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Enhanced Prediction of Reservoir PVT Properties Using Stacking Ensemble Machine Learning Approach

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Abstract - Pressure-Volume-Temperature (PVT) behaviour plays a significant role in determining reservoir fluid properties in petroleum reservoirs. Experimental data are difficult and expensive to obtain, while physics-based empirically derived equations vary from one region to another. This research proposes a Stacking Ensemble Learning (SEL) model to predict the Pressure-Volume-Temperature (PVT) properties of reservoir fluids, specifically Gas Solubility (R_s) and Bubble Point Pressure (P_b). The study compares this advanced ensemble method against Standalone Machine Learning (SAML) models (Artificial Neural Network, ANN; Support Vector Machine, SVM; and Decision Tree, DT) and traditional empirical correlations. The SEL algorithm was first designed; multiple algorithms were combined to create a stronger predictor. The base estimators used for initial predictions are the Decision Tree Regressor (DTR), the Extra Trees Regressor (ETR), and the Random Forest Regressor (RFR). The base estimators' predictions were combined using a RidgeCV meta-model to produce the final output. Statistical results on prediction accuracy, model performance, and reliability demonstrate that the Stacking Ensemble technique achieves superior accuracy compared with SAML and widely used empirical correlations, offering a cost-effective alternative to difficult experimental procedures.

Keywords - PVT Properties, Ensemble Learning, Machine Learning, Gas Solubility, Bubble Point Pressure

1.0 INTRODUCTION

Research into PVT studies continues to garner increasing interest in the petroleum industry, as accurate determination and prediction of the fluid properties of oil and gas samples from a flowing well help to understand reservoir fluid behaviour. The determination and accurate description of crude oil properties have been useful in solving reservoir engineering problems, and this is heavily dependent on a good understanding of the crude's physical properties. Areas where reservoir fluid properties play important roles in reservoir engineering include reserves estimation, well testing, material balance calculations, efficiency of enhanced oil recovery methods, and the prediction of reservoir performance. The importance of accurately estimating PVT properties cannot be overemphasised for engineering calculations and decision-making across the different stages of oil field life (Khabibullin et al., 2014; Dokla et *al.*, 1990). Since comprehensive, consistent, or experimentally measured data are often unavailable, several region-specific, empirically derived PVT correlations have been developed. Research has shown that empirical correlations, aside from being an economical method for reservoir studies and decision-making, can, with varying simplified assumptions, predict fluid properties where experimental information is insufficient, similar to the laboratory PVT method.

Today, advances in technology and the data revolution have consolidated the use of intelligent techniques such as artificial intelligence and machine learning as a fast, accurate, and effective means of prediction. These technologies are now widely accepted in fields such as manufacturing, banking, and several other industries (Brownlee, J., 2019; Hastie *et al.*, 2009; and James *et al.*, 2013).

Ensemble learning methods work by combining functions learned by contributing members, and this approach is applicable to both classification and regression problems. Predictive modelling for classification refers to problems in which a class label is to be predicted; it combines the decision boundaries of the members. Predictive modelling for regression refers to problems involving numerical values to be predicted; i.e., it combines hyperplanes of members. The different types of ensemble machine learning techniques are Bagging, Boosting, and Stacking.

This work aims to develop a predictive model for PVT properties, namely gas solubility and bubble point pressure, using stacked ensemble machine learning. Stacking is an ensemble learning method that combines various estimators to reduce bias and is applicable to both classification and regression. The Stacking technique allows a model to learn how to combine multiple predictions given by weak learner models via meta-learning models and produces a final model with better predictions and high accuracy (Breiman Leo, 1996; Marios Michailidis 2017).

