

Article

Effects of Petrophysical Parameters on Sedimentary Rock Strength Prediction: Implications of Machine Learning Approaches

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Abstract

Machine learning-guided predictive models are attractive in rock modeling for different scholars to obtain continuous profiles of rock compressive strength in rock engineering. The major objectives of the study are to assess the implications of machine learning (ML)-based connectionist models to obtain the unconfined compressive strength (UCS) of rock, to perform parametric sensitivity analysis on petrophysical parameters, and to develop an improved correlation for UCS prediction. The least-squares support vector machine (LSSVM) is applied to develop data-driven models for the prediction of UCS. Additionally, the random forest (RF) algorithm is applied to verify the effectiveness of predictive models. A database containing well-logging data is processed and utilized to construct connectionist models to obtain UCS. For the efficacy of predictive models, statistical performance indicators such as the coefficient of determination (CC), average percentage relative error, and maximum average percentage error are utilized in the study. It is revealed that the RF- and LSSVM-based models for predicting UCS perform excellently with high precision. Considering the parametric sensitivity analysis in the predictive models for UCS, the formation compressional wave velocity and formation gamma-ray are the most strongly contributing predictor variables rather than other input variables such as the modulus of elasticity, acoustic shear wave velocity, and rock bulk density. The improved correlation for predicting UCS shows high precision, achieving a CC of 96% and root mean squared error of 0.54 MPa. This systematic research workflow is significant and can be utilized for connectionist robust model development and variable selections in the petroleum and mining fields, such as predicting reservoir properties, the drilling rate of penetration, sanding potentiality of hydrocarbon reservoir rocks, and for the practical implications of boring and geotechnical engineering projects.

Keywords: random forest; least square support vector; feature selection; logging data; geomechanics



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1. Introduction

An accurate rock strength parameter model plays a vital role in predicting a safe drilling mud window (i.e., safe range of drilling pressure for wellbore stability) and wellbore failure analysis to prevent well blowouts in making decisions involving oil and gas field developments. The unconfined compressive strength (UCS) in rock engineering is a vital parameter to investigate the reservoir rock strength for safe drilling operations during petroleum productions and reservoir rock management [1]. The compressive rock strength can be obtained through an experimental study using standard and precise core specimens. The most frequently used direct experimental tests are the UCS test, triaxial confining test, Brazilian indirect test, and the Schmidt hammer rebound test to measure rock strength parameters [2–8]. Reliable core sample preparation is tedious, expensive, and time-consuming to capture formation loading conditions [9]. When reliable experimental measurement is not possible by testing rock samples, petrophysical well logs are a substitute choice to obtain a continuous curve of dynamic rock strength parameters of UCS and tensile strength [1] along the depth of the well. By integrating both core and/or log data, a reliable model can be developed to obtain a rock strength model of UCS. Accurate estimation of UCS is significant for assessing sanding potential and optimum drilling pressure for drilling operations. In addition, the selection of predictor variables is a crucial issue to eliminate less contributing logging parameters in the model of rock strength while obtaining true representative rock models. Moreover, the feature ranking and accurate predictive model can be obtained by the coupling of real field petrophysical well log data and machine learning (ML) approaches.

Recent studies have proved the superiority of ML techniques, such as the least-squares support vector machine (LSSVM) and random forest (RF), adopted for their robustness and accuracy level with limited datasets, in empirical, experimental, and statistical approaches to obtain output, including petroleum, mining, and geotechnical engineering-related problems [10–19]. A growing propensity is detected among researchers to adopt ML algorithms in several fields such as geomechanics, rock engineering, and mining slope stability studies. A list of studies has been examined to investigate the performances of predictive models in geotechnical, petroleum, and mining engineering using supervised ML and artificial intelligence (AI) tools [20–30]. Notably, numerous investigations were performed by different authors to address their research findings, efficacy, and limitations of ML and AI algorithms for obtaining UCS, which can be retrieved from the available published papers [31–52]. The present literature survey discloses that several predictor variables are implemented in AI- and ML-based models to obtain the UCS and modulus of elasticity (E) in geomechanics using rock physical properties and core/log data such as gamma-ray (GR), true resistivity (Rt), rock bulk density (ρ_b), dry density (ρ_d), porosity (ϕ), water saturation (S_w), unit weight (uw), compressional wave velocity (V_p), water content (wc), point load strength (PLS) or load index ($I_{s(50)}$), Schmidt hammer rebound number (SR_n), Brazilian tensile strength (BTS), slake durability index (I_d), Los Angeles abrasion value (LAAB), aggregate crushing value (ACV), and impact value (AIV). A list of selective scholars' models [31–48] is shown in Table 1 to depict ML-based predictive models such as artificial neural networks (ANNs), deep neural networks (DNNs), K-nearest neighbor (KNN), extreme gradient boosting (XGB), support vector machines (SVMs), artificial neural fuzzy inference systems (ANFISs), gene expression programming (GEP), convolution neural networks (CNNs), transformer (TF), and the artificial bee colony (ABC) using different input variables to obtain UCS.

Table 1. ML-based predictive models to obtain UCS.

Investigator (s)	Input Variables	ML Approach	Features Selections
Sharma et al. [31]	ρ_b, V_{sh}, V_p, V_s	ANN	No
Rabbani et al. [32]	ρ_b, ϕ, S_w	ANN	No
Yagiz et al. [33]	ϕ, SR_n, I_d, V_p, uw	ANN	No
Ceryan et al. [34]	ϕ, V_p, V_m	ANN	No
Momeni et al. [35]	$I_{s(50)}, SR_n, \rho_d, V_p$	ANN	No
Mohamad et al. [36]	$I_{s(50)}, \rho_b, BTS, V_p$	ANN	No
Barzegar et al. [37]	ϕ, SR_n, V_p	ANN, ANFIS, SVM	No
Behnia et al. [38]	$\phi, \rho_d, \text{quartz content}$	GEP	No
Tariq et al. [39]	E, ρ_b, V_s, V_p	ANN, ANFIS, SVM	No
Onalo et al. [40]	GR, ρ_b, V_{sh}	ANN	No
Abdi et al. [41]	ϕ, ρ_d, wa, V_p	ANN	No
Liu et al. [42]	V_p, PLS, SR_n	Extreme Tree	Yes
Afolagboye et al. [43]	$I_{s(50)}, SR_n, AIV, ACV, LAAV$	ANN, RF, RVM, SVM	Yes
Malkawi et al. [44]	$I_{s(50)}, \phi, \rho_d, PLS$	ANN, KNN, Extreme Tree	Yes
Zhao et al. [45]	$I_{s(50)}, \rho_b, V_p$	AdaBoost-ABC, XGB-ABC	No
Amiri et al. [46]	$I_{s(50)}, V_p, \rho_d, BTS, wa$	DNN	No
Rahaman and Miah [47]	$I_{s(50)}, SR_n, V_p, \phi$	ANN, CNN, TF, SVM	Yes
Cao [48]	$I_{s(50)}, SR_n, V_p, \rho_b, \rho_d, BTS, wa$	ANFIS	No

