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Modelling Dead Oil Viscosity Using Extreme Gradient Boosting Machine Learning for Niger Delta Region

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Abstract Dead Oil Viscosity is the viscosity of the crude oil at atmospheric pressure (no gas is in solution) and system temperature. It is a very important reservoir pressure- volume -temperature (PVT) parameter that solve numerous reservoir engineering problems and one of the most required factors for enhanced oil recovery processes. The procedures involve in measuring this reservoir property is highly exorbitant and time consuming, hence the use of empirical correlations and intelligent tools. This study utilized Extreme Gradient Boosting (XG boost) intelligent tool to estimate dead oil viscosity for Niger Delta Region. A total number of 263 data set was obtained from PVT report from the region, out of which, 70% were used to train the models, 15% for testing and 15% for validation. Quantitative and qualitative analysis was carried out to compare the performance and reliability of the new developed XG Boost model with some selected empirical correlations. The result showed that the new developed machine learning model outperformed some selected common dead oil viscosity correlations with the best rank of 0.127, highest correlation coefficient of 0.98, mean absolute error (Ea) of 0.151, with a better performance plot, followed by Ikiensikimama (2009) model with correlation coefficient of 0.95, mean absolute error (Ea) of 0.135 and the Rank of 0.141. XG Boost designed in this study is very easy to use with a higher accuracy than the existing correlation. It can be used immediately after installation without any further configuration or optimization of parameters.

Keywords Dead Oil Viscosity, EGBoost, Machine learning Algorithm, Statical Analysis, Niger Delta

1. Introduction

Crude oil viscosity is an important reservoir pressure- volume-temperature (PVT) parameter that controls and influences the flow of oil through porous media and pipelines. The pressure–volume–temperature (PVT) properties of reservoir fluid are very important parameters used by petroleum industry for proper reservoir estimation and management [1]. These reservoir PVT data are obtained from experimental measurement of the representative fluid samples collected from wellhead or wellbore of the oil reservoir. Examples of fluid pressure-volume-temperature (PVT) properties are oil formation volume factor (OFVF), solution gas - oil ratio (Rs), saturation pressure, oil viscosity and oil gravity. These PVT fluid properties are essential for estimation of reserves, reservoir performance determination, recovery efficiency, production optimization and design of production systems [2]. It is more profitable to avoid expensive, time-consuming experimental laboratory measurements and to test the validity of the test results hence the need for empirical correlation and machine learning model development. Dead oil viscosity is the reservoir PVT property of interest in this study.

The viscosity, in general, is defined as the internal resistance of a fluid to flow. Oil viscosity is a strong function of many thermodynamic and physical properties such as pressure, temperature, solution gas–oil ratio (GOR), bubble point pressure, chemical composition, gas gravity, and oil gravity ([3], [4], [5], [6], [7]). Viscosity of crude oil is a fundamental factor in simulating reservoirs, forecasting production as well as planning thermal enhanced oil recovery methods that make its accurate determination necessary. Depending on the reservoir pressure, crude oil viscosity is divided into three types, which are saturated, undersaturated, and dead oil viscosity [8]. Fig. 1 shows a typical oil viscosity diagram as a function of pressure at constant reservoir temperature.

i. **Saturated oil viscosity** (bubble point) is defined as the viscosity of the oil at the bubble-point pressure and reservoir temperature.
ii. **Undersaturated oil viscosity** is defined as the viscosity of the crude oil above the bubble point pressure and reservoir temperature.
iii. **Dead-oil viscosity**: This is the viscosity of the crude oil at atmospheric pressure (no gas is in solution) and system temperature.

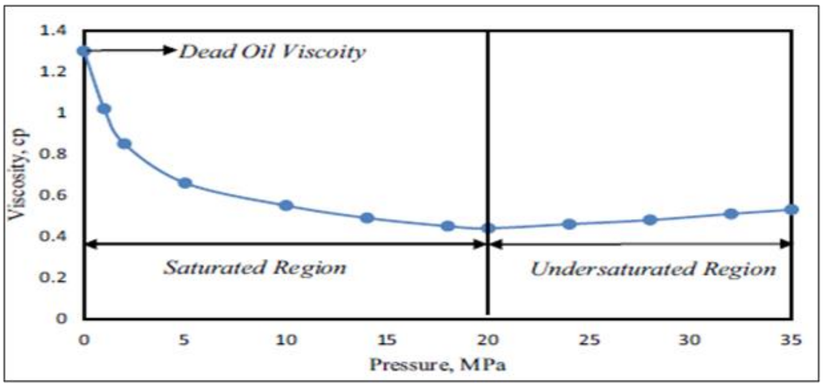

Figure. 1 Typical viscosity trend as a function of pressure [8]

