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Estimated Ultimate Recovery (EUR) Prediction in Unconventional Shale Reservoirs: A Comparative Analysis of Machine Learning Models.

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Abstract

Unconventional shale reservoirs present a distinct set of challenges for accurate production forecasting due to their complex and heterogeneous geological features. This study uses advanced machine learning techniques in predicting the estimated ultimate recovery (EUR) and production rate. The performance of the respective machine learning models (ML) was analysed using statistical performance metrics that includes MSE, RMSE, MAE and R^2. The obtained results show that virtually all the ML models performed well in terms of accuracy and robustness in predicting the actual EUR dataset with the exception of ANN, but with the Random Forest (RF) and XGBoost exhibiting superior performance with their exceptionally low values for MSE, RMSE, MAE and high R^2 values. The results for daily production rate for oil reservoirs using XGBoost and ANN show that XGBoost performed better than ANN with lower values of RMSE (0.0505), MAE (0.0025) and high R^2(0.9936) when compared to ANN with RMSE (0.0944), MAE (0.0089) and R^2 (0.9420). Generally, the obtained result in this study validates the importance of ensemble-based and gradient boosting methodologies in capturing the intricate complexities of unconventional shale reservoirs. It is then concluded that the enhanced predictive accuracy of these models can significantly contribute to more production forecasts, enabling more informed technical decision making by concerned engineers, in reservoir management and resource allocation and making it a very good and effective tools for optimizing production strategies in unconventional shale reservoirs.

Keywords: *Machine learning; Prediction; Forecasting; Unconventional shale reservoirs; Estimated ultimate recovery.*

1. Introduction

Unconventional shale simply refers to hydrocarbon- bearing rock such as shale that requires specialized drilling and hydraulic fracturing techniques in extracting its oil and gas. Pertinent among the major obstacles confronting shale reservoirs are estimating reserves and predicting shale well performance with accuracy. Formation reserves can be estimated using a variety of techniques, including volumetric calculations, material balance, numerical simulations and decline curve analysis. These methods may not be applied in the early stages of the well's life since they are linked to distinct inputs. For instance, the applicability and reliability of conventional decline curve analysis (DCA) that assumes a predictable decline in production over time, may not always accurately reflect the behavior of unconventional shale reservoirs due to the complex and heterogeneous nature of these formation.

The advent of shale oil boom in the United State triggered researches [1-3] in production forecasting in unconventional shale reservoir in the early 2000s. Study [4] on unconventional shale reservoirs revealed that they require the aid of mass stimulation or specialized recovery techniques and technologies to be produced at economically viable flow rates. The discovery of unconventional shale resources has led to a remarkable increase in oil and gas output in recent years, with a significant impact on global energy markets [5]. However, precise production projection is a difficult task due to the unique characteristics of these reservoirs. Advanced techniques such as completion design and multi-stage/multi-cluster fracturing have made it possible to extract hydrocarbon from these ultra-low permeability formations [6], which has helped operators cut costs [7]. To adequately address this challenge, researchers [8-11] have been exploring the use of machine and deep learning methods to improve production forecasting in unconventional shale reservoirs. The estimated ultimate recovery (EUR) is the primary statistics used to determine the profitability of the well. Considering the difficulty of estimating recovery factor, the traditional Arps decline curve method [12] has historically been used for forecasting estimated ultimate recovery (EUR) due to its simplicity and reliability. The Arps method is only valid for boundary dominated flow; however, it fails in shale reservoirs because of the ultra-low permeability and its resulting long transient flow regime.

Reservoir simulation from studies [13-15] has gained popularity as a method of evaluating shale wells and forecasting their performance, however, it is still questionable in many cases due to the oversimplification of the models currently in use as well as the lack of data needed to develop a realistic model. In recent years, machine learning (ML) models have emerged as a promising alternative to traditional methods for predicting EUR in unconventional shale reservoirs by incorporating a larger number of variables and accounting for non-linear relationships between them. Studies [11,16-19] have shown that machine learning methods can provide more accurate predictions and perform better for wells with more data. With the use of easily available data, several ML methods may be used to predict certain parameters [20-21]. Ibrahim *et al.* [22] in their study on production forecast in gas reservoir used machine learning model in predicting future production of a given number of wells based on time series data. They concluded from their obtained results that machine learning models can serve as efficient tool in production forecasting using large set of production data. Sayed *et al.* [23] in their comparative study evaluated the performance of three machine learning models in estimating the total organic carbon of unconventional shale gas reserve based on well logs data and concluded that rational quadratic Gaussian process regression has higher accuracy than other models. Onuoha [24] in his review study on technical and environmental issues in the prediction of unconventional shale gas reservoir stated that the development of unconventional shale reserves has resulted in increased economic benefits that includes significant rise in job creation, lower energy costs, new sources of government revenue and improved energy security.