Existing Empirical Correlations

Over the years, several PVT correlations have been developed and used to determine reservoir performance, estimate reserves, and make real-time decisions, among other applications. Standing (1947) correlation has been widely used in PVT analysis, where the pressure of any oil sample is a function of the GOR, oil gravity, gas gravity, and temperature. The correlation utilised 105 data points to develop empirical correlations for determining bubble point pressure, solution GOR, and oil formation volume factor. Lasater (1958) used 158 data points collected in Canada and the Western and Mid-Continental United States to develop an empirical correlation for predicting the bubble-point pressure of black oil. The bubble point pressures were experimentally measured. Vasquez and Beggs (1980) used 600 laboratory PVT data collected from different parts of the world. Glaso (1980) correlations were developed for North Sea Oils from 45 different samples within a 22–48 °API range of oil mixtures. Petrosky and Farshad (1993) obtained fluid samples representative of offshore reservoirs in Texas and Louisiana and conducted 81 laboratory analyses to evaluate functional model forms. Al-Marhoun (1988) determined the bubble-point pressure and the oil formation volume factor at the bubble point as functions of temperature, average oil and gas relative densities, and gas solubility for Middle East crude oil. Petrosky and Farshad (1993) introduced fitting parameters in the Standing generalised functional form equation to develop the empirical correlation. De Ghetto et al. (1994) modified existing correlations to develop new ones for heavy oil and extra-heavy oil using PVT crude oil samples obtained from the Mediterranean Basin, Africa, and the Persian Gulf. Obomanu and Okpobiri (1987) developed empirical correlations for Niger Delta crude oil to determine Bo and solution GOR. Ikiensikiimama and Ogboja (2009) developed correlations for determining bubble-point pressure based on the functional form of the Lasater equation. Table 1.0 presents widely used correlations based on samples obtained across different regions. Yacob and Marco (2023) developed a unified PVT model for the Kuwait heavy Oil field.

Table 1.0 – Correlation accuracies for Bubble Point Pressure and Gas Solubility

Correlations	Sample Origin	Property	Correlation average error	Absolute average error (%)	Standard deviation (%)	Nature of Correlation using Rs as basis
Lasater (1958)	Canada, USA	p_b	3.8			Black-Volatile Oil
Vasquez and Beggs (1980)	Global	p_b	4.700			Black-Volatile Oil
Glaso (1980)	North Sea	p_b	1.280		6.980	Black-Volatile Oil
Al-Mahoun (1988)	Middle East	p_b	0.030	3.66	4.536	Black Oil
Petrosky and Farshad (1993)	Gulf of Mexico	p_b	-0.017	3.28	4.180	Black Oil
		R_s	-0.050	3.80	4.790	
Farsard et al (1992)	Colombia	p_b	-3.490		14.61	Black Oil
Almehaideb (1997)	UAE	p_b		4.997	6.560	Black-Volatile Oil
Kartoatmodjo and Schmidt (1994)	Global	p_b	3.34	20.17		Black-Volatile Oil
Dindoruk and Christman (2004)	Gulf of Mexico	p_b	-0.27	5.70	7.51	Black-Volatile Oil

Source: Ikiensikimama and Ogboja, 2008

Application of Machine Learning in PVT Studies

Fatai et al. (2011) used SVM and ANN to predict oil and gas reservoir properties using two datasets from different geographical locations. Chukwuma (2018) compiled a dataset comprising 296 oil and 72 gas reservoirs to estimate PVT properties in the Niger Delta using machine learning models. Uzogor and Akinsete (2020) developed correlations to improve the prediction of PVT properties in the Niger Delta using advanced regression and intelligent techniques, including the KNN and Random Forest algorithms. Oladipo and Johnathan (2020) designed a novel algorithm that, when implemented, can predict PVT properties. Mohammad *et al.* (2021) developed compatible intelligent models that can estimate oil formation volume factor.

Amjed *et al.* (2020) used 250 datasets to predict PVT properties using artificial intelligence techniques. Isemin et al. (2022) used a Support Vector Machine (SVM) to predict gas-saturated and gas-undersaturated oil viscosities. While Kassem *et al.* (2022) used machine learning models to predict PVT properties. Isemin and Akinsete (2024) developed predictive models for PVT properties, namely Bubble Point Pressure and Gas-Oil Ratio, using a Bagging Ensemble.

2.0 METHODS

Data gathering and Processing

The data used in this work were obtained from nine reservoirs in the Niger Delta region of Nigeria and also from published journal articles, a total of 3424 data points. The specific range of data used is shown in Table 2.0 below. There were five input variables and predictors. To predict the target variable, bubble point pressure (pb), the input features are GOR, gas specific gravity, oil specific gravity, API, and temperature. To predict the target variable value GOR, the data input features are bubble point pressure, gas specific gravity, AP gravity, and temperature.