This study focused on estimating dead oil viscosity using machine learning procedures of XG boost algorithm rather than traditional empirical methods which is more efficient, fast, powerful, and accurate. Many empirical correlations exist for predicting dead oil viscosity ([10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25]). [26] was the first author that developed the first traditional correlation for predicting dead oil viscosity, which has one input parameter of temperature. Andrade et al correlation can predict dead oil viscosity at both low and high temperatures. [10] presented correlation charts by analyzing 953 crude oil samples from 747 oil fields in the USA and California using inputs of oil gravity and temperature. [27] and [28] summarized the ranges and data origins used by some famous authors in developing dead oil viscosity correlation.

Recently, investigators have proved that machine learning and artificial intelligent which is an advanced soft computing tools can create relationship between the input and output data gotten from laboratory experiment ([29], [30]). Machine learning is a subfield of artificial intelligent which enables machines to learn from past data or experience without being explicitly programmed [30]. Investigators has showed that the artificial intelligent can serve oil and gas industry to create a more reliable and accurate PVT predictive models ([31], [32], [33], [34], [35], [36], [37], [38], [39], [27]). [32] presented a novel approach for predicting the complete PVT behavior of reservoir oils and gas condensates using Artificial Neural Network (ANN). The method uses key measurements that can be performed rapidly either in the laboratory or at the well site as input to an ANN. The ANN was trained by a PVT studies database of over 650 reservoir fluids originating from all parts of the world. Tests of the trained ANN architecture utilizing a validation set of PVT studies indicate that, for all fluid types, most PVT property estimates can be obtained with a very low mean relative error of 0.5-2.5%, with no data set having a relative error more than 5%. This level of error is considered better than that provided by tuned Equation of State (EOS) models, which are currently in common use for the estimation of reservoir fluid properties. In addition to improved accuracy, the proposed ANN architecture avoids the ambiguity and numerical difficulties inherent to EOS models and provides for continuous improvements by the enrichment of the ANN training database with additional data.

[40] published a study on neural network model for estimation of bubble point pressure and oil FVF at bubble point. The bubble point model was developed using 137 global data sets for testing trained models, and 1106 for training. The model has two hidden layers, five nodes in the first layer and three in the second layer. The neural

model performance shows average absolute error of 15.08%. The oil FVF at bubble point model was developed using 180 global data set for testing and 1165 for training. The model has an average absolute error of 11.68%, which is much higher than the conventional numerical correlations conversions. The author, however, pointed out that the newly developed model performed better when compared with empirical correlations, but suffers from stability and had some setbacks with trend analysis; and stated that the major problem to compare published Neural network models is the unavailable of the missing parameters of the network architecture in the publications. [41] published a work based on neural network using Matlab 7.5 to predict both bubble point pressure, and oil formation volume factor with the aid of two separated networks. The data in use was a set of 160 measured points collected from the Middle East region; 140 points were used for training, and 20 for testing. The bubble point pressure network consisted of two hidden layers, with ten neurons for each layer. All hidden neurons activated by log sigmoid function. Four input data: Temperature, API gravity, gas oil ratio, gas relative density. The output neuron was designed to be activated with pure linear function. The results show that the network give accuracy in prediction than other published empirical correlation. The network has average relative error percent of 0.030704 and correlation coefficient of 0.9981.

[42] presented an Artificial Neural Network (ANN) for estimation of PVT properties of compounds. The data sets were collected from Perry's Chemical Engineers' Handbook. Different training schemes for the back propagation learning algorithm, such as; Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM) and Resilient back Propagation (RP) methods were used. The accuracy and trend stability of the trained networks were tested against unseen data. The LM algorithm with sixty neurons in the hidden layer has proved to be the best suitable algorithm with the minimum Mean Square Error (MSE) of 0.000606. The ANN's capability to estimate the PVT properties is one of the best estimating methods with high performance. [43] published a work for predicting PVT properties of Iranian crude oils by applying artificial neural networks. The applied PVT data set that was used consists of 218 crude oil samples from Iranian reservoirs. The obtained results for both training and cross validation data sets confirm the great prediction power of ANNs, for both data sets with respect to traditional PVT correlations. The ANN test data outperforms the traditional method with coefficient of correlation of 0.990.