The comparative analysis as demonstrated in this study is aimed at evaluating the performance of different ML models in optimizing EUR prediction in unconventional shale reservoirs. The study will concentrate on estimating EUR for multistage fractured horizontal shale wells in the X Ford shale by applying stronger learners—such as gradient boosting regression, random forest, and neural networks—and weaker learners—such as linear regression and decision trees.

2.Materials and method

2.1. Materials

First, comprehensive lists of all the materials and corresponding procedures employed for this study were defined accordingly. These includes dataset, in which two datasets was used with the first obtained from XY, an aggregating firm that specializes in data analyses and energy research. The X Ford shale located in the South Texas that includes 17,882 data point with 72 attributes that spans from the year 2007 to 2017 containing information on cumulative oil and gas production during specific time interval, cumulative production in barrels of oil equivalent, initial production rates of oil and gas, total production in barrels of oil and gas per day and estimated ultimate recovery of oil and gas is the subject of the dataset. The second data is also on X Ford shale containing information on well's production history and well data for over 1400 days which is useful for comprehending the dynamics in unconventional shale reservoirs. The machine learning (ML) algorithms used in this study are linear regressor, random forest, decision trees (supervisor), support vector regressor (supervised), XGBoost, and ensemble learning models. The evaluation metrics used in this study are mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), coefficient of determination (R^2) and others (i.e. accuracy, precision, recall and F1 score).

2.2. Method

2.2.1. Data collection

In petroleum production, production data are recorded as time series data; more specifically, they are reported as rate vs time (usually in months). The obtained data on production history from the X wells of Ford shale gotten from XY and X Ford used in this study contain key information on the well (i.e. well name, location, completion parameters, and reservoir properties), production data and other data. This raw data was preprocessed for further analysis which is an important step in the data mining process. Preprocessing of these data improves the accuracy and efficiency of the analysis. Features may have different scales that can impact the performance of certain algorithms. In this study, min-max scaling techniques or standardization (z-score normalization) was used in bringing features to a common scale.

2.2.2. Feature selection and training-validation-testing split

Here, the gathered and preprocessed data was converted into a format that the machine learning model can use. The well location was converted to a set of coordinates while the production rates were normalized to a standard scale. The data were divided into discrete subsets for training, validation (hyper parameter tuning), and final testing for the purpose of simplifying the training and validation of the machine learning model in order to ensure a full assessment of its performance with unknown data. 80/20 split was used for training and testing. Dataset with production data from the past that contains the required properties were created. Feature importance analysis and selection was done using the correlation plots and domain knowledge to determine the best features for model training.

2.2.3. Data visualization

The production history of both datasets were visualized to establish the production trend of oil and gas for the different (multiple) wells in the X Ford shale. Figures 1 to 3 shows the plot of the EUR of gas, oil, and the total EUR against their first production date for the multiple wells in the X Ford shale from 2007 to 2017.

