This task uses 15 features of well logging data collected from four geothermal wells in the Snake River Plain (SRP) located in Idaho (Figure 1). The SRP is characterized by high heat flow and temperature gradients and is considered one of the largest active geothermal systems in the US (Tester et al., 2006). Three machine learning algorithms: K-nearest neighbour (K-nn), Support vector machine (SVM), and Extreme Gradient Boosting (XGB) are selected because they implement three theories for classification. Moreover, the chosen algorithms are suitable for well logging data because they do not require any conditions or assumptions on the dataset. Some algorithms such as Naive Bayes classifier requires specific condition which assumes independent features.

learning algorithms should be trained by data from other wells, and then applied to classify data from new wells. In the second and third scenarios, the data from each of wells are combined as a training subset and the rest of data are used as test subset. The second scenario assigns data from three wells as a training subset and the remaining well as test subset. The third scenario uses the largest amount of data as a training subset, combining data from three wells and 70% of the data from the remaining well. By adding the second and third scenarios, our study is much more close to the application in the real world. Our study is a comparison of three approaches to general lithological classification. There is no class which is more important than other classes. Hence, precision, recall, and f1 score are not tested for this dataset. In this task, the classifiers are evaluated using classification accuracy scores and confusion matrices.

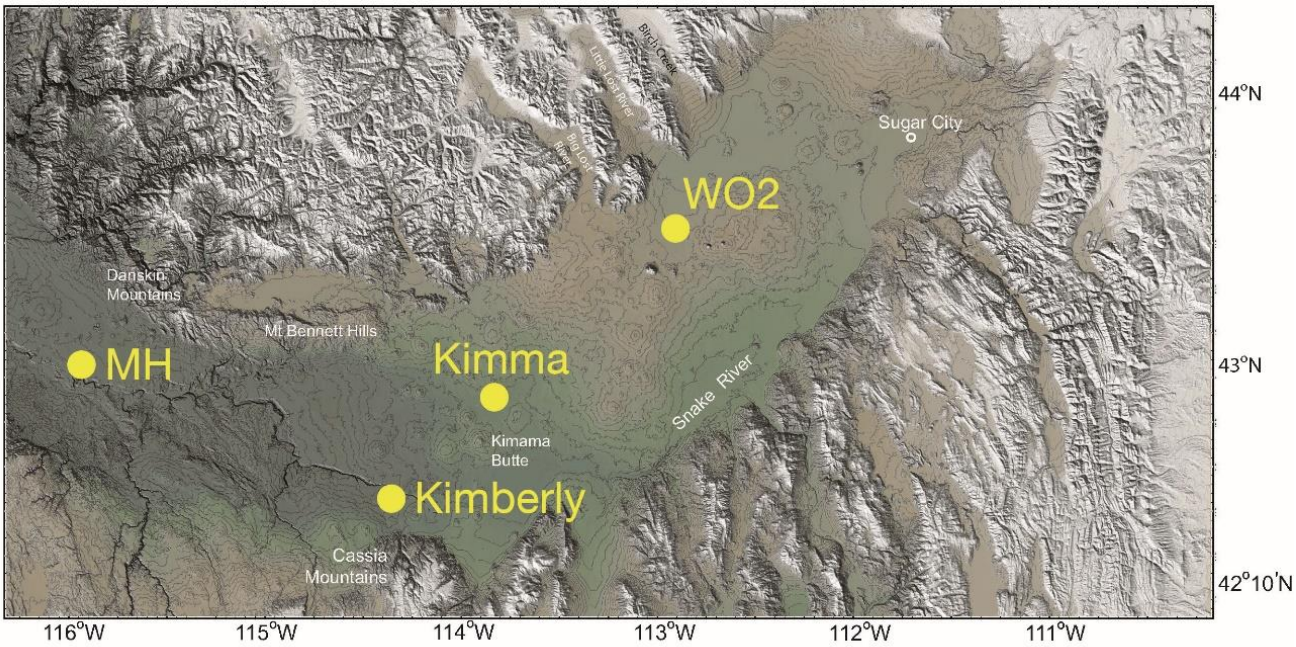

Figure 1 Location of four study wells (Mountain Home (MH), Kimma, Kimberly, and WO2) in Snake River Plain located in Idaho, USA. (Shervais et al., 2013)

To achieve comprehensive results, the algorithms are employed under three experimental conditions. In the first scenario, well logging data from each well are independent of each other. The algorithms are trained and tested with the data from the same well. However, in a real use case, machine

2. Study Area

Well logs and well reports from four geothermal wells (WO2, Mountain Home, Kimma, and Kimberly) in the Snake River Plain (SRP), published by Idaho National Laboratory, are used in this study. The location of the four

wells is shown in Figure 1. The depth in each well varies from 2000 m to 4000 m. Each well has over 8,000 data points. There is a total of fifteen types (features) of well logs and 9 rock types (classes). Although these wells are located near each other, collected features and lithological classification are different, as shown in Table 1 and 2.