[35] applied nonlinear multivariable regression and nonlinear optimization regression to optimize other correlations. They presented a neural network-based model for dead oil viscosity, in addition to optimization of published correlations. [37] employed ANN backward propagation procedure with the Levenberg-Marquardt algorithm to optimize the Nigerian crude oil viscosity. The authors utilized 1750 data points to optimize the oil viscosity models for dead and bubble point pressure oil viscosity. Furthermore, [24] proposed an ANN model that used a data set of laboratory measurements on oil samples from Yemen's oil fields involved 545 data points. They expressed that ANN models were appropriate for predicting the dead oil, saturated and under-saturated viscosity). In another study, [39] attempted to model the dead oil viscosity with various machine learning methods. They proposed that correlations can be divided into three classes: 1- Ones that predict the dead oil viscosity with limited data, 2- Ones that predict the dead oil viscosity using limited existing viscosity data, 3- Ones that check the quality of the existing data.

Recently, some authors have started investing newly machine learning algorithm like XG Boots, random Forest and Supper learn and Lightgbm etc rather than Artificial Neural Network. [27] employed 2247 PVT data points both from light and heavy oil data set to predict dead oil viscosity. The researchers implemented six machine learning algorithms of random forest (RF), lightgbm, XGBoost, MLP neural network, Support Vector machine and SuperLearner simultaneously in predicting oil viscosity. Results indicate that the Super-Learner algorithm showed high performance compared to other used algorithms. [28] developed ensemble machine learning model for the prediction of dead, saturated and undersaturated oil viscosity. The authors investigated the different functional forms that are normally used in predicting various forms oil viscosity (dead, saturated and unsaturated viscosity). The authors reported that the best functional parameter for dead oil viscosity are temperature and API gravity and for the bubble point oil viscosity, API gravity, dead oil viscosity and bubble point pressure while for oil viscosity above bubble point the best functional form are oil viscosity at the bubble point, dead oil viscosity, bubble point pressure, pressure, and API gravity for all the ensemble SVR model developed. They said that Among all the empirical oil viscosity accessed their new ensemble SVR model outperformed other existing oil viscosity evaluated by the statistical parameters they used. They also reported that error margin associated with dead oil viscosity is high.

[29] did a novel study on multi-hybrid model for estimating oil viscosity of Iranian crude oil using 600 data points. They used the new multi-hybrid to develop oil viscosity at bubble point and below bubble point using GA and GMDH model. They reported that their new multi-hybrid model performed better than other existing empirical correlations with average absolute per cent error of 3.77, 0.268 and 0.01058 for saturated and undersaturated oil viscosity respectively. [8] presented a research work on crude oil viscosity determination for light and intermediate crude oil systems using global data. Hybrid model of GA and SVM were used to predict dead oil viscosity by applying 1497 data set. The authors reported that the new machining learning hybrid gave better predictions than some of the existing dead oil viscosity with a 17.17 average absolute per cent error. More literature on dead oil viscosity for both empirical and machine learning can be found in [28]. It can be found from the literature review that oil and gas industry still has an interest to develop models that can predict oil viscosity for proper reservoir fluid management and monitoring. Considering these points, the main aim of this study is to use XG Boosts machine learning algorithm for predicting dead oil viscosity applying Niger Delta data.

2. Extreme Gradient Boosting (Xg Boost)

Machine learning is a core sub-area of Artificial Intelligence (AI) that gives it ability to learn. The learning process is achieved by using algorithms to discover patterns and generate insights from the original or measured data they are exposed to (Fig. 1).. The machine learning algorithm adopted in this study is Extreme Gradient Boosting also known as XG Boot. It is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library that helps to understand data and make better decisions [44]. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems. The XG Boost algorithms builds on supervised machine learning, decision trees, ensemble learning, and gradient boosting.

Supervised machine learning uses algorithms to train a model to find patterns in a dataset with labels and features and then uses the trained model to predict the labels on a new dataset's features.