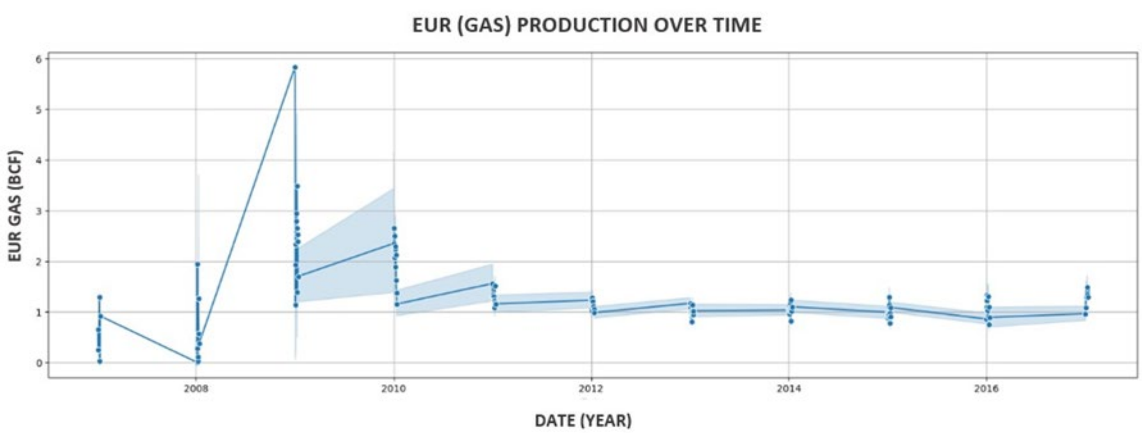

Figure 1. Gas EUR vs first production date.

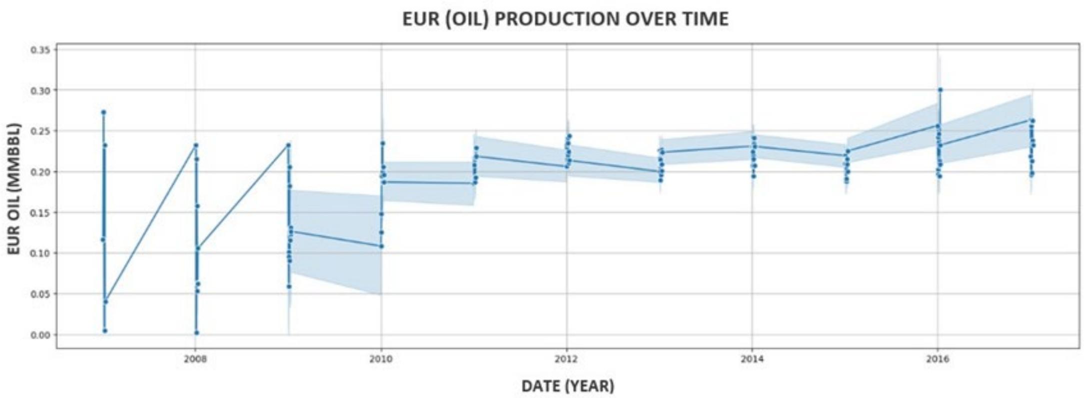

Figure 2. Oil EUR vs first production date.

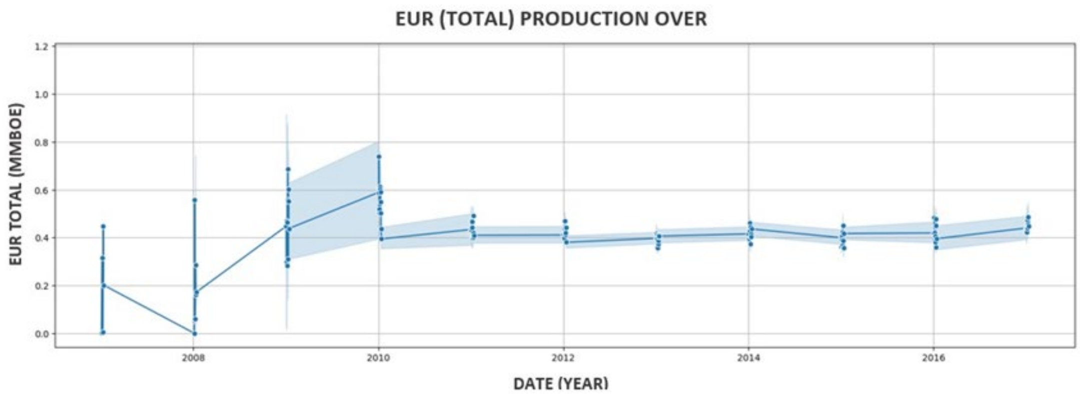

Figure 3. Total EUR vs first production date.

2.2.4. Model selection and evaluation

The selected algorithms trained on the dataset for this study includes linear regressor, decision trees, random forest, support vector regressor, artificial neural network, XGBoost and ensemble model. The parameters of each algorithm were adjusted to minimize the error between the predicted and actual production rates. The optimal parameters for each algorithm were then selected based on the validation dataset. The performance of the selected model was evaluated using MSE, RMSE, MAE, and R^2.

