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RESEARCH ARTICLE

Prediction of Filter Cake / Hole Wash-Out for Oil-Based Mud Wells Using Three Different Machine Learning Models

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ABSTRACT

Filter cake characterization is essential in drilling operations as it helps to determine the thickness and properties of the filter cake, which can impact the safety and efficiency of drilling and production. Mathematical models and experimental investigations are commonly used to predict the characteristics of the filter cake. These predictions can aid in selecting appropriate drilling fluids and determining the most effective drilling techniques. In this study, three different artificial intelligence (AI) techniques predicting filter cake / hole wash-out were developed and compared with the actual values of filter cake / hole wash-out of oil-based well. The three used models are Random forest regression (RF), Support vector machine (SVM) and Extreme gradient boosting regression (XGB). The three models were built using 2900 datasets from wells drilled using oil-based drilling fluid in the Western Desert, Egypt. The data set included information on measured depth, true vertical depth, overbalance pressure, formation porosity, well inclination, formation temperature, lithology, and logging data. The data set was divided into 80% for training and 20% for validation. A comparison between the results of the three AI techniques and the actual filter cake / hole wash-out, obtained by caliper log, was performed using statistical parameters. The results showed that RF is the best model to predict filter cake / hole wash-out with an average accuracy of 99.5%, correlation coefficient of 0.9523 and relative mean square error of 0.0361 for overall data. This indicates that the model is able to accurately predict filter cake formation / hole wash-out during drilling operations. The model can also be used to predict these phenomena for a planned well, using actual data from offset wells and planned mud properties and directional survey.

INTRODUCTION

A filter cake can be defined as a layer of materials deposited over a face of a formation in the wellbore. Filter cake development is primary determined by the size and quantity of suspended particles within the fluid loss to the formation (Chenevert et al. 1991; Civan, et al. 1996). Building a fine-quality, low permeability, and a high strength filter cake is an effective method to control particle and filtration invasion into the pay zones (Jiao and Sharma 1992). Increasing fluid movement during filter cakes formation lead to thinner and denser filter cakes which were less prone to erode compared to filter cakes formed under static and low fluid movement (Opedal et al. 2013).

In dynamic filtration Filter cake thickness is a function of the shear rate. With the increase in the shear rate, the filter cake thickness decreased. Shear rate mainly depend on the string rotation (Dangou and Chandler 2009). The filter cake thickness is a very critical parameter in modeling different drilling problems, especially the differential sticking. Additionally, Hole wash-out, which is defined as an open hole section larger than the original hole size or drill bit size, is very important factor in the cement volume calculation.

Thus filter cake and hole wash-out prediction is essential and critical in the plan phase for a new well. **Figure 1** shows the difference between filter cake and hole wash-out. Predicting the filter cake formation and erosion are investigated in some recent researches by by experimental methods (Akrami et al. 2019; Bai et al. 2022); however, no artificial intelligence model presented to predict the formation of filter cake or hole wash-out yet.

In this study, the filter cake / hole wash-out is predicted by three different AI models, compared the models results with the actual filter cake / hole wash-out data from existing well in western desert, Egypt and concluded that the best model to predict this phenomena is random forest regression.

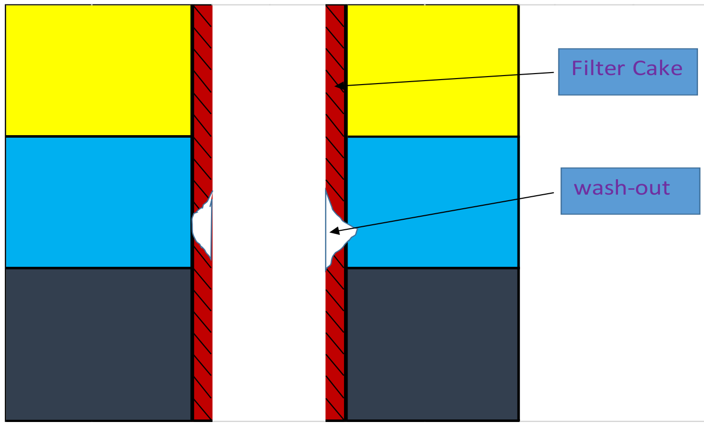


Figure 1: Schematic showing the difference between Filter Cake and Hole wash-out

AI and ML Applications

AI is a method of data analysis that learns from data, identifies patterns, and makes predictions with almost no human intervention (Cuddy 2020). In the recent years, artificial intelligence tools have widely applied in order to model nonlinear problems in various fields of science. Artificial intelligence tools have been applied in different areas of petroleum engineering, such as drilling engineering (Golsefatan et al. 2019; Gasser et al. 2022; Gasser et al. 2021), production engineering (Yakoot et al, 2021; Salem et al. 2022), reservoir engineering (Gomaa et al. 2021).

ML is a subset of AI that uses subsets of data to generate an algorithm that may use novel or different combinations of features and weights. This is in contrast to classical programming, in which algorithms are explicitly coded using known features (Choi et al. 2020). The backbone of intelligent software used to develop an efficient ML is statistical learning methods. ML algorithms require data to learn and so are interconnected to several disciplines of database: knowledge discovery from data, data mining, and pattern recognition (Suykens 2014).

Types of ML.

ML can be categorized as supervised, unsupervised, semi-supervised, and reinforcement algorithms; each are used for different tasks. Supervised ML algorithm is a type of ML in which both the input (features) and the output (target) are known, and the objective of the algorithm is to learn the mapping between the two. The model infers an algorithm from the feature-target pairs, and the target indicates whether the prediction is accurate. The two main tasks of supervised learning are classification and regression (Alpaydin 2010).