For the Bengal Basin, Miah et al. [5] proposed a log-based prediction model to obtain UCS for a sandstone reservoir instead of experimental-based measurements to estimate geomechanical properties. They used ML tools, an ANN and LSSVM, to evaluate the model performance of the predictive models with the petrophysical log parameter for UCS and to choose predictor log variable features in the model. To develop the dynamic data-driven models, the backpropagation multilayer-based ANN with the Levenberg–Marquardt (LM) algorithm and the LSSVM with the coupled simulated annealing (CSA) optimization technique were used by Miah et al. [5]. The model predictions are validated and compared to the target values with existing log-based correlations. The authors found that the acoustic travel time (Δt) and gamma-ray (GR) have the highest relative importance in estimating UCS. Moreover, Miah and Ovi [49] applied the LSSVM ML technique to predict rock strength using log data. They did not attempt to develop an improved model for clastic sedimentary rocks. Furthermore, Adjei et al. [50] adopted three types of gradient boosting (GB) machines such as standard GB, stochastic GB, and XGB to predict the UCS of carbonate sedimentary rocks using a total of 2056 measurements of drilling parameters. They also examined the feature attributes' performance using a decision tree algorithm and ranked them from higher to lower importance. Also, Komadja et al. [51] utilized principal component analysis, XGB, and adaptive boosting approaches to evaluate their efficacy for drilling feature attribute analysis. It was found that flushed air pressure is more sensitive compared to other variables such as rotation pressure, the rate of penetration, dampening feed, and percussion pressures for UCS estimation. Recently, Khatti and Grover [52] applied different ensemble machine learning techniques such as DT, extreme tree, and SVM using the input variables of geometric parameters and V_p to predict UCS for a mixed type of rocks. They did not perform feature attribute analysis to find most contributing variables for further development of an empirical correlation for UCS.

Based on the gaps in these studies, it is essential to investigate the superiority and effectiveness of the ensemble machine learning methods of RF and LSSVM-CSA and also to examine the individual effects of compressional and shear ultrasonic velocities, as well as the modulus of elasticity, to predict UCS for clastic sedimentary rocks. Additionally, the reliable and accurate rock models of UCS are essential for safe drilling mud window

prediction as well as wellbore failure analysis using geomechanical parameters for the development of the natural gas field.

The major purposes of this study are (i) to assess the efficacy of the machine learning-based hybrid connectionist models to obtain UCS, (ii) to perform parametric sensitivity analysis for evaluating the effects of petrophysical parameters, and (iii) to develop an improved correlation for UCS estimation using most contributing variables.

2. Materials and Methods

2.1. Study Location and Data Collection and Preparation

The studied field is located in the north-eastern part of Bangladesh, which is a Miocene gas-producing province in the Bengal Basin. This field is an elongate anticline with a simple four-way dip closure at the southern end, and the geological structure lies on the southern fringes of the Surma Group of the Bengal Basin. To accomplish this study, the petrophysical log datasets of 183 for each variable are compiled from a sandstone gas reservoir in the Bengal Basin. The geological setting and tectonic structural framework can be reviewed from the existing literature [53–56]. The available well log data from the studied gas field are formation gamma-ray (GR), bulk density (ρ_b), compressional and shear acoustic wave velocities (V_p , V_s), and elasticity modulus (E). These log variables are considered as input features to obtain the model output of rock compressive strength (UCS). In the current study, dynamic E and UCS are obtained from a model of Fjær et al. [12] for clastic sedimentary rocks. The well log datasets are assessed through an inspection of the formation depth shift, borehole environments, and compared borehole size with caliper logs. Also, the data quality is investigated by an outlier detection method, named inter-quartile range (IQR), to ensure the reliability of output and predictor variables for ML-based model development.

2.2. Research Methodology

In this study, the random forest (RF) ensemble machine learning technique [57] and hybrid connectionist approach using the LSSVM algorithm with the coupled-simulated annealing (CSA) process are utilized to build the data-driven predictive models due to their robustness, generalization of the models, and their capability to form high-dimensional complex associations among variables of core and log data [57–60]. The accuracy of the bagging-based RF model improves as the depth of the trees and the number of trees get larger; but at a certain point, the accuracy saturates. RF model stability can be improved by enhancing the number of trees. RF may be used to examine the relevance of predictors incorporated into it in addition to its applicability in classification and regression models. The extreme tree-based predictive model of RF is better than the single tree-based model with a decision tree (DT). By averaging multiple trees, it minimizes overfitting better than a single DT [57]. Also, it is less sensitive to noise and outliers in the datasets and does not require a data scaling process unlike other machine learning algorithms, including support vector machines (SVMs). In addition, the LSSVM is a modified version of the SVM which is more robust, computationally more efficient, less sensitive to noise data, and is capable of performing better using a smaller number of datasets compared with other ML techniques such as ANNs and SVM [6]. A generalized flowchart for the ML-based model development steps is shown in Figure 1.

The regularization and kernel parameters of gamma (γ) and squared kernel width (σ^2) are optimized through a global approach of CSA with a Gaussian radial basis kernel function (RBF) to obtain a LSSVM-guided model, which is shown in Figure 2. This RBF

can be defined mathematically to train and optimize the LSSVM-based predictive model as follows [59]:

$$K(x, x_i) = \exp\left(-\frac{|x_i - x|^2}{2\sigma^2}\right) \quad (1)$$

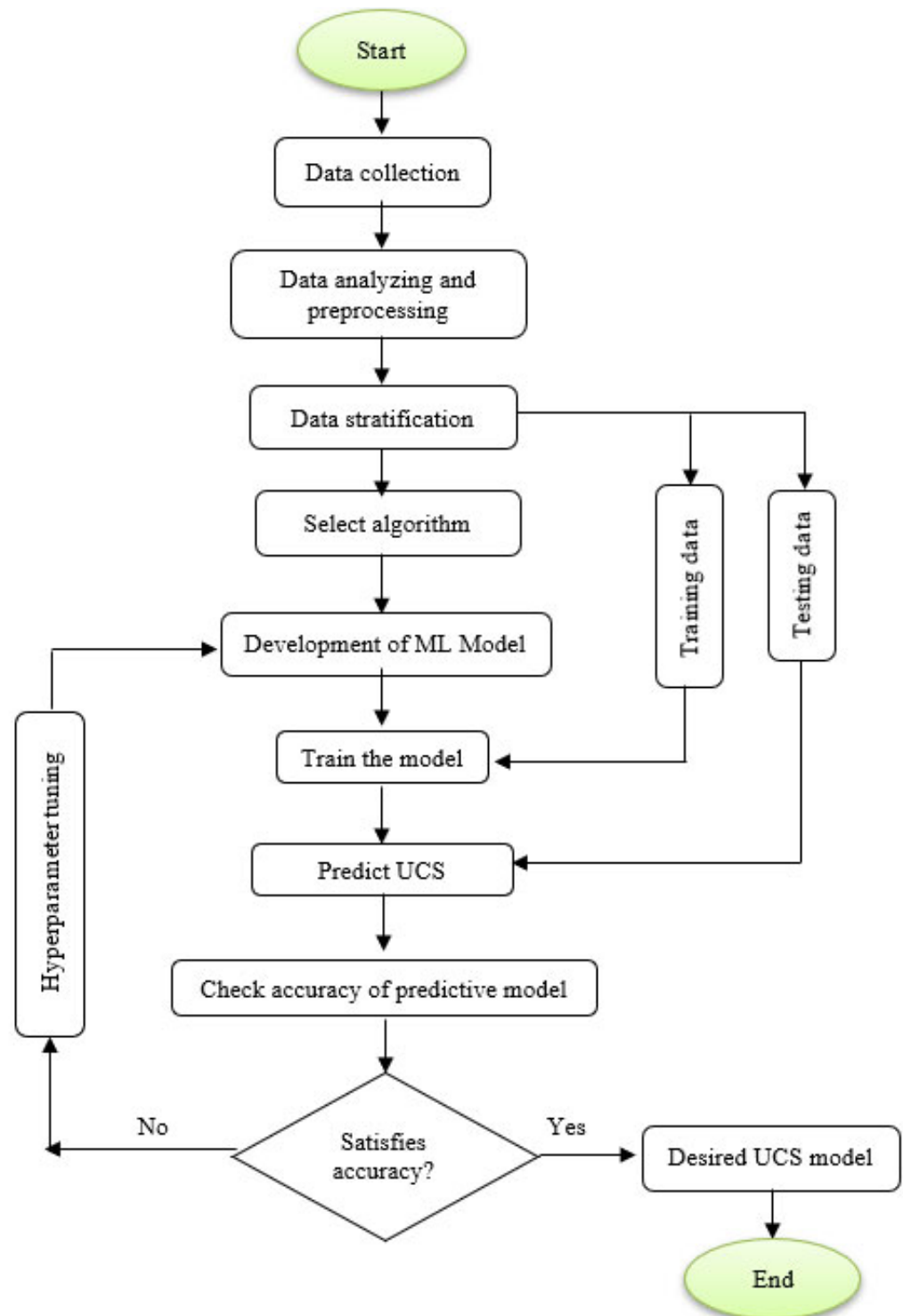


Figure 1. A generalized working flow diagram of machine learning-based model development and prediction of UCS.

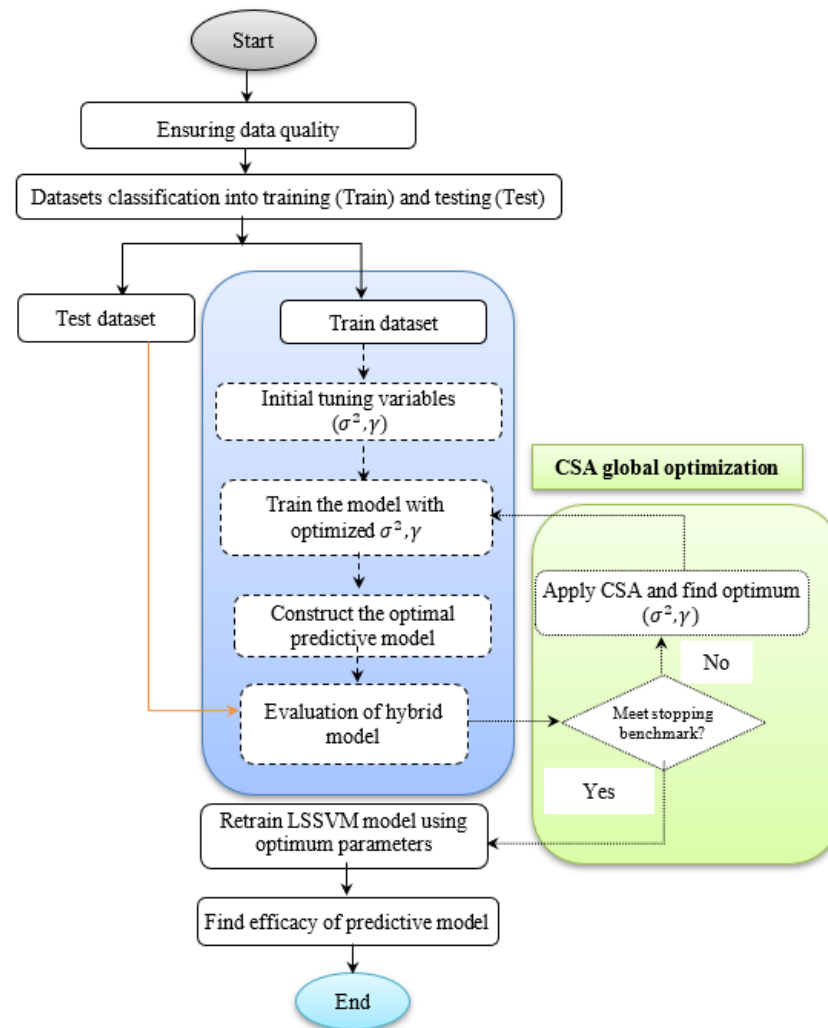


Figure 2. A generalized flowchart of a hybrid model structure with LSSVM-CSA to obtain output (modified from [6]).

Moreover, a generalized mathematical expression for the LSSVM can be expressed to predict output variable (y), like the rock compressive strength parameter (UCS) with a bias term of b , weight factor of α , training datasets of x , and support vector of x_i [60]:

$$y(x_i) = \sum_i^N \alpha_i \times K(x, x_i) + b \quad (2)$$

A list of datasets is divided into two phases, named training and testing phases to train and validate predictive models, respectively. Hyperparameters are crucial for finding an optimized model with high-precision LSSVM-CSA and RF, as well as for avoiding underfitting and overfitting issues. To ensure the model's performance to escape the overfitting of the training dataset, a cross-validation process as well as trial-and-error approach is conducted. An optimization process of random grid search is conducted once the cross-validation results verified the model's performance. Furthermore, statistical model performance indicators (MPIs) are utilized to assess the efficacy of data-driven models with RF and LSSVM algorithms as well as to evaluate the impacts of predictor variables to obtain UCS. The MPIs are the coefficient of determination (CC), average percentage relative error ($AAPE$), and the maximum average absolute percentage error ($MAPE$). The high precision level of the connectionist models is assessed based on the least statistical errors of $AAPE$ and $MAPE$ or a high score of CC and vice versa. The

mathematical expressions of MPIs to assess the predictive model effectiveness are listed below [1,6]:

$$AAPE = \frac{1}{N} \sum_{i=1}^N \frac{(UCS_{t,i} - UCS_{p,i})}{UCS_{t,i}} \quad (3)$$

$$MAPE = \text{Max.} \left| \frac{(UCS_{t,i} - UCS_{p,i})}{UCS_{t,i}} \right| * 100 \quad (4)$$

$$CC = 1 - \frac{\sum_{i=1}^N (UCS_{t,i} - UCS_{p,i})^2}{\sum_{i=1}^N (UCS_{t,i} - UCS_{t,mean})^2} \quad (5)$$

where N is the total number of measurements, UCS_{mean} represents the mean value of rock compressive strength, and UCS_t and UCS_p are the target and predicted results of the output variable, UCS.