Table 1 Available well-logs (features) in WO2, Mountain Home (MH), Kimma, Kimberly in the SRP.

Well logs (Feature)	Well name			
	WO2	MH	Kimma	Kimberly
Gamma ray	✓	✓	✓	✓
Tempera-ture		✓	✓	✓
Pressure		✓	✓	✓
Rmud		✓		✓
Rd		✓	✓	✓
Rs		✓	✓	✓
Thorium		✓		✓
Uranium		✓		✓
Potas-sium		✓		✓
Vp		✓	✓	✓
Vs		✓	✓	✓
Vw		✓		
Density	✓			
Porosity	✓			
Neutron	✓			

Note: Rmud refers to Resistivity in mud measurement, Rd refers to Resistivity in deep measurement, Rs refers to Resistivity in shallow measurement, Vp refers to p-wave, Vs refers to s-wave, and Vw refers to water wave speed.

Table 2 Rock types (classes) in WO2, Mountain Home (MH), Kimma, Kimberly in the SRP.

Rock type (Classes)	Well name			
	WO2	MH	Kimma	Kimberly
BS	✓	✓	✓	✓
CS	✓			
CG	✓			
SS	✓			
ST	✓			
TF	✓			
VP	✓			
SR		✓	✓	✓
RH				✓

Note: BS refers to Basalt, CS refers to Claystone, CG refers to Conglomerate, SS refers to sandstone, ST refers to siltstone, TF refers to Tuff, VP refers to Vitrophyre, SR refers to Sedimentaty rock, RH refers to rhyolite

Snake River Plain (SRP) was formed due to extension tectonic and magmatic processes (Bedrosian and Feucht, 2014; Humphreys, 1995). In the early Mesozoic Era, the Farallon plate subducted below the North American plate. This provided a major tectonic feature in West American. After the subducted Farallon plate failed, fragments of the Farallon plate beneath the North American plate melted in the mantle. This caused widespread volcanism along the west side of the North American plate. The fragments of the Farallon plate were renamed Juan de Fuca plate and Cocos plate (Lonsdale, 2005). During the Early Cretaceous period, worldwide plate motion changed. The Pacific plate began moving to the north, away from the North American plate. As a result, the Juan de Fuca subduction rollbacked in this period. This subduction rollback caused the North American plate to move westward over the Yellowstone hotspot and extend along the west of the North American plate (Aly et al., 2009; DeNosaquo et al., 2009).

3. Machine learning algorithms

3.1 K-nearest neighbor

K-nearest neighbour (K-nn) is a straightforward machine learning algorithm

used widely for both classification and regression tasks (Glowacz and Glowacz, 2016). It is a non-parametric and lazy classifier, meaning that it does not generalize or add any assumption to data. This classifier employs a feature similarity assumption in which data from the same class should have the same pattern of features. The K nearest data points of a dataset around test data are sought, and test data points are classified by the most popular class of K nearest data (Rastegarzadeh and Nemati, 2018). K-nn has to keep every data point in the database to calculate K nearest neighbour for every time of classification. The efficiency of K-nn is mostly dependent on the database because it does not apply any assumption to the dataset (Steinbach and Tan, 2009). K-nn cannot emphasize some features like the other classifiers since feature selection is crucial for K-nn. K is a tuning parameter which determines the number of nearest data points taken into consideration.

3.2 Support Vector Machine

Support Vector Machine (SVM) generates a function that represents the relationship between features and classes from training data and uses it to classify test data. SVM defines the decision boundaries separating each class from other classes based on training data, and applies it to predict data from test subset (De Boissieu et al., 2018). There are multiple ways to draw the decision boundaries but SVM generates optimal boundaries by maximizing margins (Bishop, 2006; Xie et al., 2018). SVM considers only some data near the class boundaries (support vectors) to maximize the margin. As a result, SVM can avoid outliers and overfitting (Smirnoff et al., 2008). SVM creates decision surfaces with a linear function thus cannot solve the non-linearity problem. Consequently, kernel functions or kernel tricks are applied to map input data to a higher dimension and linearly separate the data. For this study, Radial Basis Function (RBF) kernel which maps data into an infinite dimension is assigned to this dataset. The concept of SVM with RBF is to put a Gaussian decision surface onto every data point with Kernel coefficient for 'RBF' (γ) defining a surface spread. Some error, called soft margin, is acceptable to generalize the model (De Boissieu et al., 2018; Fan et al., 2018). The number of misclassified data points are controlled by the Penalty parameter (C). For this study, C and γ are tuned to optimize model performance.