XGBoost

XGBoost is known as one of the best performing supervised ML algorithms. XGBoost can be used for both classification and regression problems. The extreme gradient boosting (XGBoost) algorithm was created by Chen and Guestrin (Chen and Guestrin 2016). Being an effective tree-based ensemble learning algorithm, it is considered a powerful tool among data science researchers. XGBoost is based on gradient boosting architecture (Friedman 2001), A schematic of XGB prediction is illustrated in **Figure 2.**

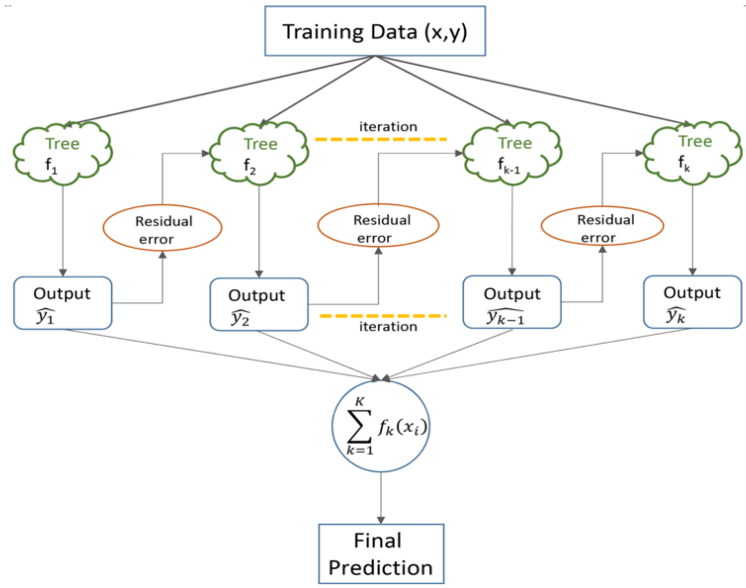


Figure2: Schematic of prediction method by the XGBoost algorithm

Random Forest Regression (RF)

RF was developed by Breiman (2001), and is a combination of two ML techniques: Breiman's bagging idea (Breiman 1996b) and random features selection introduced by Ho (1995, 1998) and Amit and Geman (1997). The simplest ensemble tree called the "bagged tree" can be obtained by using a tree as the base model. Each tree in the ensemble is grown on data samples that were randomly drawn with replacement from the original data set. In cases of large data sets, it is common to obtain the same regression tree. However, averaging the output of these trees does not guarantee an improved prediction accuracy. The second technique of RF is random feature selection. RF is an extension of the bagged regression tree. It is based on the bootstrapped sampling to grow individual trees, but it uses only a random subset of features at each splitting node of the tree and not the entire features set. This creates diversity between the base models. Furthermore, RF improves the accuracy in predictions by reducing the variance. This is achieved by averaging noisy but approximately unbiased trees (Zhang and Haghani 2015). A Schematic of predictions using the RF algorithm illustrated in **Figure 3.**

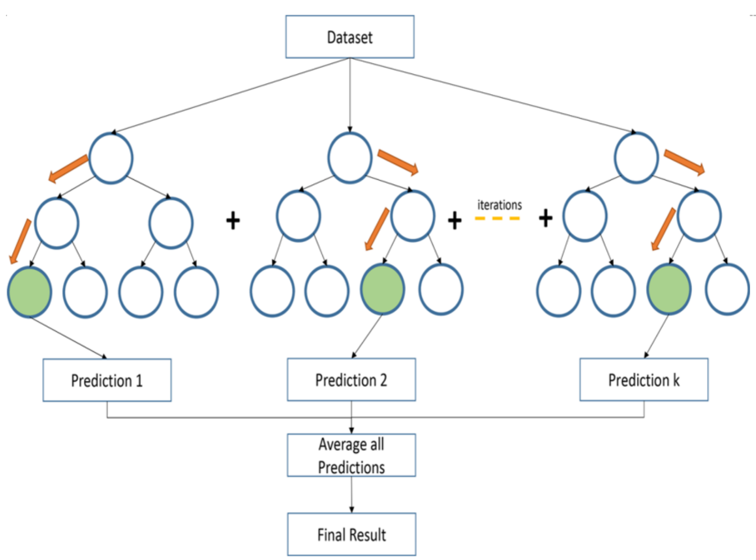


Figure 3: Schematic of predictions using the RF algorithm

SUPPORT VECTOR MACHINE

SVMs are sets of supervised ML methods used for regression, classification, and outlier detection. SVMs are an alternative training method for polynomial, radial basis function, and multilayer perceptron classifiers in which the weight of the network is found by solving a quadratic programming problem with linear constraints by using a kernel function. This is contrary to the training process seen in standard neural network training, where it is performed by solving a nonconvex, unconstrained minimization problem. This comparison

is vital because SVM models are closely related to neural networks, and they use a sigmoid kernel function that is equivalent to a twolayer perceptron neural network (Ayodele 2010). Gonzalez et al. (2005) stated that SVM performs its applications by constructing an N dimensional hyperplane that optimally separates the data into two categories. For most real-world problems, it is difficult to successfully separate the positive from negative instances in the training set. This is because most problems involve non separable data for which no hyperplane exists that can perform such a separation. This problem of inseparability can be solved by mapping the data onto a higher dimensional space and defining a separating hyperplane there. This higher dimensional space is termed as transformed feature space and not input space, which is occupied by the training instances. In SVM models, a predictor variable is known as an attribute and a transformed attribute that defines the hyperplane is known as a feature. A set of features that describe one row of predictor values are known as a vector. As mentioned earlier, the main objective of SVM modeling is to find the optimal hyperplane that separates clusters of vectors in a manner that one category of target variables fall on one side of the plane and another category of target variables fall on the other side of that plane. In addition, the vectors that occur near the hyperplane are called support vectors (Kotsiantis 2007; Muhammad and Yan 2015). This is illustrated in **Figure 4**.