A Gradient Boosting Decision Trees (GBDT) is a decision tree ensemble learning algorithm similar to random forest, for classification and regression. Ensemble learning algorithms combine multiple machine learning algorithms to obtain a better model. Both random forest and GBDT build a model consisting of multiple decision trees. The difference is in how the trees are built and combined. The term "gradient boosting" comes from the idea of "boosting" or improving a single weak model by combining it with several other weak models to generate a collectively strong model. Gradient boosting is an extension of boosting where the process of additively generating weak models is formalized as a gradient descent algorithm over an objective function. Gradient boosting sets targeted outcomes for the next model to minimize errors. Targeted outcomes for each case are based on the gradient of the error (hence the name gradient boosting) with respect to the prediction. GBDTs iteratively train an ensemble of shallow decision trees, with each iteration using the error residuals of the previous model to fit the next model. The final prediction is a weighted sum of all the tree predictions. Random forest "bagging" minimizes the variance and overfitting, while GBDT "boosting" minimizes the bias and underfitting.

XG Boost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms, being built largely for energizing machine learning model performance and computational speed. With XG Boost, trees are built in parallel, instead of sequentially like GBDT. It follows a level-wise strategy, scanning across gradient values and using these partial sums to evaluate the quality of splits at every possible split in the training set.

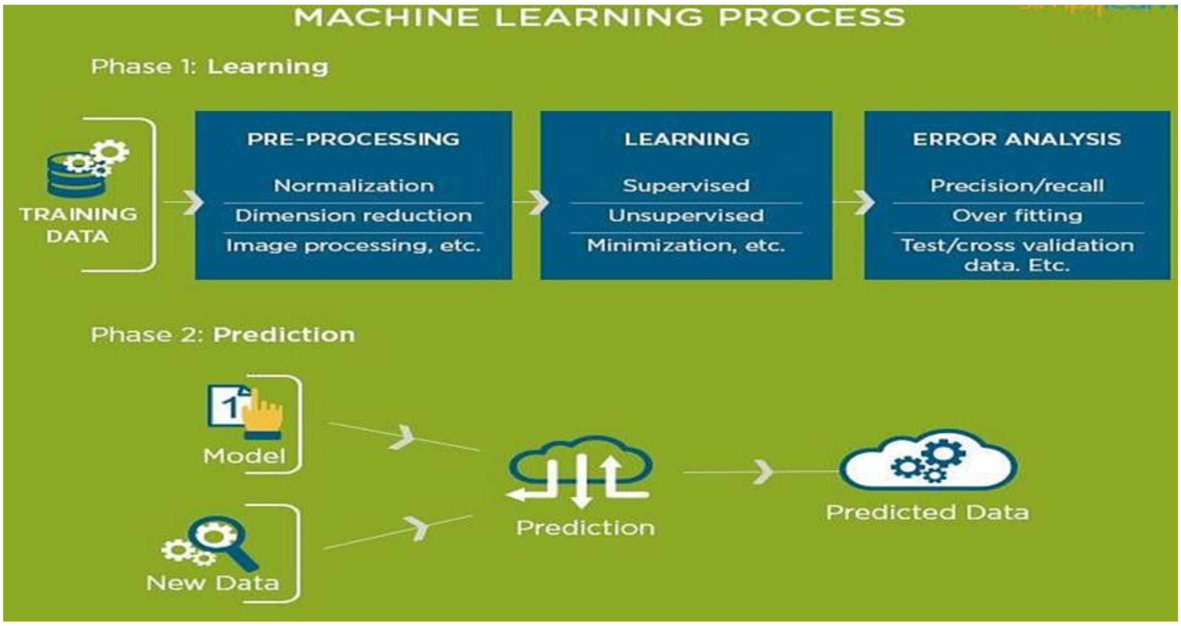

Figure. 2 Machine learning Process

3. Methodology

3.1 Data Description

The data used was obtained from conventional PVT reports that derive the various fluid properties through liberation process from the Niger-Delta Region of Nigeria. The data parameters include. The data parameters applied are gas specific gravity, API gravity of the crude oil, separator temperature, separator pressure and separator gas-oil ratio. The ranges of the data applied are $0.6 < \gamma_g < 2.218, 20.5 < \gamma_{API} < 44.0, 75 < T_S <$ 104 °F,$115 < P_S < 2970\ psia, 1007.0 < R_s < 2970\ scf/stb$. The minimum (Min), maximum (Max), mean, standard deviation (SD) values of data used for, training, test and validation data are shown in Tables 1, 2 and 3.

Table 1. Summary of minimum, maximum, mean and Standard Deviation values of training data for dead oil viscosity.