3.3 Extreme Gradient Boosting

Extreme Gradient Boosting (XGB) is a highly efficient and generalized decision tree based algorithm. This classifier generates many decision trees and then combines the results from every tree by vote (Carmona et al., 2018). Decision trees define if-clause conditions to partitions data into subdivisions based on their features iteratively until every class of training dataset is clearly separated from each other (Friedl and Brodley, 1997). By doing this, decision trees have the capacity to select the helpful features and to determine the unused value (missing value). Each decision tree is built up sequentially through the knowledge of previous trees by XGB and becomes more effective than the previous one. The size of the tree is restricted for conserving computational costs, allowing XGB more simplified and generalized than other tree classifiers (Fan et al., 2018). There are various parameters that affect the performance of XGB, but only three parameters are adjusted for this study: learning rate (how much the model changes in each iteration), min child weight (the minimum number of samples at each leaf node), and max depth (the maximum depth of an individual tree) (Chen and Guestrin, 2016).

4. Methodology

4.1 Pre-processing

Well logging data are correlated with lithology from well reports. After every data

point is labeled, the process of cleaning data begins. Data points which have less than three features and also negative data points are removed. A problem with this dataset is missing data. There are various techniques to tackle this problem, including, replacing missing value with the mode or creating a new algorithm to predict the missing value. However, we do not have much data to do that so we replace the missing data points with -999.25 instead. We aim that our model will recognize -999.25 is a missing value. After pre-processing is finished, the data are prepared for each experiment in the next process.

4.2 Data training, model building, and model evaluation

The data are divided into training, validation, and test subsets depending on each experiment while preserving class distribution using stratified sampling (Figure 2). The training dataset is used to train the classifiers. The validation dataset is applied to determine the optimal tuning parameters. The test dataset is employed in order to grain the classification accuracy and confusion matrix. However, when machine learning algorithms are optimized on one dataset, the model can overfit to the specific dataset. To ameliorate generalization and hinder overfitting with one dataset, each classifier is trained and tested 5 times with different sampling data.

Figure 2 A diagram shows stratified sampling where the data are split while class distribution remains constant.

4.3 Test experiments

Machine learning algorithms are employed under three conditions to a simulate real-world application for this study. In the first scenario (Experiment I), well logging data from each well are randomly split into training (70%), validation (10%), and test (20%) subsets, and then used to train and test with all three classifiers. For this experiment, well logging data and classes of each well are kept independent from those of other wells.

The second scenario (Experiment II) assigns data from three wells as training data and the remaining one well as test data. As there are four wells in this dataset, the test data is also permuted between wells four times until every well has been the test data. The validation subset is randomly selected from 10% of each training well. Data from three wells are combined together since it should be transformed into the same format. Lithology is reclassified into three classes for this condition: basalt, sedimentary rock, and other because some classes such as rhyolite, vitrophyre, and tuff do not appear in every well. If a class is not presented in the training data, the classifiers cannot classify it in the test phase. Consequently, rhyolite, vitrophyre, and tuff were grouped into other, and claystone, conglomerate, sandstone, and siltstone were merged with sedimentary rock. For this experiment, only gamma ray was a helpful predictive feature. We tried to add the other features but they gave worse results than only gamma ray.

The third experiment (Experiment III) uses the largest amount of data as a training subset, combining data from three wells and 70% of the data from the remaining well. Then the remaining data are separated into validation (10%) and test (20%) subsets. This scenario was created to solve the problem in the second scenario where some classes were not included in the training data. Lithology is grouped into five classes: basalt, sedimentary rock, tuff, vitrophyre, and rhyolite. Features are prepared into 15 features while missing values are filled with -999.25. As some features were not collected in every well, their values are -999.25 in some wells. For example, the values of

temperature logs are -999.25 in every data point in WO2 well.

4.4 Hyperparameter tuning

Hyperparameter or tuning parameter is essential to improving the performance of machine learning algorithms. A robust parameter selection process (tuning) is a process which ranks the accuracy of each classifier with different parameters to obtain the optimal parameters for each algorithm. Tuning parameter ranges for this study are exhibited in Table 3. The optimal parameter ranges are determined with the help of the validation dataset.

Table 3
The optimal range of tuning parameters for SVM, K-nn, and XGB algorithms.

Model	Tuning parameters	Search range	Optimal range
SVM	C	0.1 – 1000	0.1 - 100
	γ	0.00001 - 0.01	0.00001 - 0.0001
K-nn	K	1-10	6 - 10
XGB	Learning rate	0.01 - 0.3	0.01 - 0.1
	Min child weight	0.1 - 100	60 - 100
	Max depth	3 - 10	3 - 6

5. Results

5.1 Model Performance

In this study, we make an attempt to design experiments to emulate the real-world, so experiments are divided into three conditions. Moreover, each experiment is iterated 5 times to reduce the effect of the random seeds. The average accuracies with standard deviation are shown in Table 4. Results suggest that XGB and SVM give comparable results, although XGB gives the highest overall prediction accuracy at 90.67% (s = 8.21). SVM accuracy at 89.60% (s = 10.40) whereas K-nn provides the lowest accuracy at 88.84% (s = 9.92).