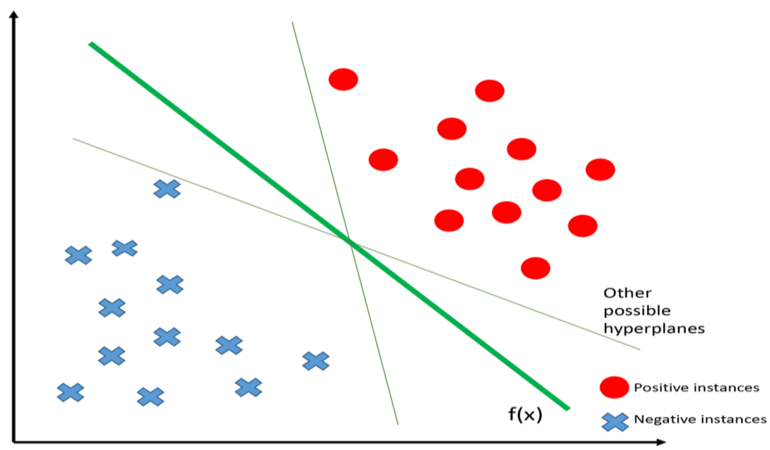


Figure 4: Schematic of the functioning of an SVM.

METHODOLOGY

Data Collection and Description

In this study, actual data sets are collected from oil based mud wells drilled in the western desert of Egypt. Each row of the data includes the following:

A- The data for input parameters include:
   1- Depth of the formation.
   2- Overbalance pressure: the difference between hydrostatic pressure and pore pressure.
   3- Drilling parameters:
      - Rate of penetration (ROP),
      - Drill string rotation (RPM).
      - Flow rate.

4- Survey data that include inclination angle.
5- Logging data that include:
- Formation porosity.
- Formation Gamma Ray
- Formation resistivity.
- Formation temperature at each point.
- The percentage of minerals that forms the drilled formation which are mainly sand, silt, lime and clay.

B- The output data includes hole diameter from caliper log.

Model Construction

A total number of 2900 data sets are used to build the three models of random forest (RF), Extreme gradient boosting regression (XGBoost) and support vector machine (SVM). These data points are randomly divided into two categories that are named training data and testing data. In order to check the performance of the model in predicting the target, these two categories must be apart from each other and do not have any points in common. For this purpose, the training data consist of about 80% of the main data points, and the remaining 20% of the main data points are used as testing data. The statistical description of the data bank used in this study is given in Table 1. **Figure 5** shows the workflow of model construction, model training, and statistical analysis.

Table 1 Statistical description of the data bank used in this study

Parameter	Minimum	Maximum	Average	SD
Overbalance (psi)	724.2208	872.9368	799.2491	46.82263
Porosity (fraction)	0.0195	0.4422	0.192723	0.094374
Temperature (°F)	208.8042	253.0461	230.9213	13.47775
Inclination (Degree)	0	24.38	13.1258	10.28226
Flow rate (gpm)	251.7128	545.5241	499.5439	16.09912
Rate of penetration (ft)	3.9426	198	55.14454	44.46834
Drill string rotation (RPM).	24.625	157.9172	117.9097	12.21442
Formation Gamma Ray (gAPI)	6.5743	144.0692	68.81838	39.32248
Formation resistivity (ohm.m)	0.259	1200	9.23	51.44695
Hole diameter (inch)	8.1447	9.0302	8.501459	0.199647
Sand (fraction)	0	0.9297	0.326555	0.318509
Lime (fraction)	0	0.5464	0.104841	0.102505
Clay (fraction)	0	0.9978	0.454565	0.300128
Silt (fraction)	0	0.8071	0.08071	0.142033

Error Assessment

Measuring the data fitness of the three models in predicting the target is determined by correlation coefficient (R2), mean-squared error (MSE), root-mean-squared error (RMSE), average relative error (ARE), average absolute error (AAE). Equations 1 to 5 express the definitions of the above parameters:

1- Mean Absolute Error

$$MAE = \frac{\sum_{i=1}^{n} \left| y_{pred,i} - y_i \right|}{n}$$

2- Average Relative Error

$$ARE(\%) = \left(\frac{1}{N}\sum_{i=1}^{N}\frac{Y_i^{pr} - Y_i^{ac}}{Y_i^{ac}}\right) \times 100$$

3- Correlation Coefficient

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(Y_i^{pr} - Y_i^{ac}\right)^2}{\sum_{i=1}^{N}\left(\overline{Y^{ac}} - Y_i^{ac}\right)^2}$$

4- Mean Squared Error

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i^{pr} - Y_i^{ac}\right)^2$$

5- Relative Mean Squared Error

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left(Y_i^{pr} - Y_i^{ac}\right)^2\right]^{0.5}$$