The data was cleaned, normalised, and pre-processed to get high-quality PVT data. The data was split into a training set, validation set, and testing set. Statistical evaluation metrics were used for the analysis of results, such as the correlation coefficient (R^2), the root mean squared error (RMSE), the mean absolute error (MAE), and the average absolute percentage relative error (AAPRE), to analyse and compare results of the SEL, the SAML, and some selected existing empirical correlations. All models were built using Python Anaconda version 3.11.5, an interpreted, object-oriented, high-level programming language with dynamic semantics

Table 2.0 - Descriptive statistics of Data range

	Mean	Min	Max	Std.
Pressure	3335	105	9999	2019
Temperature	171.65	101	275	28.13
Gas Oil Ratio	1099.19	-16.63	999999	17090.28
Specific gravity	0.66	0	2.13	0.07
API	35.46	4	97	7.74

Model Training

i. Stacking Ensemble Technique

As shown in Table 3.0, a Stacking ensemble algorithm was designed in this study to predict PVT properties of bubble point pressure and gas solubility, a concept designed by Wolpert David (1991).
The conceptual idea here is to first combine multiple algorithms to create a stronger predictor. The base estimators used for initial predictions are the Decision Tree Regressor (DTR), the Extra Trees Regressor (ETR), and the Random Forest Regressor (RFR). Next, use a RidgeCV meta-model to combine the base estimators' predictions into the final output. To implement this method for the stacking algorithm, the data was split into train and test data. The training data was split into n-folds before fitting the individual models on the training set. Afterwards, prediction performance is evaluated on the test set. Furthermore, RidgeCV was used as a meta-model regressor to combine the base estimators via stacking; weights were assigned to the estimators before training RidgeCV on the cross-validated base-case predictions. Finally, the prediction is done for the stacking ensemble.

Table 3.0 – Design of Stacking Ensemble Learning Algorithm

Stacking Algorithm

- From the dataset, create multiple samples of n subsets
- Input: training data $\boldsymbol{D} = \; [(\boldsymbol{x_i}, \boldsymbol{y_i})]_i^n \; = \boldsymbol{1}$

- Learn base models DTR, ETR, and RFR representing $\boldsymbol{h_1}, \boldsymbol{h_2}, \boldsymbol{and}\ \boldsymbol{h_3}$
- Output: estimators $\boldsymbol{h_i}(\boldsymbol{x_i})$ for DTR, ETR, and RFR representing $\boldsymbol{h_1}(\boldsymbol{x_1}), \boldsymbol{h_2}(\boldsymbol{x_2}), \boldsymbol{and}\ \boldsymbol{h_3}(\boldsymbol{x_3})$
- Learn meta-regressor $\boldsymbol{\beta}$ based on $\boldsymbol{h_i}(\boldsymbol{x_i})$
- Predict stacked ensemble, $\boldsymbol{\hat{y}_i} = \boldsymbol{\beta}[\boldsymbol{h_1}(\boldsymbol{x_1}), \boldsymbol{h_2}(\boldsymbol{x_2}), \boldsymbol{and}\ \boldsymbol{h_3}(\boldsymbol{x_3})]$

For optimal predictions, the two most important hyperparameter tuning parameters were the number of estimators (which specifies the number of models to be built) and the random state (set to 43 to control the random number seed and reproduce the same number at each call for each estimator). Figure 1.0 shows the result of stacking the base estimators using the RidgeCV meta-model. The tuning during the cross-validation search was necessary to identify the best strategy for improved prediction performance.