Furthermore, considering the influence of predictor log variables to predict UCS, these parameters are ranked using statistical error analysis with the ‘single-variable elimination strategy’ in the predictive model enlargement. For instance, the predictive model is excellent for the lowest score of CC and high values of MAPE and AAPE. Afterward, only the most dominant and practically significant log variables are adopted to establish an improved dynamic UCS model to measure rock strength through the amalgamation of petrophysical parameters and multivariable regression analysis.

3. Results and Discussion

3.1. Datasets Patterns and Efficacy of Predictive Models

The petrophysical log variables vary due to a complex interaction of physical and chemical factors with geological environments such as diagenesis and cementation processes. These dissimilarities reflect the heterogeneity of the petrophysical log variables and are critical in understanding geomechanical properties and rock strength behavior. The summarized results of descriptive statistics are listed in Table 2 to address the dataset patterns and trends with mean values for measuring central tendency, standard deviation (STD) to measure variability, and Kurtosis and skewness for understanding the shape of the data distribution.

Table 2. Summary of the statistical scores of the used dynamic petrophysical log data.

Statistical Values	GR (API)	ρ_b (gm/cm ³)	V_s (km/sec)	V_p (km/sec)	E (GPa)	UCS (MPa)
Mean	100.19	2.37	3.2893	1.7927	19.61	31.13
Maximum	157.82	2.53	3.5506	1.9903	24.17	42.60
Minimum	76.28	2.30	3.1294	1.6498	17.02	26.57
STD	13.84	0.04	0.0862	0.0702	1.47	2.76
Standard error	1.023	0.003	0.006	0.005	0.108	0.204
Kurtosis	3.816	2.745	0.554	0.323	0.562	4.545
Skewness	1.588	1.563	0.359	-0.079	0.341	1.748
Confidence level (95%)	2.018	0.006	0.013	0.010	0.214	0.402

The variability of gamma-ray (GR) is high because of changes in the concentration of natural radioactive materials in the formation. For instance, the modulus of elasticity (E) and rock compressive strength (UCS) also varied significantly over the entire depth interval. The range of the output variable (UCS) reservoir depth in the studied sandstone lithology

was 26.57–42.60 MPa, whereas the mean value is 31.13 MPa. In addition, a correlation matrix is demonstrated in Table 3 to represent the variable features and correlations of predictor variables to output variables. All predictor variables are positively correlated with the output response of UCS in the field data studied.

Table 3. Correlation matrix to show the relationship of predictor variables to target output of UCS.

Variables	GR	ρ_b	V_p	V_s	E	UCS
GR	1					
ρ_b	0.52	1				
V_p	0.59	0.31	1			
V_s	0.43	-0.034	0.94	1		
E	0.58	0.28	0.99	0.95	1	
UCS	0.91	0.64	0.84	0.65	0.83	1

To obtain the rock strength parameters of UCS from petrophysical datasets, two predictive regression models, RF and the LSSVM, have been developed with data stratification of 70% and 30% for training and testing phases. For the RF technique, the tuning parameters are ‘bootstrap’: True, ‘max_depth’: 20, ‘maximum features’: ‘auto’, ‘maximum leaf nodes’: 40, ‘minimum samples leaf and split’: 1 and 3, and ‘n estimators’: 15. On the other hand, the hyper-parameter of γ is 1.47×10^{11} and σ^2 is 26.33 through an iterative approach to meet the CSA convergence criteria for the connectionist model with the LSSVM.

3.2. Effects of Petrophysical Parameters on UCS Prediction

Scatter plots are illustrated in Figures 3–7 to signify a correlation with a squared Pearson’s correlation coefficient (R^2) between the independent formation log variable to the rock strength parameter and to observe the effects of petrophysical parameters while predicting UCS in a case study of a sandstone reservoir in the Bengal Basin. Based on the nature of the studied data, the two petrophysical log variables that contributed the most are GR and V_p to estimate UCS.

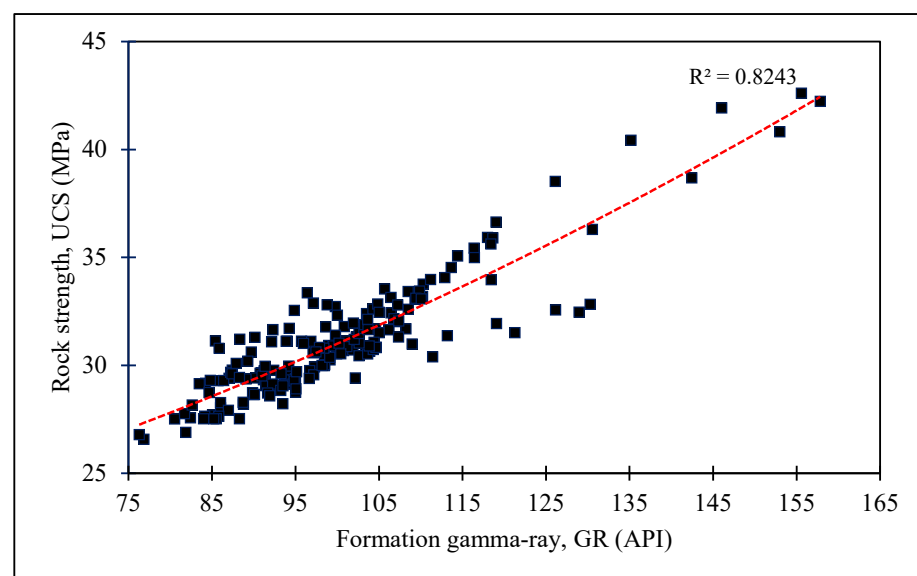


Figure 3. A scatter plot with a polynomial correlation between gamma-ray and UCS.