	γ_g	T_s(°F)	P_s (Psia)	R_{sp}(scf/stb)	γAPIr	μ(cp)
MIN	0.6080	75.000	115.00	1007.00	21.20	0.1300
MAX	2.2180	100.000	1371.00	2970.00	43.60	0.6700
MEAN	1.3545	96.535	306.41	1807.86	36.46	0.4238
SD	0.34284	6.8236	191.48	570.56	4.174	0.1098

Table 2. Summary of minimum, maximum, mean and Standard Deviation values of test data for dead oil viscosity.

	γ_g	T_s(°F)	P_s(Psia)	R_{sp}(scf/stb)	γAPIr	μ(cp)
MIN	0.7050	100.00	115.00	1039.00	24.80	0.2500
MAX	1.6270	104.00	315.00	2533.00	43.90	0.5780
MEAN	1.1418	100.83	226.38	1673.15	39.18	0.4453
SD	0.2373	1.6594	76.089	393.80	4.03	0.0885

Table 3. Summary of minimum, maximum, mean and Standard Deviation values of Validation data for dead oil viscosity

	γ_g	T_s(°F)	P_s(Psia)	R_{sp}(scf/stb)	γAPIr	μ(cp)
MIN	0.6200	86.90	195.00	1028.00	20.50	0.2160
`MAX	1.7157	100.00	315.00	2597.00	44.00	0.5910
MEAN	1.1518	98.77	270.77	1746.68	35.22	0.4327
SD	0.3434	3.304	44.13	452.53	6.013	0.0965

3.2 Data Validation

Before any experimental PVT data are used for design or study purposes, it is necessary to ensure that there are no error or major inconsistencies that would render any subsequent work useless. Two such means of data validation are the Campbell diagram (Buckley plot) and the Mass Balance Diagram which are otherwise known as cross plot. These techniques were used to validate the data set used in this work.

3.3 Modeling Technique

Extreme gradient Boost (XGBoost) was used to build the oil dead viscosity model using the quadratic extreme gradient function procedure with MATLAB (2021) version.

The procedure involves the importation of input and output data into the MATLAB environment using the import command. The input parameters are gas gravity, separator temperature, separator pressure and API gravity and output parameter is dead oil viscosity.

3.4 Evaluation Methods (Correlation Comparison)

To compare the performance and accuracy of the new model to other empirical correlations, two forms of analyses were performed which are quantitative and qualitative screening. For quantitative screening method, statistical error analysis was used, which are percent mean relative error (MRE), percent mean absolute error (MAE), percent standard deviation relative (SDR), percent standard deviation absolute (SDA) and correlation coefficient (R).

For correlation comparison, a new approach of combining all the statistical parameters mentioned above (MRE, MAE, SDR, SDA and Rank) into a single comparable parameter called Rank was used. The use of multiple combinations of statistical parameters in selecting the best correlation can be modeled as a constraint optimization problem with the function formulated as;

$$Min\ Rank = \sum_{j=1}^{m} S_{i,j} q_{1,j} \qquad (1)$$

$$\text{Subject to } \sum_{i=1}^{n} S_{i,j} \qquad (2)$$

$$\text{With } 0 \le S_{ij} \le 1 \qquad (3)$$

Where $S_{i,j}$ is the strength of the statistical parameter j of correlation i and q_{ij}, the statistical parameter j corresponding to correlation i. j = MRE, MAE, …. R^1, where R^1 = (1-R) and the rank (Z), (or weight) of the desired correlation. The optimization model outlined in Equations 1 to 3 was adopted in a sensitivity analysis to obtain acceptable parameter strengths The final acceptable parameter strengths so obtained for the quantitative screening are 0.4 for MAE, 0.2 for R, 0.15 for SDA, 0.15 for SDR, and 0.1 for MRE. The correlation with the lowest rank was selected as the best correlation for that fluid property. It is necessary to mention that minimum values were expected to be best for all other statistical parameters adopted in this study except R, where a maximum value of 1 was expected [25].

Performance plots were used for qualitative screening. It is a graph of the predicted versus measured gas compressibility data with a 45^o reference line to readily ascertain the correlation's fitness and accuracy. A perfect correlation would plot as a straight line with a slope of 45^o.

4.Results and Discussion

The XG Boosts model was tested with 15% of training data (36 data) points that were not previously used during training and validation. These data were randomly selected by the Extreme gradient Boosts model to test the accuracy and stability of the newly developed model. These data points were randomly selected by the MATLAB tool to test the accuracy and stability of the new developed model. The predictions and performance of the new intelligent soft computer model was compared with data from the field and the estimations from other empirical correlations like [16], [15], [25], [17] and [10]. These empirical correlations were carefully selected having reported by some researchers of about their excellent performance in predicting dead oil viscosity. Two out of these five selected correlations were developed precisely for Niger-Delta Region ([16], [25]).