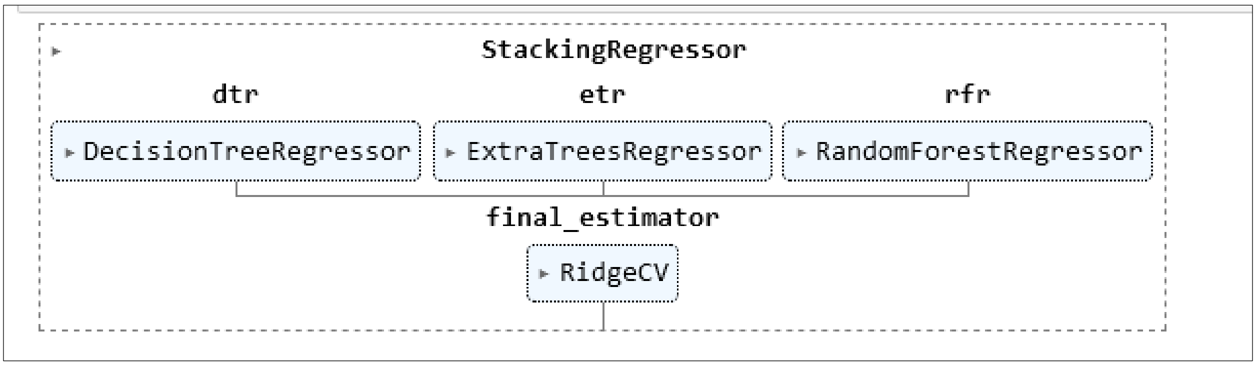

Figure 1.0 - Stacking of base estimators

ii. Standalone Artificial Neural Network (ANN) Modelling

The type of artificial neural network was selected before randomly generating the architectures to define the layers, neurons, and activation functions. The model was compiled, then the optimiser, loss function, and metrics were set. The model was trained by adjusting weights (w) and biases (e) using backpropagation. Hyperparameter tuning was performed while also updating the network. The model was fine-tuned, and the evaluation mode was done. The Model was tested on unseen data to assess generalisation performance. Statistical analysis performed using metrics of RMSE and AAPRE. Figure 1.0 shows the ANN modelling framework.

iii. Standalone Support Vector Machine (SVM)

The RBF kernel was chosen due to the data's complexity. Feature selection was performed for correlation analysis. The SVM model was initialised, and GridSearchCV was used to tune hyperparameters such as C, gamma, and kernel. This was followed by k-fold cross-validation (commonly k=5 or 10) on the training set. The SVM model was trained using the best parameters from the tuning process. The model was tested on unseen data, and predictions were made using the evaluation metrics.

iv. Standalone Decision Tree

The decision tree was built by first initialising its parameters, such as max_depth and min_samples_split. The model was trained to fit the decision tree model, and afterwards, a decision tree regression was created on the training data. We conduct hyperparameter tuning using GridSearchCV to find optimal settings like max_depth, min_samples_split, and max_features. Evaluate the model performance using the test set and metrics like MAE, RMSE etc. Make predictions using the tuned and validated model to make predictions on new or test data

3.0 RESULT

Bubble Point Pressure

Shown in Table 4.0 is the statistical analysis of the stacking ensemble machine learning (SEL) and the standalone machine learning models of SVM, ANN, and DT, while Figure 2 depicts the performance evaluation of the SEML, SAML, and widely used empirical correlations for bubble point performance prediction. Stacking of estimators DTR, ETR, and RFR) with a final RidgeCV regressor and the tuning parameters influenced the model prediction performance of SEL with an R^2 of 0.9263 when tested on an unseen data set. The next-best-performing model was the SVM, outperforming the best empirical correlation model by Petrosky and Farshad, with a value of 0.8810. Also, in terms of prediction accuracy and reliability, measured by RMSE and AAPRE. The SEL model performed better with an AAPRE of 0.1479, outperforming the best predicted correlation of 0.2166 from Petrosky and Farshad, while the best SAML was 0.2198 from the ANN model.