2.2.5. Model training

For this study, the ensemble learning model, support vector regressors, random forest regressors, linear regressors, decision tree regressors, and artificial neural networks (ANN) were used in predicting the estimated ultimate recovery (EUR) and their choice was influenced by the dataset's unique properties and the availability of data. The models were constructed using the sklearn pipeline, which loads the data, trains the model, and then generates predictions. The pipeline was evaluated using a holdout validation set, in order to identify the best performing model. The number of wells, the production rate, and the reservoir pressure were the most important features used for production prediction. The voting regressor ensemble model combines the predictions of SVR, LR, DT, and XGB models to improve the overall accuracy of the predictions. The neural network was constructed using a sequential model, which is a type of neural network architecture that consists of a sequence of layers. The input layer of the ANN receives the input data, the hidden layers process the data, and the output layer generates the predictions. The two hidden layers in the ANN were used to learn the complex relationships between the input data and the output data. The ensemble model has 4 models as estimators. The neural network has four inputs with 128 neurons, one output with 38 neurons, and two hidden layers with 64 neurons each.

2.2.6. Model testing and validation

After the models were trained, they were validated on a separate dataset of production data. This is to ensure that the models are not overfitting to the training data. Overfitting occurs when the model learns the training data too well and is unable to generalize to new data. In this study, the models were validated on the test and validation datasets. The test dataset was used to evaluate the overall performance of the models, while the validation dataset was used to fine-tune the parameters of the models. The test dataset is a holdout dataset that was not used to train the models. This is to ensure that the models are not able to memorize the test data and perform well on it by chance. The validation dataset is a subset of the training dataset that was used to tune the hyper-parameters and also used to evaluate the performance of the models during training to prevent overfitting by stopping the training process when the performance on the validation dataset starts to decrease.

3. Results and discussion

3.1. EUR prediction

The results and discussions on the study on estimated ultimate recovery prediction analysis on unconventional shale reservoirs using machine learning models is presented and discussed below. Table 1 shows the obtained results for the developed artificial neural networks, linear regression, decision trees, random forest, support vector regressor, Xgboost and ensemble learning model that was tested using historical production data and relevant reservoir parameters. All the machine learning models performed well in terms of accuracy and robustness. The obtained statistical performance metrics results for each employed model during training is presented on Table 2 while Figure 4 envisages how the machine learning models performed with respect to the actual values in the dataset.

Table 1. Actual vs predicted EUR for each model.

Actual EUR	ANN	LR	DT	RF	SVR	XGB	ENS
0.394000	0.348293	0.397675	0.387159	0.389420	0.422557	0.385757	0.368669
0.215000	0.362976	0.228879	0.216878	0.216500	0.258512	0.219985	0.255923
0.274000	0.288941	0.241310	0.262571	0.279736	0.348892	0.292784	0.280061
0.242000	0.271995	0.328534	0.241406	0.255540	0.338922	0.246555	0.251948

Table 2. Performance metrics for all the models.

Model	MSE	RMSE	MAE	R2
ANN	0.04089	0.20221	0.14143	0.43897
Linear regression	0.01794	0.13395	0.05299	0.75381
Decision trees	0.01269	0.11266	0.03256	0.82585
Random forest	0.00805	0.08970	0.02092	0.88959
SVR	0.01256	0.11206	0.06004	0.82767
Xgboost	0.00835	0.09136	0.02973	0.88549
Ensemble learning	0.01084	0.10412	0.05134	0.85124

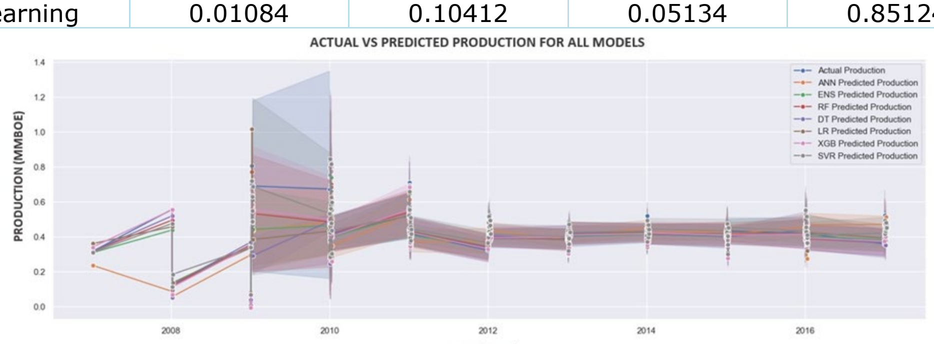

Figure 4. Actual vs predicted values by models.