4.1 Statistical Analysis Result

The results of the statistical assessment as presented in Fig. 3 gives the statistical accuracies for all the dead oil viscosity correlations and XGboost model examined. The results show that the XGboost algorithm has both reliable and efficient performance as to compare to other existing correlations with the best rank of 0.127, mean absolute error of 0.151, standard deviation absolute error of 0.145 and the highest coefficient of correlation of 0.981. Table 3 shows the numerical values of all the models accessed with XGboost model. The two indigenous correlations performed better than other evaluated empirical correlations. The trend is expected because correlations performed better in their region of originality. [25] gave the best Rank of 0.141 with Mean absolute Error (MAE) of 0.135 and correlation coefficient (R) of 0.95 followed [16] which gave the rank of 0.176, Mean absolute Error (MAE) of 0.301 and correlation coefficient of 0.94. This study recommends [25] as a good predictive model for dead oil viscosity for Niger Delta region in absence of the machine learning algorithm developed in this study.

[17], [15] and [10] are foreign correlations accessed. Among the foreign correlations [17] performed better than others with a rank of 0.206, followed by [15] and finally [10]. [17] Correlation can be used to forecast dead oil viscosity for Niger Delta region in absence of the newly developed intelligent model, [25] and [16]. This study showed again the supremacy of machining learning in predicting reservoir PVT properties particularly in applying XG Boosts algorithm.

Table 3: Statistical Accuracy of Oil Formation Volume Factor Using Niger-Delta Data

AUTHORS	%MRE	%MAE	%SRE	%SAE	R	Rank
Extreme Gradient	**0.162**	0.151	0.166	0.145	0.98	**0.127**
Ikiensikimama (2009)	0.371	0.135	0.198	0.107	0.95	**0.141**
Egbogah and Jack (1990)	0.141	0.301	0.147	0.101	0.94	**0.176**
Labedi (1982)	0.301	0.223	0.185	0.363	0.92	**0.206**
Petrosky and Farshad (1995)	0.316	0.324	0.211	0.31	0.94	**0.243**
Beal (1947)	0.412	0.4.25	0.322	0.345	0.91	**0.265**

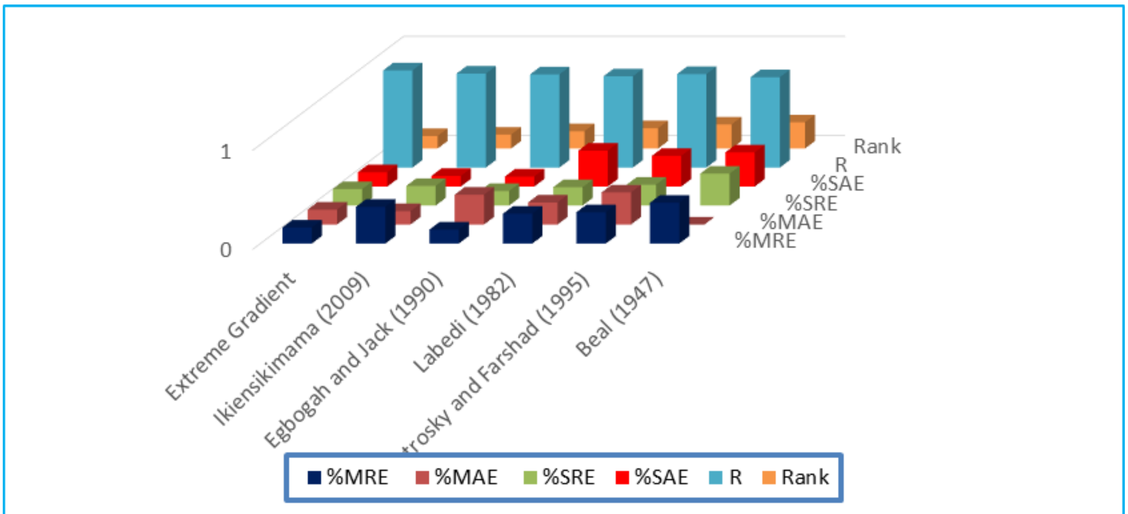

Figure. 3. Comparison of the Statistical Accuracy for Different correlations using Niger -Delta Data

4.1.2 Cross Plot Result

Cross plots of the predicted versus experimental data for dead oil viscosity are illustrated in Figs. 4 to 8. It is a plot of predicted versus measured properties with a 45° reference line to readily ascertain the correlation's fitness and accuracy.