Table 4
Classification accuracies of each algorithm. (s stands for standard deviation)

Model	Accuracy		
	EX I	EX II	EX III
SVM	90.55% (s = 7.73)	93.92% (s = 2.62)	84.32% (s = 20.86)
KNN	87.85% (s = 11.05)	92.99% (s = 3.44)	85.69% (s = 15.28)
XGB	91.38% (s = 9.04)	93.56% (s = 2.20)	87.07% (s = 13.39)

5.2 Confusion matrix

The results of confusion matrices from three scenarios show that the classifiers predict basalt, tuff, and rhyolite accurately. Other classes such as vitrophyre and sedimentary rocks tend to be misclassified to three classes above. For example, in WO2 well in Experiment I, every classifier predicts basalt class accurately, with over 95% of accuracy but more than 35% of conglomerate class is predicted to basalt (Figure 3). This is because sedimentary rocks are classified by grain size, which is difficult to determine with well logging data. The second reason is the effect of imbalanced classes. Since these wells were in a volcanic area, the vast majority of the data is volcanic rocks such as basalt and rhyolite. As a result, the classifiers have more instances to learn the characteristics of volcanic rocks than the other classes. Furthermore, the effect of imbalanced classes encourages the models to dramatically recall the major classes more so than the minor classes. One of the particular examples is SVM in which predicts classes in three classes for WO2 well in Experiment I: basalt, claystone, and tuff as shown in Figure 3. As a result, the classification accuracy of these three classes is over 95% and the overall classification accuracy of WO2 well in Experiment I is about 90%. As every classifier predicts the major classes accurately in every experiment, the best classifier is decided by the prediction of the minor classes. Consequently, XGB achieves the

highest accuracy in lithological classification because of its capacity to predict the minor classes precise than the other classifiers.

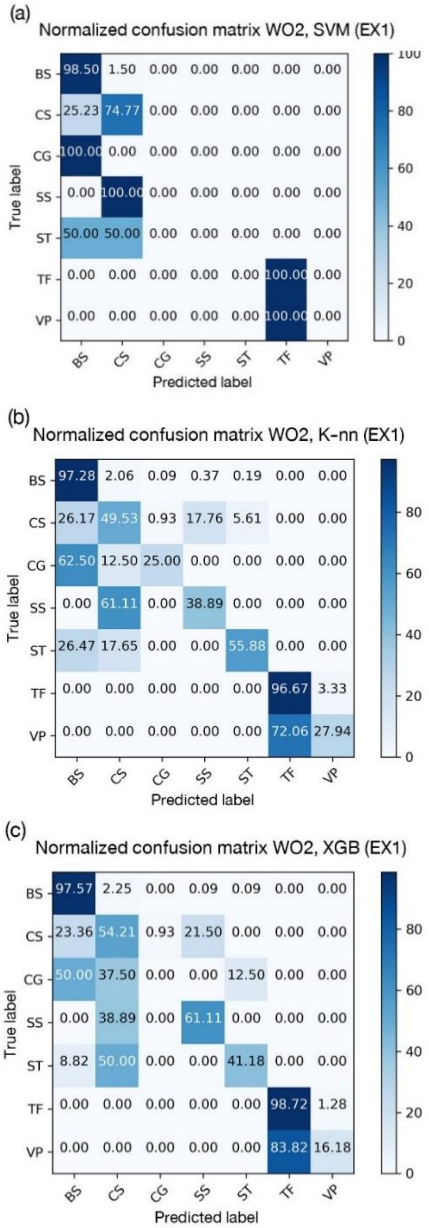

Figure 3 Normalized confusion matrix of three classifiers of seven rock types in the prediction of WO2 well (a) SVM, (b) K-nn, and (c) XGB.

6.Discussion

Previous studies (e.g. Dubois et al. (2007); Konaté et al. (2015); Xie et al. (2018)) uses various classical parametric methods such as linear, quadratic and Mahalanobis, fuzzy logic and machine learning algorithms such as Artificial Neural Network (ANN), SVM, K-nn, and Gradient tree boosting to evaluate lithological classification in Experiment I. Gradient tree boosting gives the highest f1 score at 82% in Xie et al. (2018) while ANN has the highest f1 score at 68% in Dubois et al. (2007). ANN achieves the best performance in Konaté et al. (2015). In this study, XGB exhibits approximately 91% of classification accuracy in Experiment I. Results of Xie et al. (2018) is comparable to our study because XGB and gradient tree boosting are a subset of random forests. A study by Dubois et al. (2007) and Konaté et al. (2015) shows that ANN is better than K-nn and SVM. However, random forests was not applied in their study. The results from each study are different because all classes in Xie et al. (2018) and Dubois et al. (2007) are sedimentary rocks, which feature values are varied by both composition and grain size. The classes of Konaté et al. (2015) are metamorphic and igneous rocks: orthogneiss, paragneiss, eclogite, amphibolite, and ultramafic rocks. For this study, the major classes are igneous rocks. Not only are the rock types different, but also the collected features are varied. Moreover, Lopes and Jorge (2017) uses ANN, Random Forests, and three algorithms of linear regression to fill the missing values in well logging data (regression task). Although ANN performs better than the other algorithms, the statistical difference is not significant. This informs that each machine learning algorithms are applicable to various tasks depending on types of problem and data. Even if task and data are almost the same, for example well logging data, the efficiency of algorithms is still depended on the study area.