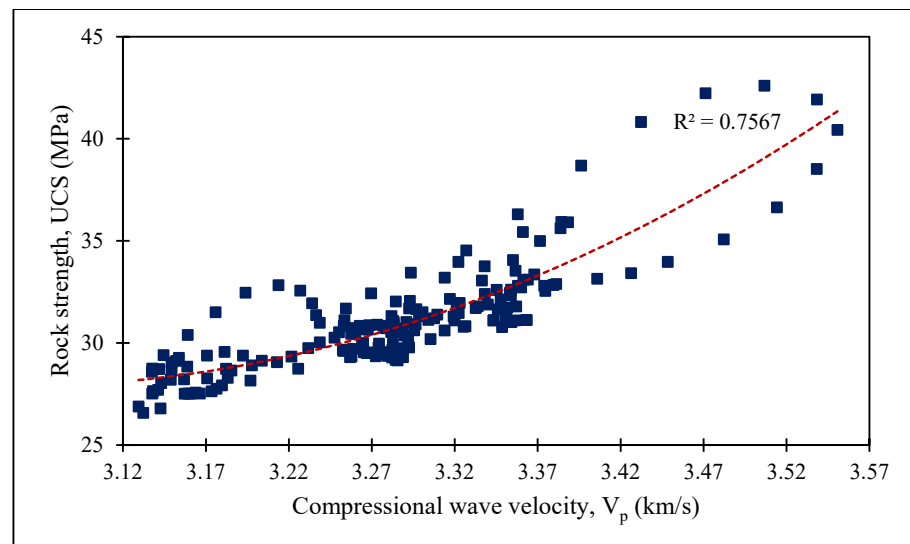


Figure 4. A scatter plot with a polynomial correlation between V_p and UCS.

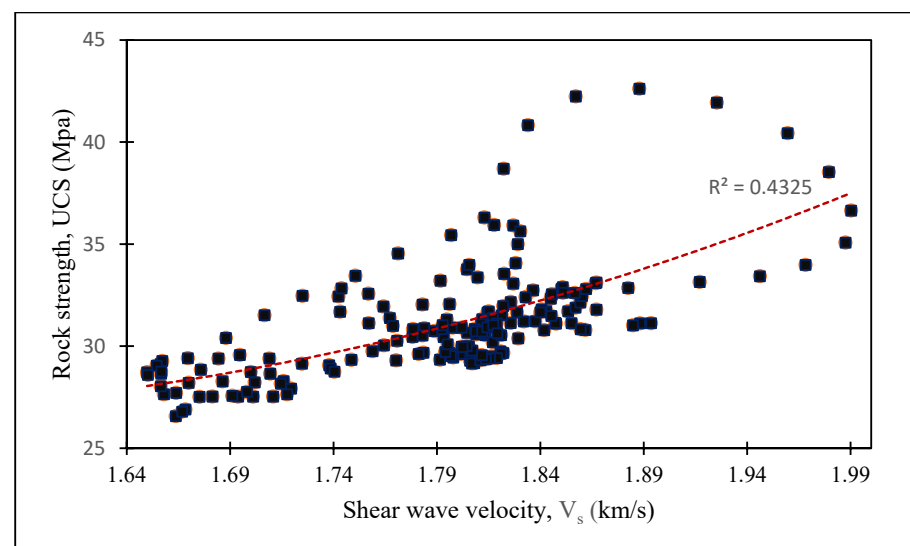


Figure 5. A scatter plot with a polynomial correlation between V_s and UCS.

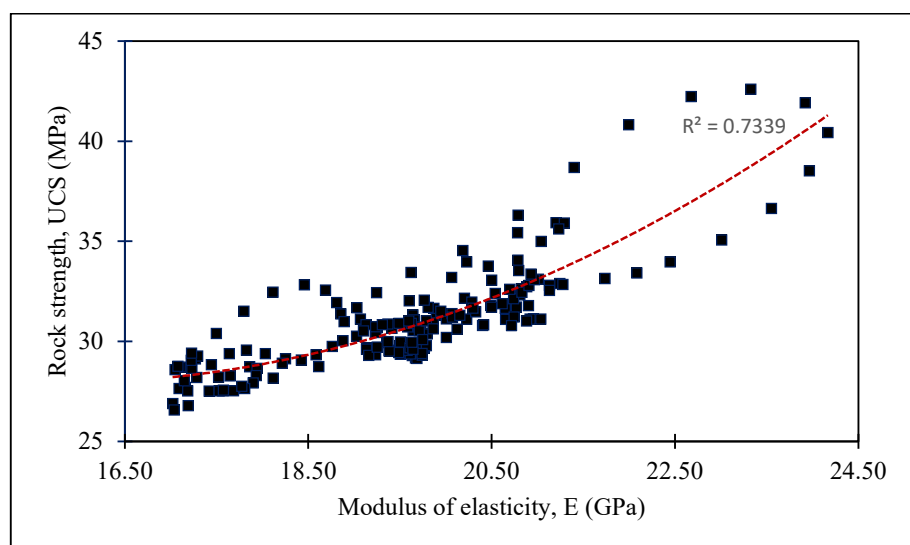


Figure 6. A scatter plot with a polynomial correlation between E and UCS.

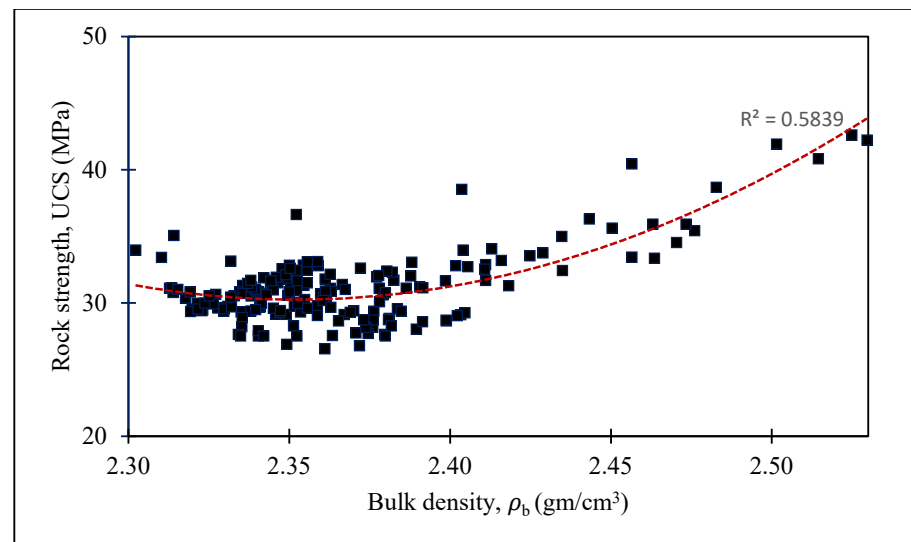


Figure 7. A scatter plot with a polynomial correlation between ρ_b and UCS.

In addition, five hybrid models are implemented to predict UCS by coupling LSSVM-CSA and four predictor variables with a single variable elimination process, for example, using variables V_p , V_s , ρ_b , and E , excluding GR. In the absence of the radioactive property, GR, the predictive model shows a low score of CC (%) (training: 90.92, testing: 89.64) and high statistical error, which is revealed in Figure 8. This indicates the high predictive value of GR. The summarized results for the four model schemes are listed in Table 4 using the hybrid LSSVM-CSA model. On top of that, five data-driven models, schemes A to E, with four input variables (excluding a single variable in each petrophysical log) using a random forest (RF) approach applied are presented in Table 5.