Table 4.0 – Performance evaluation for Bubble Point Pressure using SEL and SAML

PVT Properties	Train/Test	*R^2*	*MAE*	*RMSE*	*AAPRE*
Stacking Ensemble	Train	0.9753	102.2458	158.5732	0.0782
	Test	0.9263	395.3771	603.3621	0.1479
SVM Model	Train	0.9318	339.0377	411.6338	0.1991
	Test	0.9011	850.6271	633.7100	0.2216
ANN Model	Train	0.8801	448.2268	429.9201	0.2006
	Test	0.8904	861.3348	673.7100	0.2198

Decision Tree Model	Train	0.8810	707.0811	511.3766	0.2161
	Test	0.8908	875.6604	640.3800	0.2203

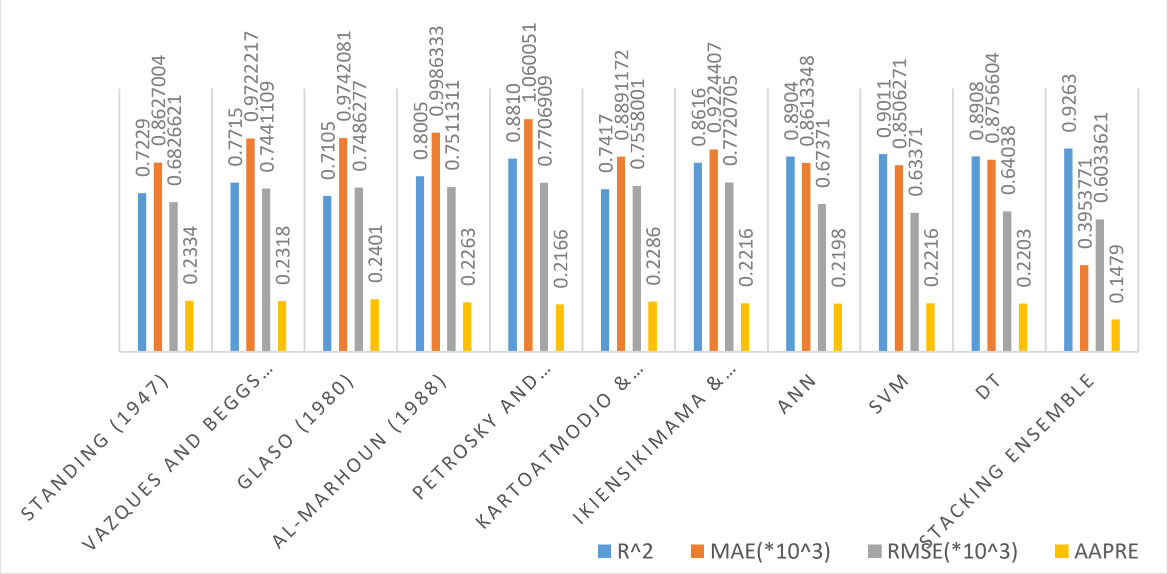

Figure 2.0 - Performance evaluation of SEL, SAML, and empirical correlations for bubble point pressure

Gas Solubility

It is important to note that in statistics, the higher the R^2, the better the ensemble model will predict. The lower the MAE and RMSE values, the better the prediction accuracy. The AAPRE metric represents the average percentage difference between predicted and actual values and is used to assess model reliability. Table 5.0 presents the statistical analysis of SEL and SAML, while Figure 3.0 shows a representative performance evaluation of SEML, SAML, and widely used empirical correlations. The stacking ensemble performed better at predicting gas solubility, achieving higher R2, lower RMSE, and AAPRE of 0.9521, 279,1145, and 0.1782, respectively. Again, stacking estimators and tuning parameters improved prediction, accuracy, and reliability for the Stacking ensemble. The SVM outperforms other SAML models and existing correlation models.

Table 4.0 – Performance evaluation for GOR prediction using SEL and SAML

PVT Properties	Train/Test	*R^2*	*MAE*	*RMSE*	*AAPE*
Stacking Ensemble	Train	0.9858	140.8317	280.8092	0.1662
	Test	0.9521	279.1145	469.9535	0.1782
SVM Model	Train	0.9331	420.3382	409.9920	0.1696
	Test	0.9000	498.0172	592.8100	0.1746
ANN Model	Train	0.9281	454.0118	408.3331	1.1711
	Test	0.8900	522.5148	592.9800	0.1821
Decision Tree Model	Train	0.9278	509.1914	481.5005	0.1744
	Test	0.8900	619.1048	602.4000	0.1822