The experimental design in second and third scenarios are more realistic in geophysical application. To change experimental design, the results from the classifiers are dissimilar to Experiment I. A study by Bestagini et al. (2017) uses the same data from Dubois et al. (2007) but the classifiers are tested under Experiment II. Results suggest that gradient tree boosting provides the highest f1 score at 61% while the winner of Experiment I gives 68% of f1 score.

Nevertheless, our results show that the classifiers evaluated on Experiment II give higher accuracy than Experiment I. This is because rock types or classes are grouped into three classes in the second condition. By doing this, the difficulty of the task has decreased because of reducing variety and specification of classes or rock types. Furthermore, SVM gives the highest accuracy score in Experiment II but there is no significant difference (less than 1%). In contrast, the accuracy of the classifiers evaluated in Experiment III is lower than Experiment I because of different sets of features or types of well logs. The number of features in Experiment III (15 features) is more than Experiment I (4 - 14 features) because features in each well are combined. To prepare the data in the same format, the uncollected features in each well are valued at -999.25. Although this leads data to be noisier, it makes the data to be trainable.

The models are expected to be used on data come from different wells, similar to Experiments II and III. By merging data from different wells, two issues have emerged from the data: different sets of classes and features. Regarding the study area, lithological classification and the collected feature in each well are varied by the objectives of the study (Table 1 and 2). The models cannot predict the classes which are not included in training data and they cannot be trained with the dataset which has different sets of features. Therefore, the data should be turned into the same format in term of classes and features. The former is solved by class grouping, reduces the variety and specification of rock types. For instance, seven classes (BS, CS, CG, SS, ST, TF, and VP) in WO2 well are grouped into three classes (basalt, sedimentary rock, and the other) in Experiment II. By doing this, gamma ray is the only feature that helps with classification in Experiment II because it refers to the volume of the radiometric elements in the rock formations. The latter is tackled by replacing missing value with -999.25. This has an adverse effect on the efficiency of most algorithms excepted XGB. For example, SVM generates decision boundaries from training data since replacing missing value with -999.25 shifts the decision boundaries from the optimal. Likewise, it increases the distance between the test data points and the optimal training data points in K-nn. However, replacing missing value with -999.25 do not affect XGB because it can select the used features on its own. Figure 4 presents the importance of each feature which is used by XGB. The information shows that some features which is 0% of feature scores are not used for the classification. There are other techniques to fill the missing values. For example, Lopes and Jorge (2017) applies machine learning algorithms to predict the missing values from

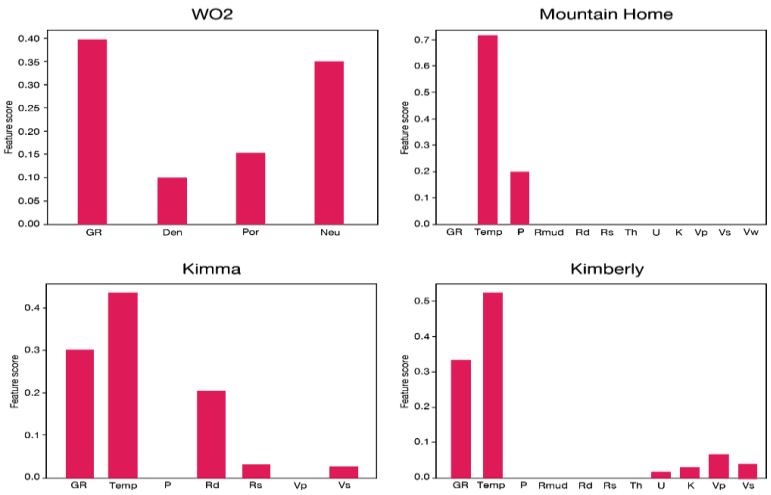

Figure 4 The used features by XGB in Experiment I. Feature score represents the importance of each feature in classification

the remaining well logging data but they used 600,000 data points for regression.

Class imbalance is another problem for this dataset. The effect of imbalance classes causes the classifiers to recall the major classes more so than the minor classes. As result, the minor classes are misclassified into the major classes. This effect influences the classifiers using the decision surfaces for classification such as SVM than the other. This is because decision surfaces which are generated from small data points are not fully comprehensive the distribution of classes. This problem can be solved by up-sampling or down-sampling. Up-sampling is to randomly generate pseudo minor classes from the minor classes and down-sampling is to randomly eliminate major classes. However, we cannot do that on this dataset because the minor classes are too small. Moreover, standardization and variance scaling are not helpful for this dataset. We try to scale data and standardize the data but it gives the worse results than original data. This is because the original well logging data represent the characteristics of the rock types and the importance of each feature for this dataset. Furthermore, classifying sedimentary rock is the challenge for well logging interpretation. As sedimentary rocks are determined by grain size and there are no logging tools detecting grain size directly, this is hard to classify sedimentary rock by machine learning algorithms accurately. Hence, the other methods should be applied to improve the performance of the classifiers in classifying sedimentary rock. For example, Bestagini et al. (2017) adopts feature argumentation. As a result, the accuracy of the classifier improves 55% to 61%.