Fig. 8 shows the cross plots of predictions from GX Boost and measured data. It shows the tightest cloud of points around the 45° line with very good clusters at low band, indicating the excellent agreement between the experimental and the calculated data values when compared to Figs. 4 to 7. In addition, this indicates the superior performance of the XG Boots model over empirical correlations evaluated. The accuracy of the model indicates that the Extreme Gradient Boost intelligent model does not over fit the data, which implies that it was successfully trained.

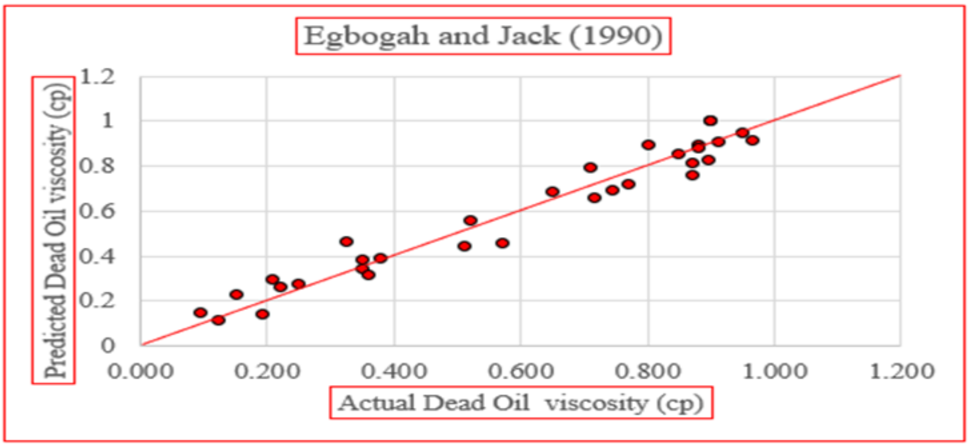

Figure. 4. Cross Plot of Egbogah and Jack (1990) Model for Dead Oil Viscosity

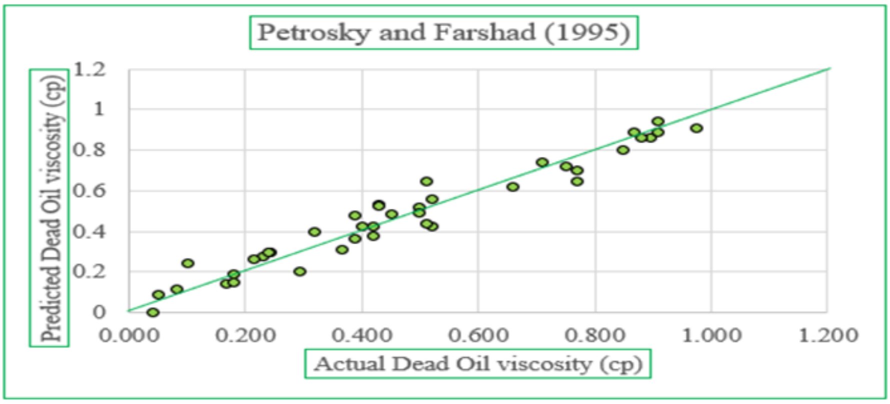

Figure. 5. Cross plots of Petrosky and Farshad (1995) Model for Dead Oil Viscosity