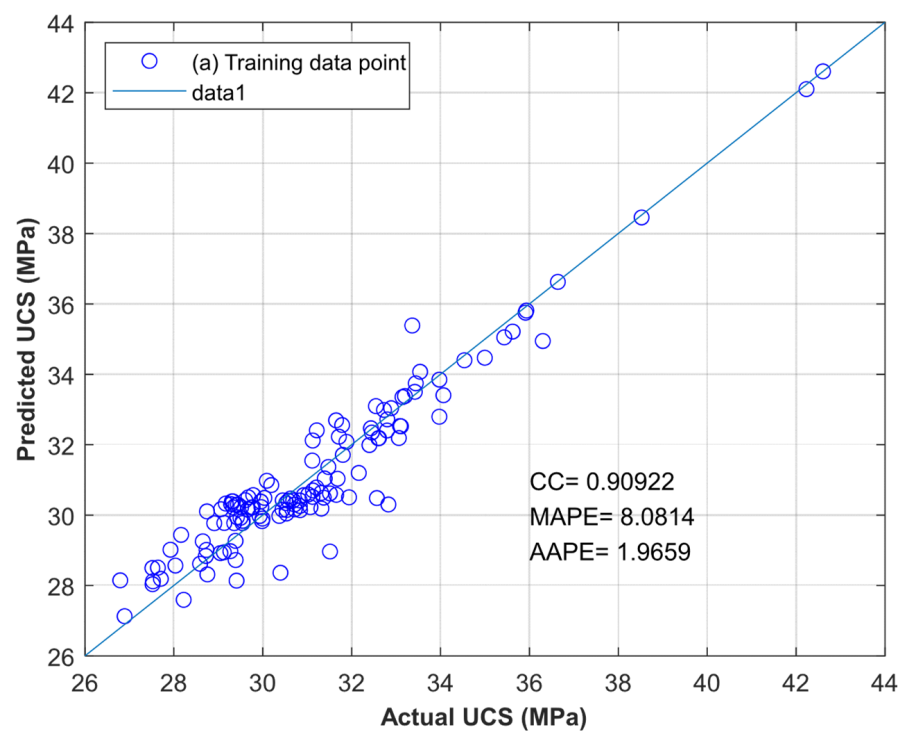


Figure 8. Cont.

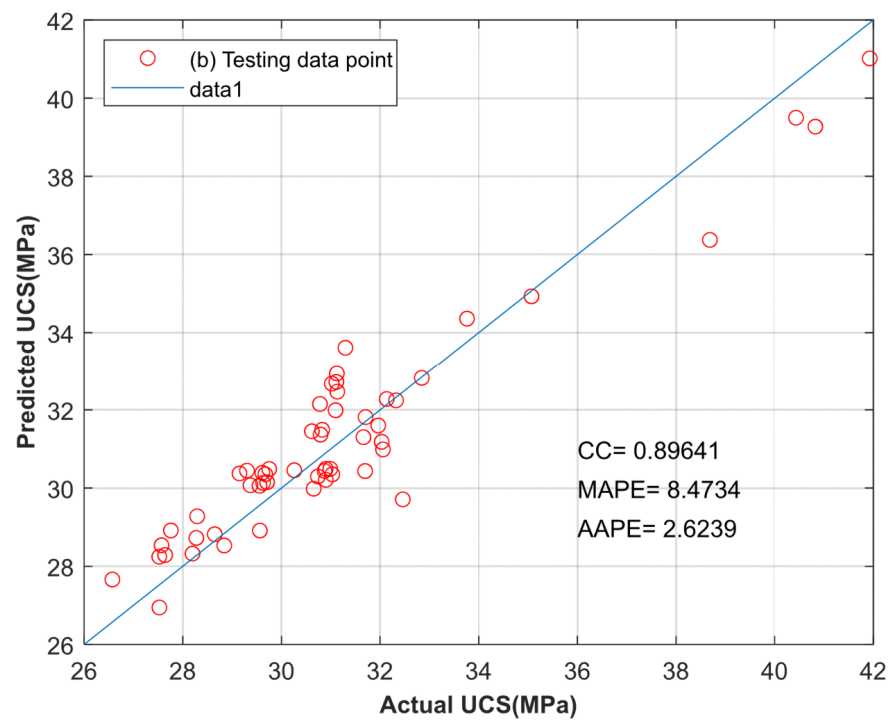


Figure 8. Performance of the LSSVM predictive model to obtain UCS for (a) training and (b) testing phases in the absence of GR.

Table 4. Predictive model results for the effect of the petrophysical parameter to obtain UCS using LSSVM-CSA.

Model Scheme	Input Variables	Excluded Variable	CC (%) Train (Test)	AAPE (%) Train (Test)	MAPE (%) Train (Test)	Feature Ranking
A	ρ_b, V_p, V_s, E	GR	90.92 (89.64)	1.97 (2.63)	8.08 (8.47)	1
B	GR, ρ_b, V_s, E	V_p	98.31 (94.97)	1.27 (1.32)	2.79 (5.99)	2
C	GR, ρ_b, V_p, V_s	E	99.32 (95.42)	0.64 (1.18)	3.51 (5.36)	3
D	GR, ρ_b, V_p, E	V_s	99.36 (96.62)	0.44 (1.09)	3.24 (4.06)	4
E	GR, V_p, V_s, E	ρ_b	1.00 (99.60)	0.01 (0.02)	2.02 (3.22)	5

Table 5. Predictive model results for the effect of the petrophysical parameter to obtain UCS using RF.

Model Scheme	Input Variables	Excluded Variable	CC (%) Train (Test)	AAPE (%) Train (Test)	MAPE (%) Train (Test)	Feature Ranking
A	ρ_b, V_p, V_s, E	GR	95.65 (83.46)	1.19 (2.69)	6.13 (9.26)	1
B	GR, ρ_b, V_s, E	V_p	98.31 (94.97)	0.47 (1.22)	2.69 (5.99)	2

Table 5. Cont.

Model Scheme	Input Variables	Excluded Variable	CC (%) Train (Test)	AAPE (%) Train (Test)	MAPE (%) Train (Test)	Feature Ranking
C	GR, ρ_b , V_p , V_s	E	99.32 (95.42)	0.44 (1.08)	2.71 (5.36)	3
D	GR, ρ_b , V_p , E	V_s	99.26 (95.62)	0.43 (1.09)	2.24 (4.06)	4
E	GR, V_p , V_s , E	ρ_b	99.915 (96.739)	0.31 (0.98)	1.19 (3.67)	5

Also, the graphical illustration is shown in Figures 9 and 10 to highlight the relative performance of each model scheme using the LSSVM and RF techniques.