Consequently, feature engineering should be done in further study to ameliorate the performance of the classifiers. Moreover, the tuning parameter is another issue because it affects model performances to much as shown in Figure 5. This study uses the validation subset to determine the tuning parameters. However, the results from the validation subset do not always be compatible with the test subset.

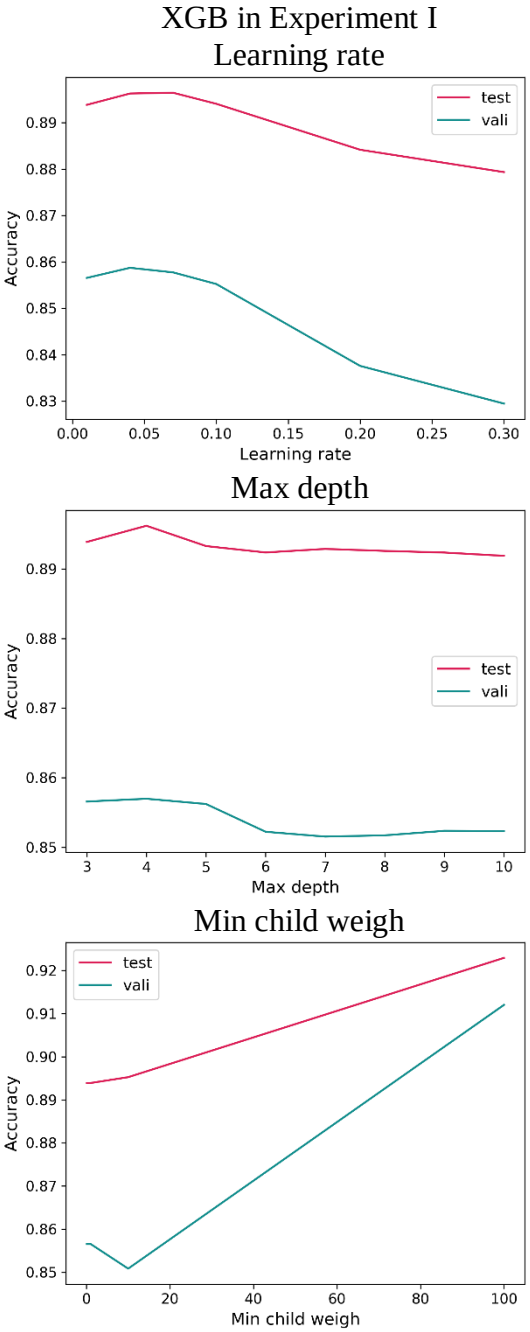

Figure 5 The effect of tuning parameter to the accuracy of XGB in Experiment I. Red lines represent test subset and green lines represent validation subset.

Each of classifiers has different benefits and drawbacks and they are suitable with various dataset. SVM is a generalized algorithm because it considers merely support vectors (Smirnoff et al., 2008). By doing this, SVM can avoid noise and ambiguous data. However, its generalization leads SVM to misclassify the minor classes and SVM spends the longest time in the training phase. K-nn is suitable for the data which are no explicit knowledge and there is no time spent in the training phase for K-nn. K-nn is over-reliant on training data because it does not assign any assumption into the data (Glowacz and Glowacz, 2016). There is no feature weigh function and noise filter for K-nn. Hence, feature selection and cleaning data greatly influence the performance of K-nn than other algorithms. Results from Xie et al. (2018), Bestagini et al. (2017), and this study present that XGB or Gradient tree boosting exhibits the highest the classification accuracy for lithological classification using well logging data. This is because XGB can select the used features in its own without human influence. Figure 6 shows the importance of each feature for this dataset in Experiment III. Gamma ray, temperature, and neutron logs are important features to classify the rocks in SRP in which is dominated by volcanic rocks. As humans do not have the capacity to know which features are appropriate for each algorithm, it is better if algorithms choose the used features by itself. As a result, XGB can recognize that -999.25 is missing value for this dataset and it does not use this value in classification. Moreover, XGB classifies the data by decision trees which generate if-clause rules from characteristics of training data to classify test data. This is close to how human classify the data since XGB is appropriate with well logging data which is invented for the human to classify rock types. For further study, hybrid models for well logging classification should be used. The hybrid model is the new machine learning algorithm which combines the advantages of more than one models since its performance might be better than the ordinary model. For example, Zhu et al. (2016) and Zhu et al. (2018) apply the hybrid model between ANN and random forest to predict permeability and total organic carbon using well logging data, respectively. Results show that the hybrid model gives a lower error than both ANN and random forest.