The result of the predicted production forecasting against the actual production rate as obtained using XGBOOST and ANN are given in Table 3 while Table 4 shows the statistical performance evaluation metrics results for the XGBOOST and ANN. The choice of these machine learning models in predicting the production rate was as a result of their ability to understand complex relationships between traits and the variables they were attempting to influence. Figures 5 and 6 shows the plot of the forecasted predictions from XGBOOST and ANN models against the actual production rate. Figure 7 shows the ANN forecast for about 200 days indicated by the yellow lines at the end of the plot.

Table 3. Actual total production rate vs predicted.

Actual rate	XGBOOST	ANN
0.172162	0.15758702	0.165566
0.155476	0.13972186	0.145984
0.169913	0.15289922	0.166480
0.158807	0.14309907	0.158229
0.158807	0.14310901	0.163636

Table 4. Models metric evaluation values.

Model	RMSE	MAE	R2
XGBOOST	0.0505	0.0025	0.9936
ANN	0.0944	0.0089	0.9420

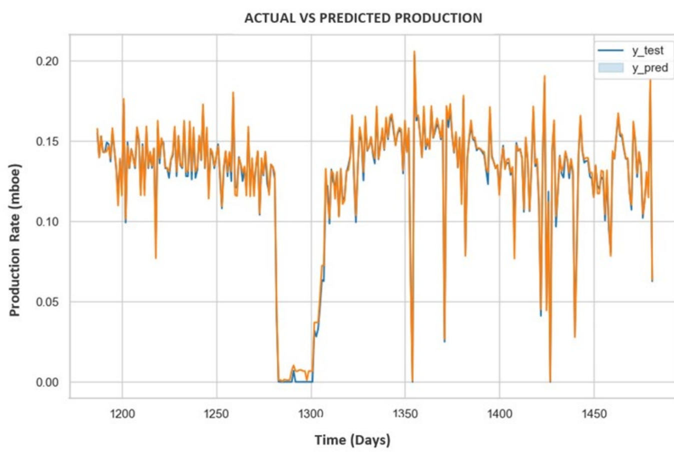

Figure 5. XGBOOST prediction vs actual rate.

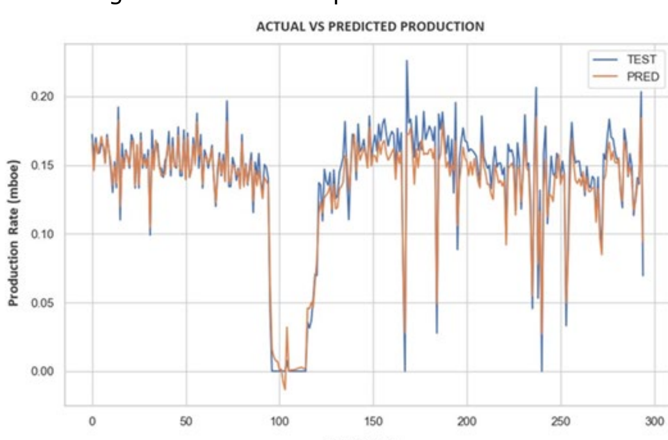

Figure 6. ANN prediction vs actual rate.