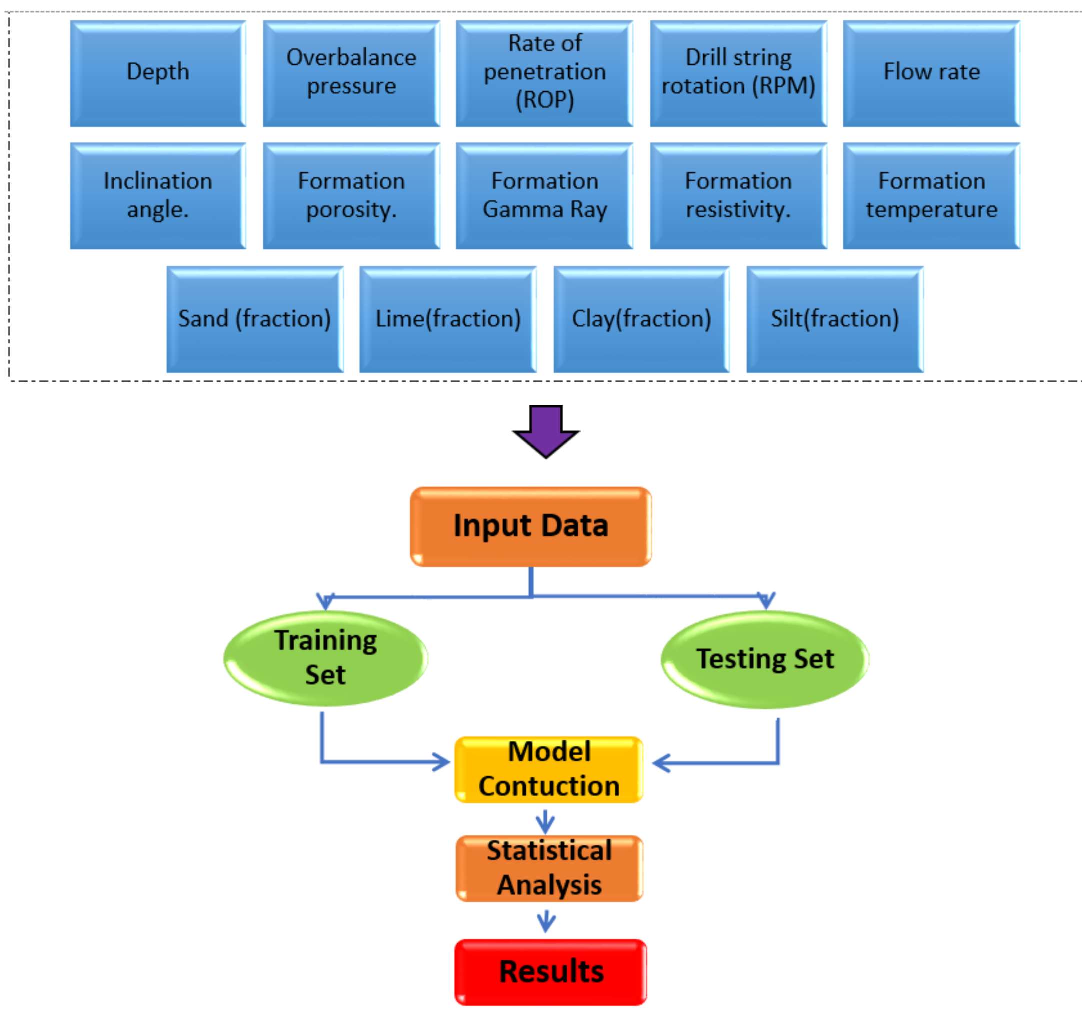


Figure 5: Workflow showing model construction, model training, and statistical analysis

RESULTS AND DISCUSSION

In order to evaluate the proposed models, the predefined statistical parameters were calculated for each model for training, testing and overall data sets as shown in **Tables 2-4** respectively.

Based on the results shown in T**ables 2-4,** it is evident that the prediction accuracy delivered by the RF model is much higher than those of the other two models (SVR and XGBoost). From the results presented in **Tables 2–4,** it can be seen that **RF** model performs high accuracy predictions, where the **RMSE** value was equal to 0.031, 0.052 and 0.039 for the training, testing and overall data sets, respectively and $\mathbf{R^2}$ value equal 0.963, 0.941 and 0.952 for the training, testing and overall data sets, respectively. Outperforming the other two models in terms of the accuracy of prediction, the **RF** model was recognized as the best for filter cake / hole wash-out prediction in the present study.

Table 2 Prediction accuracy for filter cake / hole wash-out by the three models training data set

Model	MAE	ARE(%)	R^2	MSE	RMSE
RF	0.011	0.141	0.963	0.0009	0.031
SVM	0.016	0.158	0.939	0.0011	0.032
XGBoost	0.022	0.188	0.931	0.002	0.037

Table 3 Prediction accuracy for filter cake / hole wash-out by the three models testing data set

Model	MAE	ARE(%)	R^2	MSE	RMSE
RF	0.022	0.21	0.941	0.0028	0.052
SVM	0.028	0.33	0.915	0.004	0.062
XGBoost	0.037	0.42	0.91	0.006	0.066

Table 4 Prediction accuracy for filter cake / hole wash-out by the three models overall data set.

Model	MAE	ARE(%)	R^2	MSE	RMSE
RF	0.015	0.17	0.952	0.0011	0.039
SVM	0.018	0.22	0.929	0.0017	0.041
XGBoost	0.03	0.29	0.923	0.0024	0.046

The predicted and actual data were plotted versus each other. **Figure 6** represents the cross plot of the model predicted hole diameter versus the actual hole diameter for overall data for **RF, SVM** and **XGB**, respectively. The precision of the model is determined via the tight accumulation of data points around the y=x line. The amount of this precision is usually measured by correlation coefficient. The correlation coefficient is calculated by fitting the best line that passes through the data, which has the lowest amount of this coefficient between all the other lines that could pass from the data.

To obtain a precise comparison between the proposed model output and the actual output, the obtained data from the model and the actual data are simultaneously plotted versus the index of data points in **Figure 7** for overall data for **RF, SVM** and **XGB**, respectively.

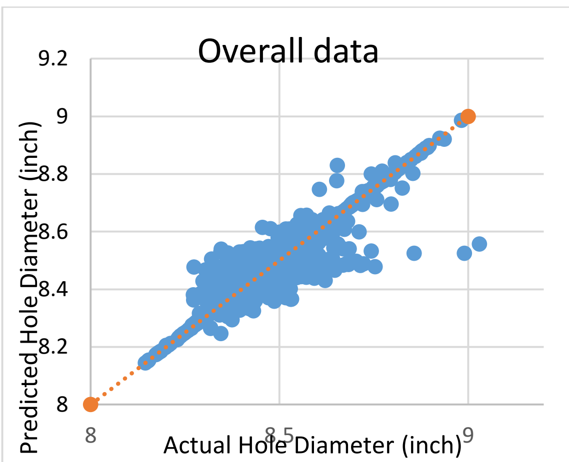
Figure 8 shows the value of Correlation coefficient (R^2)for overall data for **RF, SVM** and **XGB**, respectively. Correlation coefficient measures the strength of relationship between two variables and ranges from 0 to 1, a value of zero indicates that there is no relationship and a value of 1 indicates perfect positive correlation, as seen in this figure RF outperforms SVM and XGB with R^2 with equal 0.952 for overall data that indicates very high positive correlation between the actual and predicted hole diameter value.