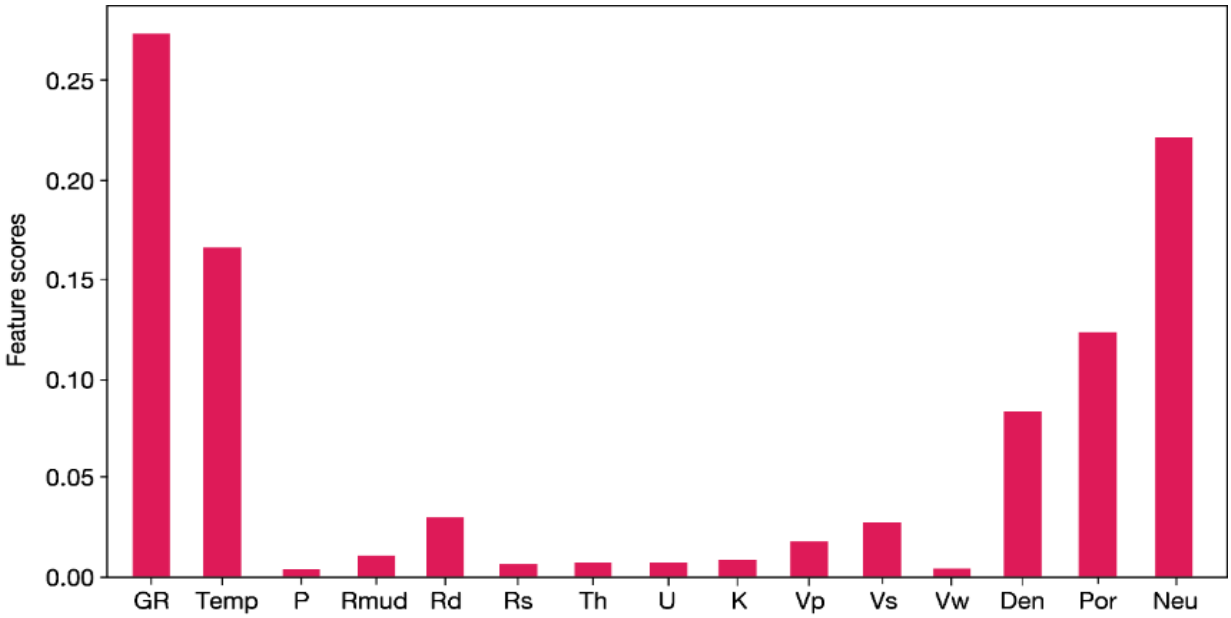

Figure 6 Average feature importance scores of types of well logs in XGB algorithm from Experiment III.

7. Conclusions

Three machine learning algorithms are employed under three conditions in this study in order to evaluate the performance of each

classifier and identify the most suitable algorithm for the well logging data of SRP located in Idaho, USA. Results suggest that XBG shows the highest accuracy in lithological classification. K-nn and SVM give acceptable results in well logging interpretation even if K-nn exhibits the lowest accuracy. This study covers both individual and combined well tests. For further study, the task which some classes are more important than the other classes should be done. Well logging data from petroleum is a case in point. The oil bed is more important than other rocks so this class should be predicted accurately than other classes. Feature engineering should be applied in a further study to incorporate information about grain and pore size and to improve model performance. Last but not least, the hybrid models should be developed to improve the efficiency of well logging classification.

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References

Aly, M.H., Rodgers, D.W., Thackray, G.D., and Hughes, S.S. 2009. Recent magmatotectonic activity in the Eastern Snake River Plain–Island Park region revealed by SAR interferometry. Journal of Volcanology and Geothermal Research 188: 297-304.

Bedrosian, P.A., and Feucht, D.W. 2014. Structure and tectonics of the northwestern United States from EarthScope USArray magnetotelluric data. Earth and Planetary Science Letters 402: 275-289.

Bestagini, P., Lipari, V., and Tubaro, S. 2017. A machine learning approach to facies classification using well logs.

Bishop, C.M. 2006. Pattern Recognition and Machine Learning. Singapore: Springer Science Business Media, LLC.

Carmona, P., Climent, F., and Momparler, A. 2018. Predicting failure in the U.S. banking sector: An extreme gradient boosting approach. International Review of Economics & Finance.

Chen, T., and Guestrin, C. 2016. XGBoost. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16, 785-794.

De Boissieu, F., Sevin, B., Cudahy, T., Mangeas, M., Chevrel, S., Ong, C., Rodger, A., Maurizot, P., Laukamp, C., Lau, I., Touraivane, T., Cluzel, D., and Despinoy, M. 2018. Regolith-geology mapping with support vector machine: A case study over weathered Ni-bearing peridotites, New Caledonia. International Journal of Applied Earth Observation and Geoinformation 64: 377-385.

DeNosaquo, K.R., Smith, R.B., and Lowry, A.R. 2009. Density and lithospheric strength models of the Yellowstone–Snake River Plain volcanic system from gravity and heat flow data. Journal of Volcanology and Geothermal Research 188: 108-127.