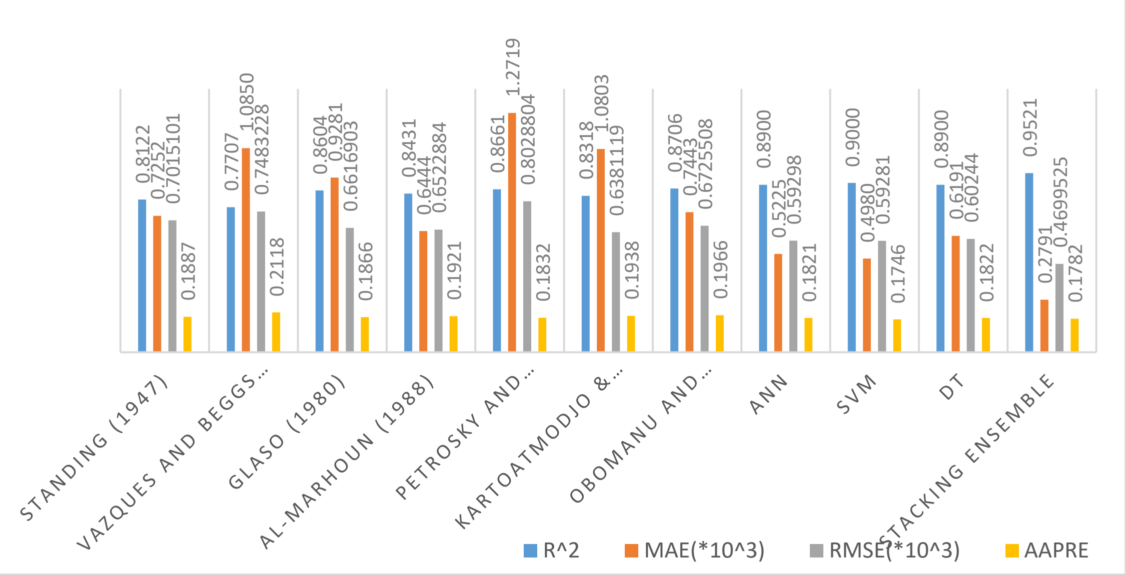

Figure 3.0 - Performance evaluation of SEL, SAML, and empirical correlations for gas oil ratio

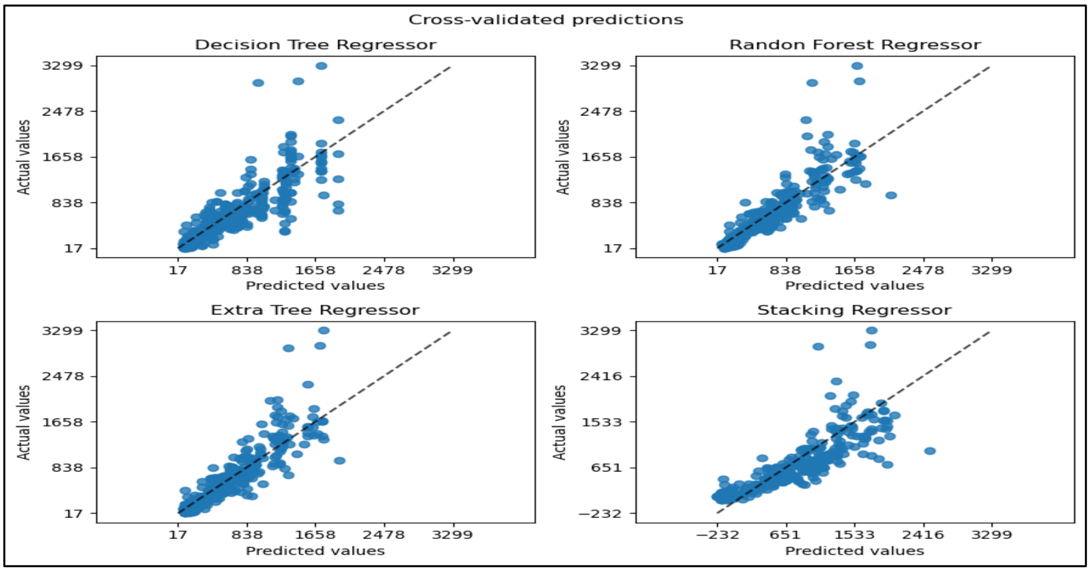

Figure 4.0. - Prediction accuracy showing actual values vs predicted values of GOR with Stacking Ensemble technique