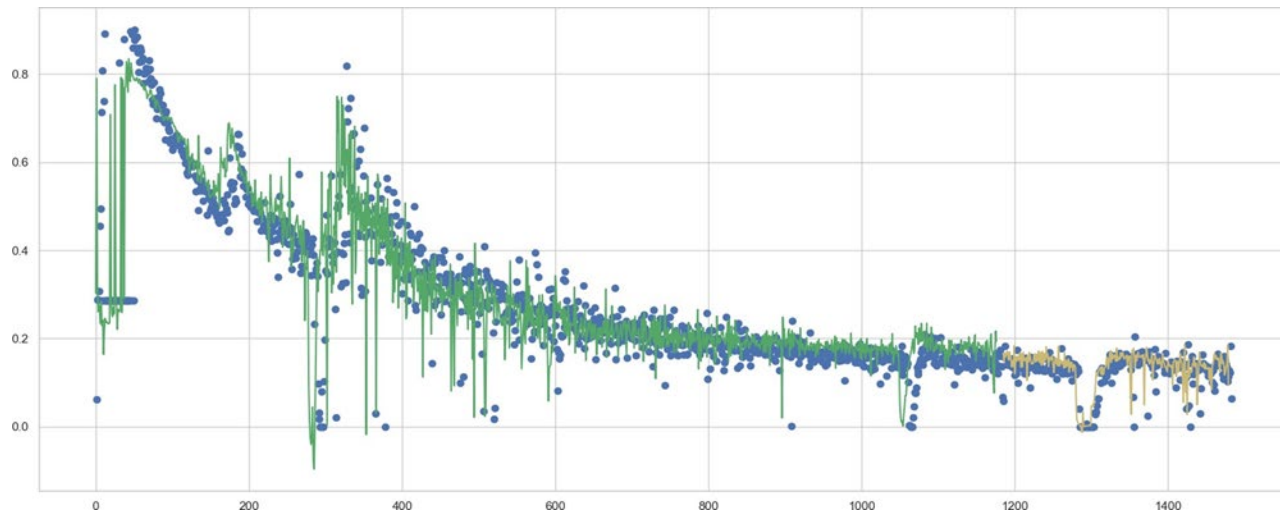

Figure 7. ANN production prediction forecast for about 200 days.

3.2. Result discussion

3.2.1. Models EUR prediction

The EUR model prediction as presented in Table 1 shows the obtained models EUR prediction results. These result indicates that virtually all the machine learning models performed well in terms of accuracy and robustness in predicting the actual EUR dataset. This can be explained from the obtained results from the statistical error parameters presented in Table 2, which is the performance metrics used in this study. The closer the MSE, MAE, and RMSE is to zero, the more accurate the prediction, implying that the regression line is very close to the set points of the data and indicates a very good fit. Thus, with the obtained result of the MSE, RMSE and MAE certifying this criterion implies that the analysed models prediction was highly accurate with minimal error. Similarly, R^2 values closest to 1 indicates very high degree of fit of the predicted response to the actual data. The analysed models in this study significantly performed in this regard with exception of ANN. The plot of Figure 4 visualizes how the machine learning models fared with respect to the actual values in the dataset just as indicated in Table 1. Though, generally speaking, the obtained result from the developed models shows they all performed well in terms of accuracy and robustness thereby making them good models to be used in EUR prediction. But in this study, the essence or aim of analyzing these models on individual basis is to determine the best performing model that will give the best prediction in all ramifications. Hence, the ranking of these models in order of best performing to the least performing using the statistical performance metrics as presented in Table 2. Therefore, from the result in Table 2, the ranking order is now Random Forest, XGBoost, Ensemble learning, Support Vector Regression (SVR), Decision tree, Linear Regression and ANN. However, slight change in order was only noticed between Decision tree, Ensemble learning, Linear Regression and Support Vector Regression for MAE. The obtained result from this study shows that Random Forest and XGBoost emerge as the superior performers across all examined statistical performance metrics. Their exceptionally low MSE values of 0.00805 and 0.00835 respectively, underscore their ability to discern intricate patterns and interdependent within the production data. The RMSE values of 0.08970 and 0.09136 further attest to their accuracy, indicating relatively small deviations from the observed data. The MAE values of 0.02092 and 0.02973 further affirm their precision in predicting production levels. Finally, the high R^2 values of 0.88959 and 0.88549 indicate the substantial proportion of variance explained by these model implying a good prediction and reliability of the models.