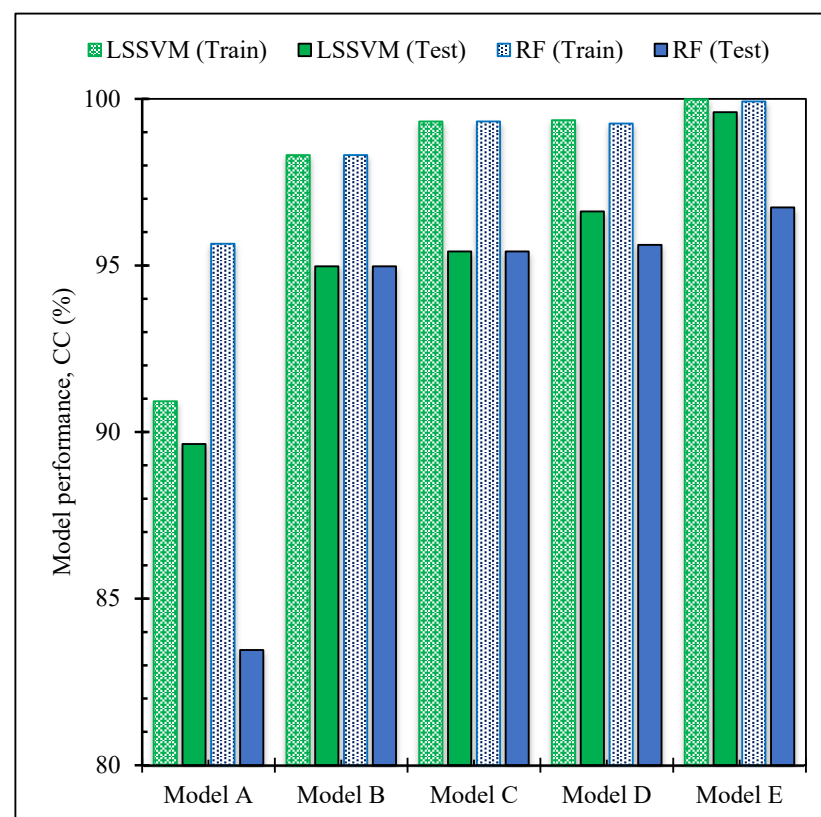


Figure 9. A comparison of CC performance for different model schemes.

According to results from Table 4, Table 5, Figure 9, and Figure 10 using the LSSVM and RF techniques with the single-variable elimination process in model scheme A, GR is the primary log (predictor) variable to estimate the rock strength of UCS because model scheme A exhibits low CC (%) in training at 89.64 and testing at 95.65 for the LSSVM and 95.65 and 83.46 for RF, respectively. For instance, model scheme A also had a high AAPE (%) at 1.19 and 2.69 with the RF approach, while it was 1.97 and 2.63 with the LSSVM for training and testing datasets, respectively. This differed from predictive model schemes B through E. For instance, the effects of predictor variables E and V_s are less significant compared to V_p and GR to obtain UCS for sandstone reservoir rocks of the studied field, Bengal Basin. Based on the studied findings, it is revealed that the GR radioactive property and acoustic compressional wave velocity (V_p) have foremost impacts on rock strength estimation for the sandstone sedimentary rocks, while E, V_s , and ρ_b have

minor effects. Considering the order from highest to lowest importance of predictor variables, the well-logging parameters of the studied sandstone gas reservoir can be ranked as $GR > V_p > E > V_s > \rho_b$.

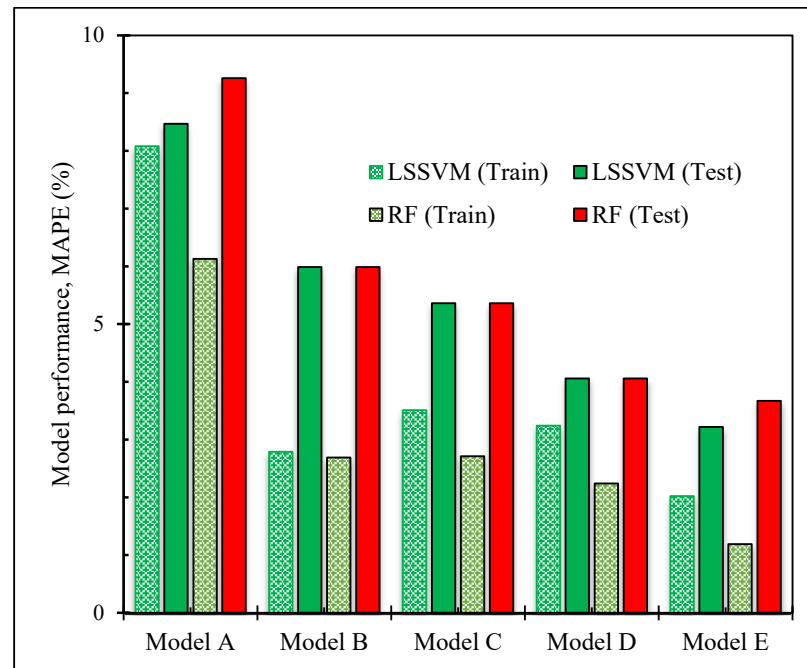


Figure 10. A comparison of MAPE performance for different model schemes.

3.3. Improved Model Development

The two most influential petrophysical logging parameters of gamma-ray (GR) and compressional sonic velocity (V_p) are adopted to capture the formation radioactive property and the intensity of elastic wave energy propagation into the sedimentary formation, respectively, to develop an improved model to obtain an in situ UCS profile, which is represented by a surface plot in Figure 11.