Devak, M., Dhanya, C.T., and Gosain, A.K. 2015. Dynamic coupling of support vector machine and K-nearest neighbour for downscaling daily rainfall. Journal of Hydrology 525: 286-301.

Dubois, M.K., Bohling, G.C., and Chakrabarti, S. 2007. Comparison of four approaches to a rock facies classification problem. Computers & Geosciences 33: 599-617.

Fan, J., Wang, X., Wu, L., Zhou, H., Zhang, F., Yu, X., Lu, X., and Xiang, Y. 2018. Comparison of Support Vector Machine

and Extreme Gradient Boosting for predicting daily global solar radiation using temperature and precipitation in humid subtropical climates: A case study in China. Energy Conversion and Management 164: 102-111.

Friedl, M.A., and Brodley, C.E. 1997. Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment 61: 399-409.

Glowacz, A., and Glowacz, Z. 2016. Recognition of images of finger skin with application of histogram, image filtration and K-NN classifier. Biocybernetics and Biomedical Engineering 36: 95-101.

Humphreys, E.D. 1995. Post-Laramide removal of the Farallon slab, western United States. Geology 23.

Konaté, A.A., Pan, H., Khalid, M.A., Li, G., Yang, J.H., Deng, C., and Fang, S. 2015. Machine Learning Interpretation of Conventional Well Logs in Crystalline Rocks. pp. 360-370. Cham. Springer International Publishing.

Lonsdale, P. 2005. Creation of the Cocos and Nazca plates by fission of the Farallon plate. Tectonophysics 404: 237-264.

Lopes, R., and Jorge, A. 2017. Mind the Gap: A Well Log Data Analysis. The Workshop on Data Mining for Oil and Gas, Houston, Texas, USA. 1-6.

Rastegarzadeh, G., and Nemati, M. 2018. Primary mass discrimination of high energy cosmic rays using PNN and k-NN methods. Advances in Space Research 61: 1181-1191.

Shervais, J.W., Schmitt, D.R., Nielson, D., Evans, J.P., Christiansen, E.H., Morgan, L., Pat Shanks, W.C., Prokopenko, A.A., Lachmar, T., Liberty, L.M., Blackwell, D.D., Glen, J.M., Champion, L.D., Potter, K.E., and Kessler, J.A. 2013. First Results from HOTSPOT: The Snake River Plain Scientific Drilling Project, Idaho, U.S.A. Sci. Dril. 15: 36-45.

Smirnoff, A., Boisvert, E., and Paradis, S.J. 2008. Support vector machine for 3D modelling from sparse geological information of various origins. Computers & Geosciences 34: 127-143.

Soltani, S., Kordestani, M., and Karim Aghaee, P. 2016. New estimation methodologies for well logging problems via a combination of fuzzy Kalman filter and different smoothers. Journal of Petroleum Science and Engineering 145: 704-710.

Steinbach, M., and Tan, P.-N. 2009. kNN: k-Nearest Neighbors. In Wu, X. and Kumar, V. (eds.), The Top Ten Algorithms in Data Mining, pp. 151-161. New York: Taylor & Francis Group, LLC.

Tester, J.W., Anderson, B.J., Batchelor, A.S., Blackwell, D.D., DiPippo, R., Drake, E.M., Garnish, J., Livesay, B., Moore, M.C., Nichols, K., Petty, S., Toksöz, M.N., Ralph W. Veatch, J., Baria, R., Augustine, C., Murphy, E., Negraru, P., and Richards, M. 2006. Geothermal ResourceBase Assessment. In The future of geothermal energy: impact of Enhanced Geothermal Systems (EGS) on the United States in the 21st Century, pp. 35-81. Geothermal Program, MS 3830 Renewable Energy and Power Department Idaho National Laboratory: U.S. Department of Energy.

Tsangaratos, P., and Ilia, I. 2016. Comparison of a logistic regression and Naïve Bayes classifier in landslide susceptibility assessments: The influence of models complexity and training dataset size. Catena 145: 164-179.

Wu, H., and Zhao, J. 2018. Deep convolutional neural network model based chemical process fault diagnosis. Computers & Chemical Engineering 115: 185-197.

Xie, Y., Zhu, C., Zhou, W., Li, Z., Liu, X., and Tu, M. 2018. Evaluation of machine learning methods for formation lithology identification: A comparison

of tuning processes and model performances. Journal of Petroleum Science and Engineering 160: 182-193.

Zhu, L., Zhang, C., Wei, Y., and Zhang, C.-m. 2016. Permeability Prediction of the Tight Sandstone Reservoirs Using Hybrid Intelligent Algorithm and Nuclear Magnetic Resonance Logging Data. Arabian Journal for Science and Engineering 42.

Zhu, L., Zhang, C., Zhang, C., Wei, Y., Zhou, X., Cheng, Y., Huang, Y., and Zhang, L. 2018. Prediction of Total Organic Carbon Content in shale reservoir Based on a New Integrated Hybrid Neural Network and Conventional Well Logging Curves. Journal of Geophysics and Engineering 15: 1050-1061.