The Ensemble learning incorporating the predictions of various models while though not quite reaching the performance of Random Forest and XGBoost has an MSE value of 0.01084 which is still an acceptable value. Its RMSE value of 0.10412 and MAE value of 0.05134 indicate a relatively small margin of error in prediction. The R^2 value of 0.85124 reinforces the model's capability in explaining variance within the data. Support Vector Regressor (SVR) delivered a competitive performance, with an MSE value of 0.01256, RMSE value of 0.11206 and MAE value of 0.06004. These metric values signify a respectable level of prediction accuracy. The R^2 value of 0.82767 indicates a strong proportion of variance captured by the model. Decision tree still presents commendable results across board. An MSE value of 0.01269 indicates a relatively low level of prediction error, while the RMSE value of 0.11266 signifies a small degree of deviation from the observed values. The MAE value of 0.03256 further underscores the models accuracy, while the R^2 value of 0.82585 reflects a strong level of explained variance. Linear regression while exhibiting a higher MSE value of 0.01794 when compared to other models, still provides a reasonable level of prediction accuracy. The RMSE value of 0.13395 and MAE value of 0.05299 indicate a slightly degree of deviation from the observed data, though the R^2 value of 0.75381 reflects a moderate level of explained variance. Artificial Neural Network (ANN) displayed a comparatively higher MSE value of 0.04089 signifying more prediction error. The RMSE value of 0.20221 and MAE value of 0.14143 further underscores the model's higher level of deviation from observed data. The R^2 value of 0.43897 indicates a very low degree of fit of the predicted response to the actual data. Considering all the analysed models based on their obtained performance metrics value, there is a clear evident that Random Forest and XGBoost emerge as the top performing models, demonstrating exceptional accuracy and precision in forecasting production in unconventional shale reservoir. The obtained result for the Random Forest and Support vector regressor having R^2 values of 89% and 83% in this study, compares favourably well and surpass that obtained from the work of [25] with R^2 values of 68% and 62%. This improvement can be attributed to the quality of data and the hyper parameter tuning for both models.

3.2.2. Production forecasting using XGBoost and ANN

Thorough examination of the performance of the two prominent machine learning models, XGBoost and Artificial Neural Network (ANN) in the estimation of total daily production rate for oil reservoir has been clearly demonstrated and analysed according to Table 3 and Table 4 respectively. The obtained results based on the statistical performance metrics used in analyzing their respective performance shows that XGBoost, a robust ensemble learning algorithm demonstrated a notable RMSE value of 0.0505, showcasing its aptitude for handling complex correlations within the data. Its MAE value of 0.0025 further affirm its efficacy in this application. The high R^2 value of 0.9936 indicates an exceptionally goodness of fit, underscoring its precision in forecasting production. This model proficiency is particularly valuable in scenarios where intricate interdependencies between reservoir parameters are prevalent. Conversely, the ANN model exhibited an RMSE value of 0.0944, signifying a slightly higher level of error compared to XGBoost. The MAE value of 0.0089, though slightly higher than that of XGBoost still showcase good prediction. The R^2 value of 0.9420, though slightly lower than that of XGBoost, still denotes a goodness of fit. ANNs are well regarded for their ability to discern complex patterns in data, making them well suited for application in reservoir engineering especially when dealing with substantial datasets and intricate interactions. Considering the performance of XGBoost and ANN in forecasting based on our analysed statistical performance metrics, it is evident that XGBoost model emerge as the superior performer in forecasting the production of unconventional shale reservoirs. However, the ANN still demonstrate a strong fit to the dataset and its performance in this study with respect to RMSE compares favourably well and surpass that obtain from studies by [9,26].

4. Conclusion

Based on the obtained results and discussions on this study, the potential of machine learning techniques as a valuable tool for EUR and production forecasting in unconventional shale reservoirs is emphasized. The obtained result for production forecasting using XGBoost and ANN shows that the XGBoost performs better with a lower value of RMSE, MAE and higher value of R^2 when compared to ANN. However, it is concluded that both models have that aptitude for discerning complex correlations within data, making them well suited for application especially when dealing with substantial datasets and intricate interactions. The obtained results generally demonstrate the importance of ensemble-based and gradient boosting methodologies in capturing the intricate complexities of unconventional shale reservoirs. It is then concluded that the enhanced predictive accuracy of these models can significantly contribute to more reliable production forecasts in unconventional shale reservoirs, enabling more informed decision making in reservoir management and resource allocation.

Recommendation

Researchers and practitioners seeking to implement advanced predictive techniques in reservoir engineering and management should appreciate a comprehensive comparative analysis of machine learning models as a valuable reference.

Conflict of interest*. Conflict of interest, on behalf of all authors, the corresponding author states that there is no conflict of interest.*

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