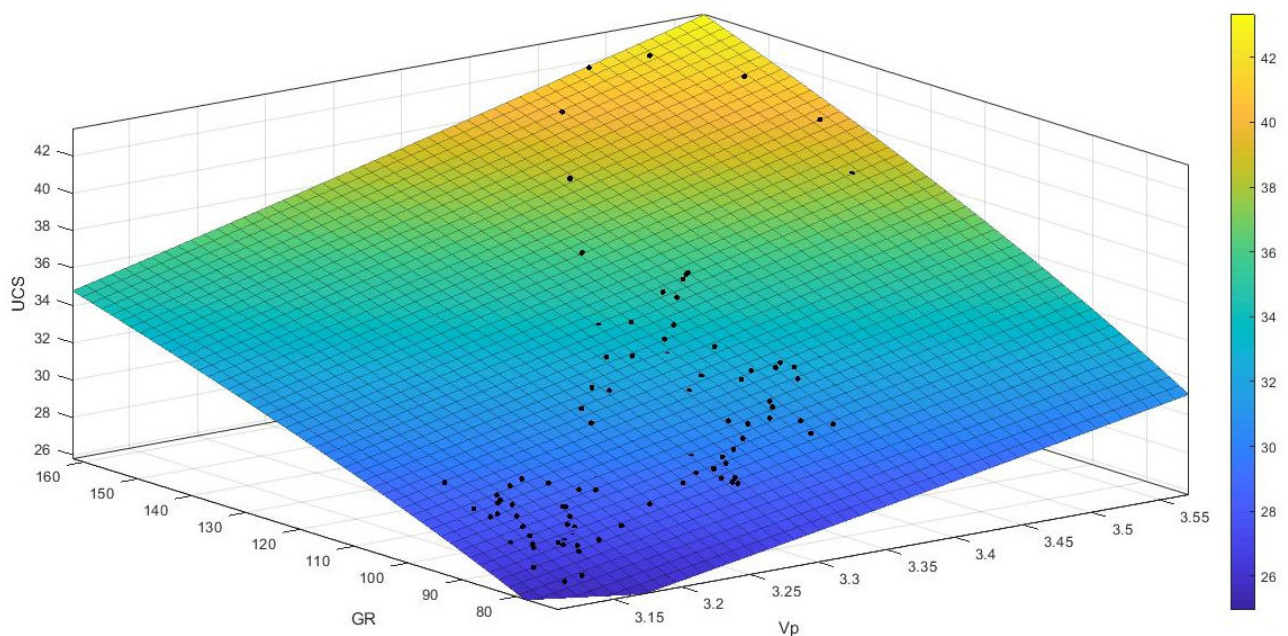


Figure 11. The relationship between GR and V_p with UCS in the developed model.

A power law-based regression model is constructed using the two influential well-logging variables to obtain a dynamic UCS profile, which had a low statistical root mean square error of 0.54 MPa and a CC of 96.25%.

$$UCS = 0.712 \times GR^{0.4108} \times V_p^{1.586} \quad (6)$$

For instance, a comparison with different models such as that by Moos et al. [10], Chang et al. [11], and Miah et al. [5] is shown in Figure 12 to demonstrate the proposed model performance for clastic sedimentary rocks using petrophysical dynamic well log data of a gas reservoir, Bengal Basin.

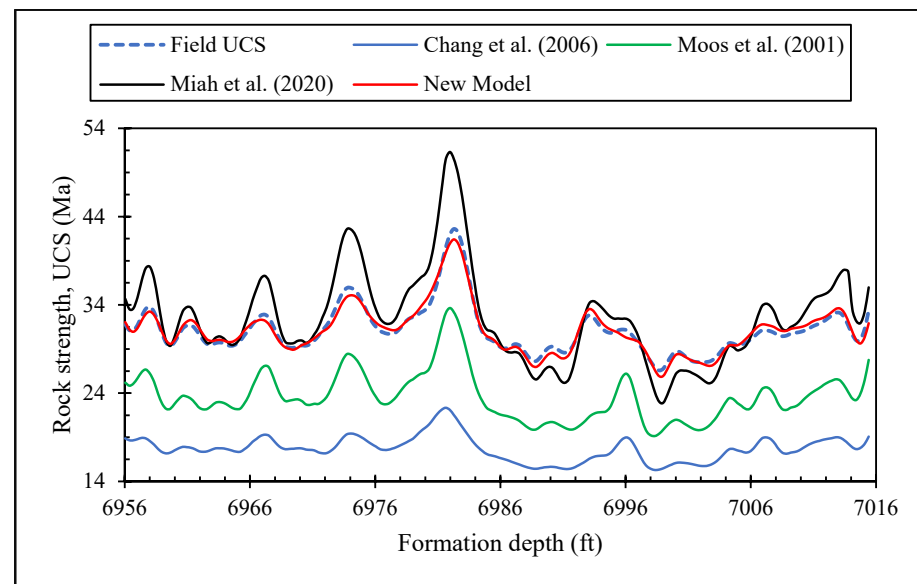


Figure 12. Comparison between developed models with existing correlations for clastic sedimentary rocks [5,10,11].

The main strength of this model over existing correlations for clastic sedimentary rocks is its capability to estimate in situ rock strength, as well as the UCS continuous profile to determine the lithology effect with the formation radioactive property concentration and acoustic compressional wave velocity in a porous medium.

4. Conclusions and Recommendations

The supervised machine learning (ML) algorithms of the least-squares support vector machine (LSSVM) and random forest (RF) are employed to predict the dynamic rock compressive strength (UCS) using well petrophysical logging data, including gamma-ray (GR), bulk density (ρ_b), the modulus of elasticity (E), compressional wave velocity (V_p), and shear wave velocity (V_s). The model performance indicators (such as the average percentage relative error, maximum average absolute percentage error, and the coefficient of determination) are applied to assess well log data-based connectionist models. The major conclusions of this study are enumerated as follows:

- The ML-guided data-driven models of LSSVM-CSA and RF are proficient in precisely assessing the dynamic rock strength of UCS.
- The formation V_p and GR are the two most significant petrophysical variables to obtain UCS, and they are verified and confirmed by the LSSVM and RF ML techniques.
- The rank of importance of petrophysical well log variables (higher to lower) is $GR > V_p > E > V_s > \rho_b$, considering simulated results with data-driven predictive models for clastic sedimentary rocks.

- A new correlation is exhibited for forecasting dynamic UCS profiles of clastic sedimentary rock by implementing GR log to capture the radioactive property concentration and acoustic compressional wave intensity. This correlation was achieved with high precision, succeeding a coefficient of determination, 96% and minimal error.

As a future research direction, the proposed correlation of UCS can be adopted to assess wellbore stability and the near-wellbore failure criterion of clastic sedimentary formations during drilling exploration activities in a cost- and time-effective manner. The proposed model in the study is only applicable to clastic sedimentary formations to estimate UCS. In the future, scholars can work to develop a common UCS model with large datasets for different rock types. Moreover, similar research strategies for variable selections can apply to obtain UCS models for tunnel boring projects by the integration of existing geotechnical practices. On top of that, meta-heuristic algorithms (i.e., evolutionary, physics-informed, and swarm-based algorithms) and explainable AI techniques could be applied to assess the log-driven predictive model efficacy and feature attribute ranking in the discipline of wellbore stability and rock mechanics using a large number of datasets for future studies.

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Abbreviations

ACV	Aggregate crushing value
ANFIS	Adaptive neuro fuzzy interference system
ANN	Artificial neural network
AIV	Aggregate impact value
AI	Artificial intelligence
BTS	Brazilian tensile strength
CC	Coefficient of determination
CSA	Coupled simulated annealing
DT	Decision trees
E	Modulus of elasticity
GEP	Gene expression programming

GR	Gamma-ray
I_d	Slake durability index
$I_{s(50)}$	Point load index
LAAV	Los Angeles abrasion value
LSSVM	Least-squares support vector machine
ML	Machine learning
PLS	Point load strength
RF	Random forest
R^2	Squared Pearson's correlation coefficient
SR_n	Schmidt hammer rebound number
SVM	Support vector machine
uw	Unit weight
V_m	P-wave velocity in solid part of the sample
V_p	Compressional wave velocity
V_s	Shear wave velocity
V_{sh}	Shale volume
wa	Water absorption
wc	Water content
ρ_b	Formation bulk density
α	Weight factor
ϕ	Rock porosity

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