Figure 9 shows the value of MAE for overall data for **RF, SVM** and **XGB**, respectively. In statistics mean absolute error is a measure of errors between paired observations expressing the same phenomenon, as MAE tends to zero; this indicates that no error between the observations, as seen in this figure RF gives the highest accuracy with MAE equal 0.0017 for overall data.

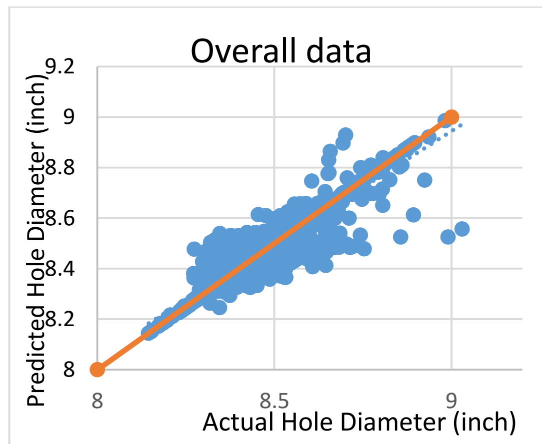
Figure 10 shows the value of average relative error (ARE) for overall data for **RF, SVM** and **XGB**, respectively. Average relative error is defined as the ratio of the absolute error of the measurement to the actual measurement and we can multiply by 100 % to get the percent error, as shown in this figure; RF have the minimum (ARE %) which equal 0.17% for overall data, that reflect the high efficiency of RF model.

Figure 11 shows the value of mean squared error MSE for overall data for **RF, SVM** and **XGB**, respectively. In statistics, mean squared error measures the average squared difference between the estimated and the actual values. As shown in this figure RF has the lowest value of MSE that equal 0.0011 for overall data, that reflects the highest accuracy given by the model.

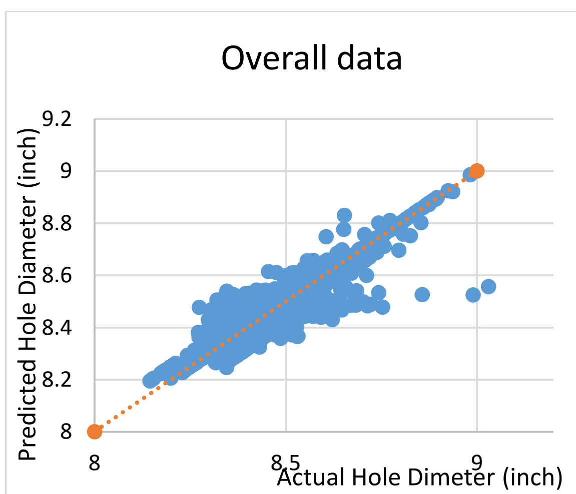
Figure 12 shows the value of relative mean squared error (RMSE) for overall data for **RF, SVM** and **XGB**, respectively. In statistics, RMSE is the squre root of MSE, small errors have low value of RMSE. As shown in this figure, RF outperforms SVM and XGB with RMSE = 0.039 for overall data.