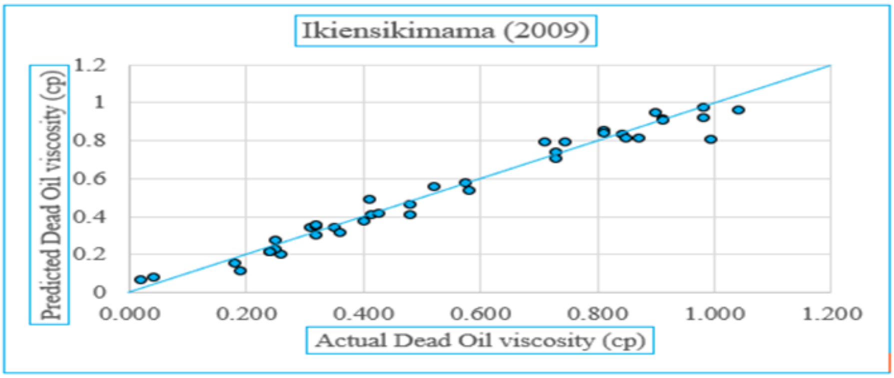

Figure. 6. Cross Plots of Ikiensikimama (2009) Model for Dead Oil Viscosity

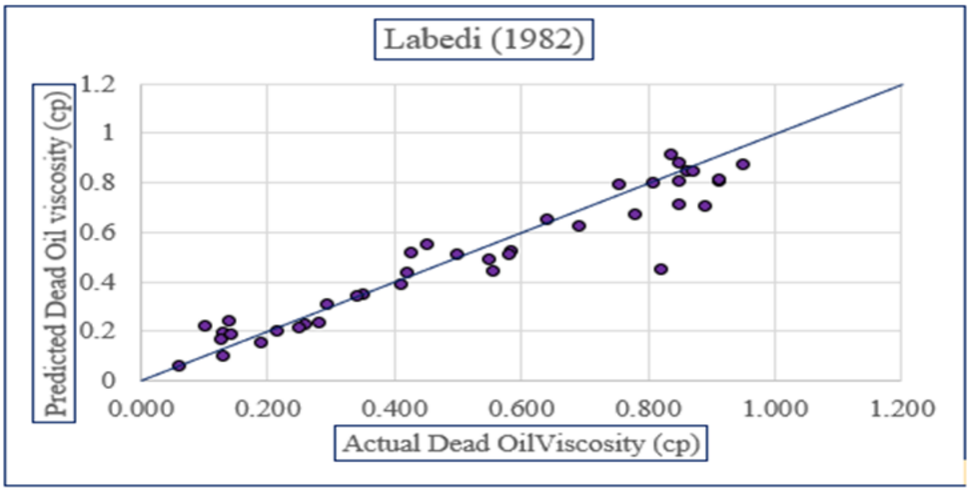

Figure. 7. Cross Plots of Labedi (1995) Model for Dead Oil Viscosity

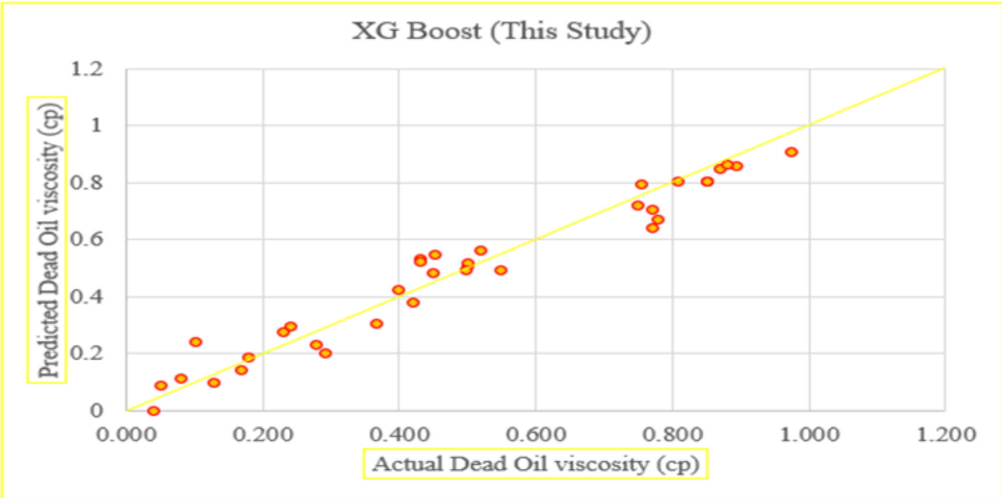

Figure. 8. Cross Plots of XG Boots Model for Dead Oil Viscosity

5.Conclusion

The newly developed XG Boots model for predicting crude oil dead viscosity for Niger-Delta region was developed in this study using MATLAB 2021 Version. The quadratic extreme imbedded in the Extreme Gradient boost was used to estimate the model parameters. The new intelligent tool outperformed the existing correlations by the statistical parameters used. It shows a best rank with a numerical value of 0.127, correlation coefficient of 0.98 and superior performance plot as compared to the existing empirical correlations for those regions where the data was used. This leads to a bright light of machine learning modeling and will assist petroleum exploration engineers to estimate various reservoir properties with better accuracy, leading to reduced exploration time and increased productions.

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