4.0 CONCLUSION

This study highlights the potential of Ensemble Learning in petroleum engineering. By stacking "weak" or diverse learners (such as Extra Trees, Decision Trees, and Random Forests) and optimising their combination with a meta-learner (RidgeCV), engineers can achieve higher accuracy in reservoir characterisation without relying on costly lab experiments or region-specific equations.

APPENDIX A

Bubble Point Pressure

- Standing's Correlation
  $P_b = f\left(GOR, \gamma_g, T, API\right)$
- Modified Standing's correlation
  $$P_b = 31.7648\left[\left(\frac{R_s}{\gamma_g}\right)^{0.7857} \cdot \frac{10^{0.0009 \cdot T}}{10^{0.0148 \cdot API}}\right]$$
- Lasater
  $$p_b = \frac{P_f(T + 459.67)}{\gamma_g}$$
- Vasquez and Beggs
  $$p_b = \left[A\left(\frac{R_s}{\gamma_{gc}}\right)10^{a}\right]^{c}$$
- Glaso
  $$p_b^* = \left[\left(\frac{R_s}{\gamma_g}\right)^{0.816} \cdot \frac{T^{0.172}}{\gamma_{API}^{0.989}}\right]$$

- Ikiensikiimama and Ogboja

$$\rho_b = \frac{(\rho_b^*)\ (T + X10)}{\gamma_g}$$

Gas Oil Ratio

- Standing

$$R_S = \left(\left(\frac{p}{18.2} + 1.4\right) . \frac{10^{0.0125}\gamma API}{10^{0.0091}T}\right)^{\frac{1}{G}} . G$$

- Vasquez and Beggs

$$R_s = C_1 \gamma_g p^{c_2} exp\left(C_3\left(\frac{\gamma_{API}}{T + 459.7}\right)\right)$$

- Glaso

$$R_s = \left(\frac{x \times \gamma_{API}^{0.989}}{T^{0.172}}\right)^{\frac{1}{0.816}} \gamma_g$$

- Obomanu and Okpobiri

$$R_s = \frac{0.03008P^{0.927}\ \gamma_g^{2.15}\left(\frac{141.5}{\gamma_o} - 131.5\right)^{1.27}}{1O^{0.811}(1.8T - 459.67)^{0.497}}$$

Machine Learning Models

- Artificial Neural Network

$$y_k = f_o\left[\sum_j W_{kj}\, f_h\left(\sum_i W_{ji}X_i + b_j\right) + b_k\right]$$

APPENDIX B

Table A – extract from dataset

Press (Psia)	Gas Gravity (g/cm^3)	API	Temp (F)	GOR (Scf/Stb)
1560.15	0.65	37	145.748	240
1550	0.65	23	109	914.65
1529	0.65	33	130	547
1515	0.624	35.38	180	56
1513	0.65	36	142	232
1507	0.65	30	108	396.7
1500	0.8208	41	187.3	470.8
1500	0.8579	36.07	158.9	270.6
1500	0.591	36.07	123	16
1500	0.708	35	180	235
1500	0.79	26	180	202
1482	0.65	35.38	136	28
1478	0.65	26	136	187
1471	0.65	38	136	282
1441.35	0.65	29	140.91	175
1436	0.65	30	139	188
1413	0.65	30	135	175
1400	0.8189	38.2	175	810.4
1400	0.821	41.55	209.3	497.3
1400	0.8271	40.6	209.3	615.7
1395	0.65	26	138.783	180
1379	0.65	28	134	166
1363.95	0.65	29	137.821	175
200	0.8189	36.14	175	312.1
200	0.634	32	180	440.4
165	0.627	38.4	156.2	39
115	0.733	36.14	180	16

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[32] **Competing Interests**

[33] The authors declared no potential conflict of interest with respect to the research, authorship, and/or publication of this article