(a) Random forest regression

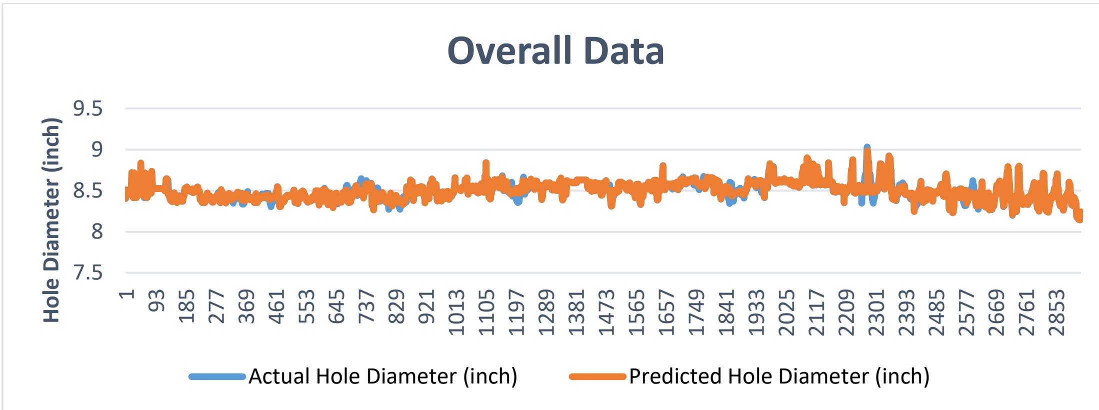


(b) Support vector machine

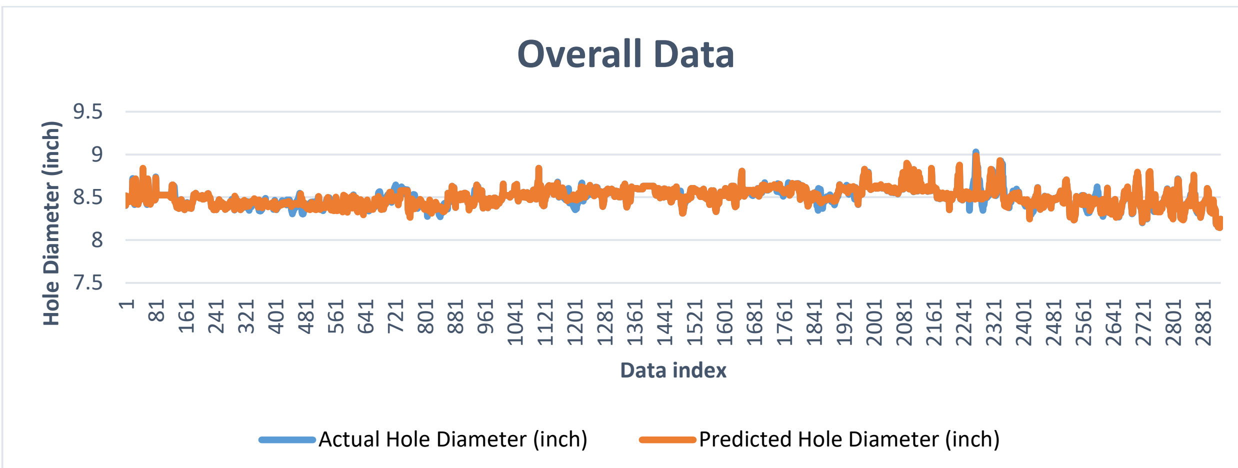


(c) XGBoosting regression

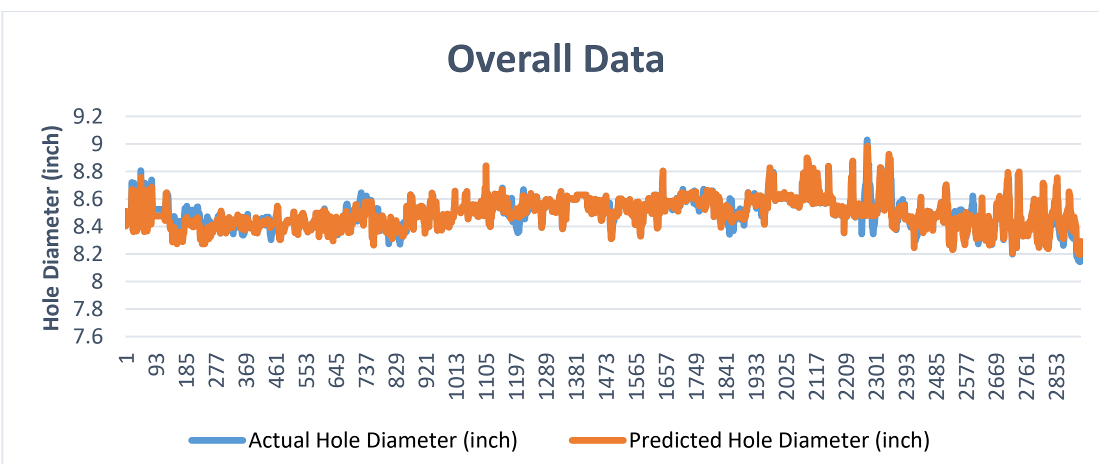
Figure 6: The cross plot of the model predicted hole diameter versus the actual hole diameter for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression

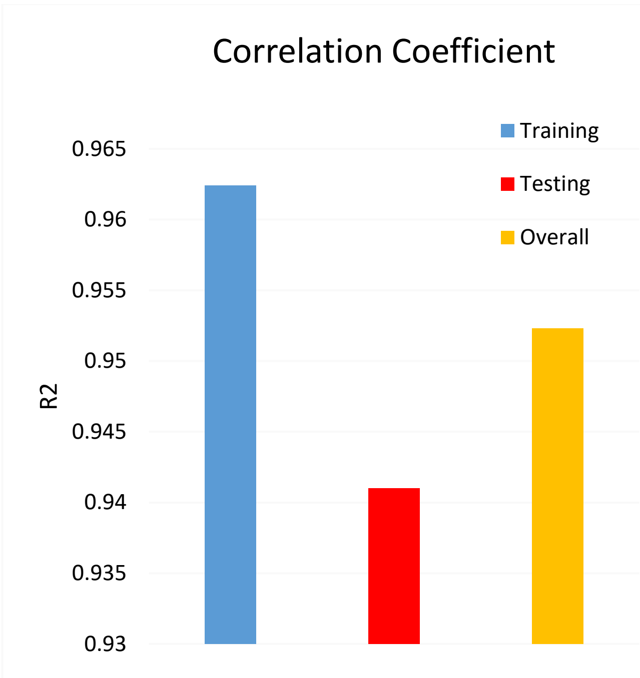


(b) Support vector machine

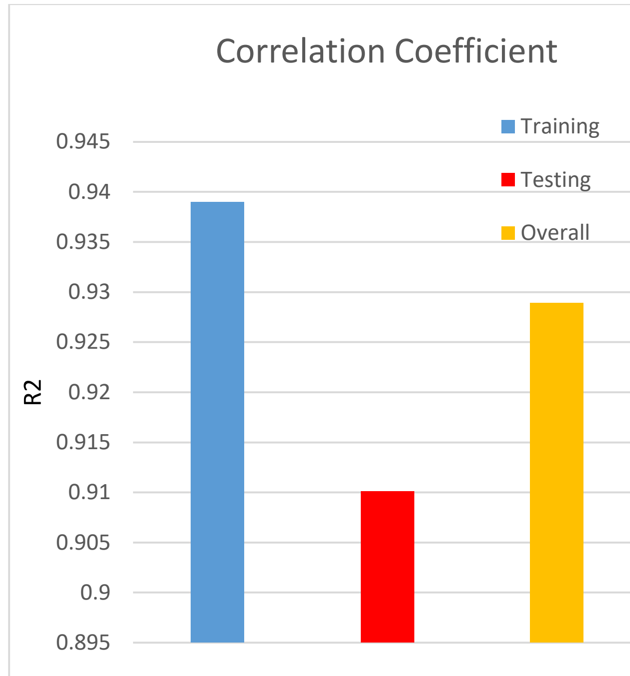


(c) XGBoosting regression

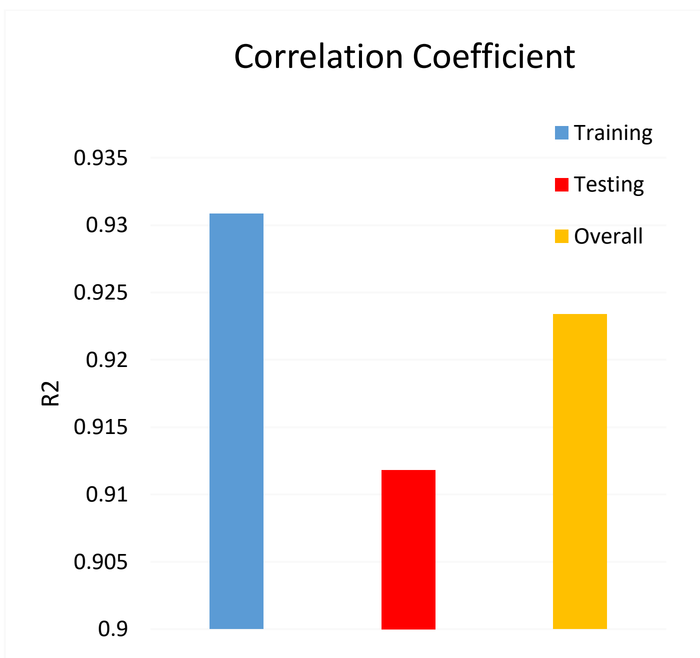
Figure 7: Simultaneous representations of model data and actual data of Hole Diameter for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression

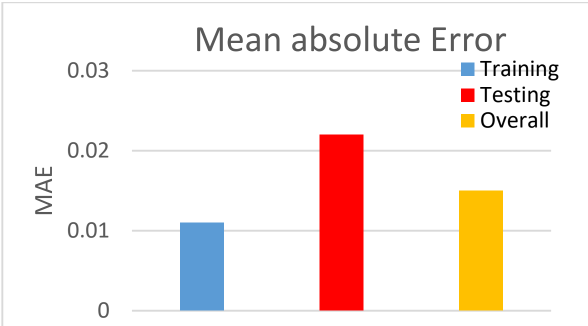


(b) Support vector machine

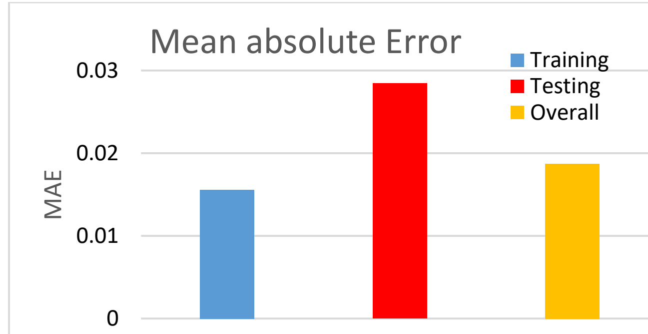


(c) XGBoosting regression

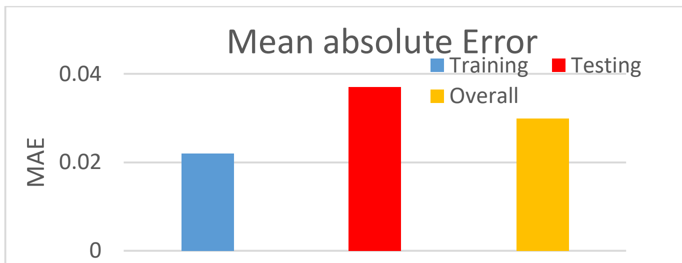
Figure 8: Correlation coefficient (R^2) for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression

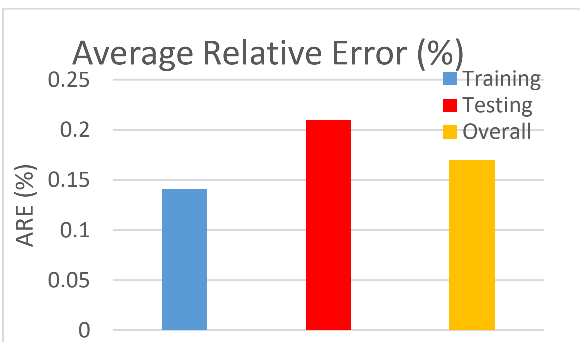


(b) Support vector machine

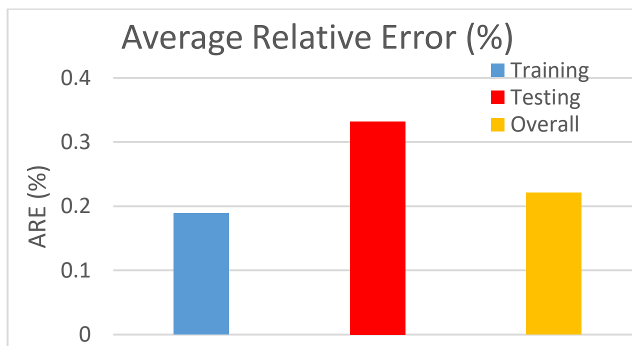


(c) XGBoosting regression

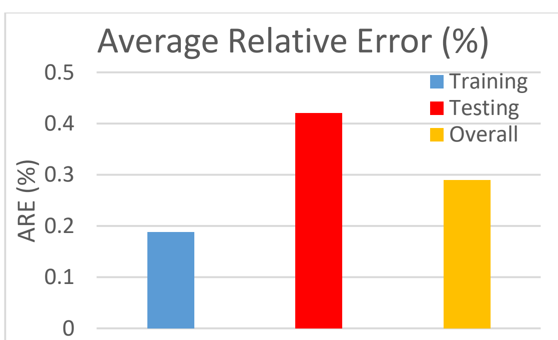
Figure 9: MAE for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression

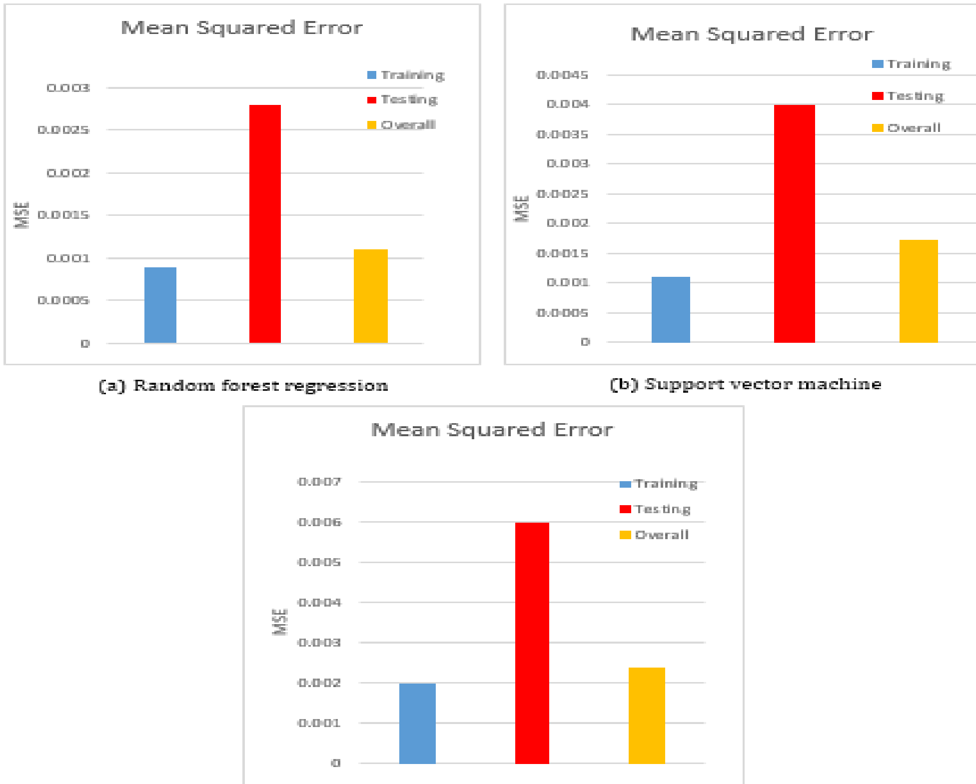


(b) Support vector machine



(c) XGBoosting regression

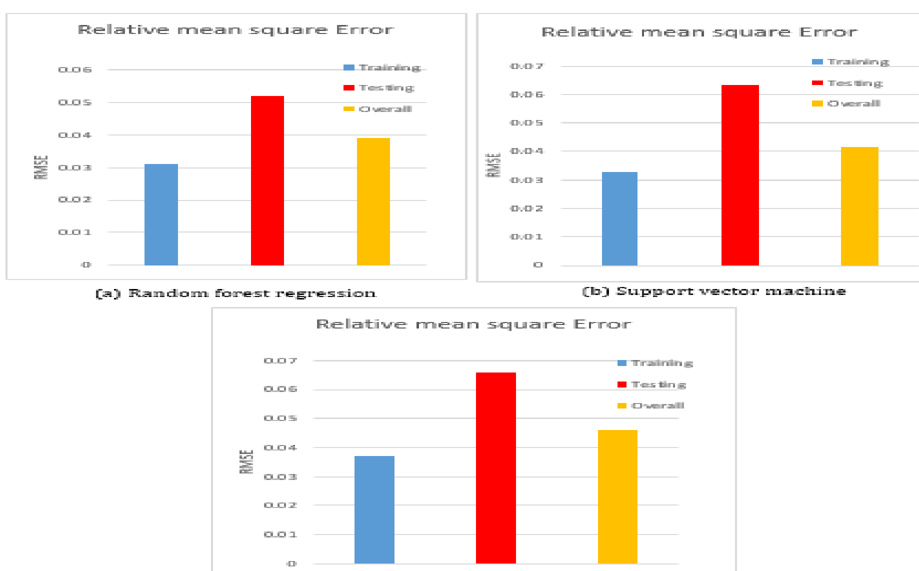
Figure 10: ARE for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression (b) Support vector machine

(c) XGBoosting regression

Figure 11: MSE for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression



(a) Random forest regression (b) Support vector machine

(c) XGBoosting regression

Figure 12: RMSE for overall data for (a) Random forest regression, (b) Support vector machine, and (c) XGBoosting regression

CONCLUSIONS

Fast and accurate prediction of filter cake / hole wash-out is critical in the planing phase of the upcoming wells. The main findings of this work can be summarized as follows:

- This paper proposed three AI models, namely, RF,SVM and XGB to predict this phenomena based on formation depth, overbalance pressure, drilling parameters, namely, rate of penetration (ROP), drill string rotation (RPM) and flow rate, inclination angle and logging data, namely, formation porosity, formation Gamma Ray,formation resistivity, formation, formation temperature, the percentage of minerals that forms the drilled formation which are mainly sand, silt, lime and clay and hole diameter from caliper log.
- The predicted values of filter cake / hole wash-out by the three AI techniques was compared to actual values of filter cake / hole wash-out obtained by caliper log.
- RF was determined to be the best technique among the tested AI techniques to predict filter cake / hole wash-out with high accuracy (R^2= 0.952 and RMSE = 0.039).

Nomenclature

R2	= Correlation Coefficient
MSE	= Mean Squared Error
RMSE	= Mean Squared Error
MAE	= Mean Absolute Error
RPM	= Drill string rotation
ROP	= Rate of penetration
ML	= Machine learning
SVM	= Support vector machine
ANN	= Artificial neural network
RF	= Random forest regression
XGB	= Extreme gradient boosting regression

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