Prediction of Leak on Gas Pipeline Using a Hybrid Machine Learning Model

Aniyom Ebenezer* and **Anthony Chikwe,** Federal University of Technology, Owerri, Nigeria

Abstract

Leak detection is an important problem during transportation of natural gas through pipelines for downstream operations. The investigation into solving this problem has led to the adoption of data science and machine learning approaches providing an optimal solution to this problem. In this study, a machine learning hybrid model was developed to detect natural gas leakages in pipelines. The hybrid model referred to as voting regressor assembles two machine learning models, the Random Forest Regressor and the XGBoost Regressor for improving performance during leak detection. The input parameters to the hybrid model are temperature, pressure, and flow rate. Results from this study showed an improvement in the performance of the hybrid model (voting regressor) in comparison to others in leak detection. This is depicted by an accuracy score of 93% and an error of 0.44%, and a recommended approach for leak detection.

Introduction

Pipeline networks are built with the goal of moving various chemical and petrochemical products over long distances in liquid and/or gas phase conditions. Pipelines are extremely secure when compared to other modes of transportation, but they may have to operate under different circumstances, necessitating appropriate operation inspection.

The need to transport fluid from the site of production to the place of use has resulted in a rapid increase in the number of pipelines being built (Chris and Saguna 2007). Due to the toxic and hazardous nature of the products flowing through the pipeline, these products could cause accidents and environmental hazards if leaks occur. These leaks are sometimes caused by complexities of environmentally or human induced factors and disturbances generated along the pipeline flow network (Obibuike et al. 2020). With the increasing awareness and empathy for the environment, most of the leakage from gas pipelines have shown cost effective and the demand for reliable detection systems is very high (Boaz et al. 2014). This implies that the financial costs usually incurred by the company is often significantly high; including the cleaning cost of the environment and the payment for the pollution as being stated by the Environmental Guidelines and Standards for the Petroleum Industry in Nigeria (EGASPIN), which was issued to the Department for Petroleum Resources (DPR) at the Ministry of Petroleum Products in 1991 (Olawuyi and Tubodenyefa 2019).

To avoid any further pipelines incidents and saving the environment, the promising solution is implementing better pipeline monitoring and leak detection equipment and practices. If proper maintenance is carried out, pipelines can last void of leaks (Boaz et al. 2014). Early detection of leaks and probably identification of the location using various best techniques allows for shutdown and cleanup works to avoid further pollution and spillage.

There is a need to have a reliable leak detection system in oil and gas industries since this has become a priority when transporting petroleum products through a pipeline. Because uncontrolled release of gas into the

Improved Oil and Gas Recovery

DOI: 10.14800/IOGR.1344

Received December 6, 2024; revised January 5, 2025; accepted February 1, 2025.

*Corresponding author: eaniyom@gmail.com

atmosphere has both environmental and economic impact on both the industry staff and to the host community. Although there has been a huge technological improvement over the decades, there still exists leaks and failures in practices adopted by most industries (Skalle and Aamodt 2020). Thus, the early detection of leakages in the gas pipeline offers several advantages amidst the economic advantages; safety of the gas transportation, environment gas quality protection, and avoiding pipeline breakages which could be used for subsequent transportation (Nicola et al. 2018).

Leak Detection Methods

Over the years, there have been different leak detection methods adopted over the years to monitor the integrity of a pipeline (Bose and Olson 1993). Leak detection systems have been broadly classified into three major categories which are, Biological methods, Hardware-based methods, Software-based methods.

Biological Methods of Leak Detection. This is a traditional method for detecting leaks, it requires the presence of experienced personnel that walk along a pipeline, where they seek unusual occurrences close to the pipeline. it involves smelling of substances that may have been released as a result of the leak which occurred there. Other times, it involves listening to noises which are generated because of the escaping substance from the pipeline. With this, the outcome from such an occurrence largely depends on the wealth of the experience which these personnel have. Most times, this method also involves the use of trained dogs with a highly sensitive smell of substance which are released from the leak.

Hardware Based Methods for Leak Detection. Several hardware devices can be used or are being used to assist the detection and localization of a leak. This method can be subdivided into four different types with respect to the principles of which these devices are designed as follows.

Visual Devices. Just as the name implies, it involves the detection of leaks through the identification of temperature changes within the surrounding environment of the pipeline. The method involves the use of vehicles, helicopters or portable systems which cover hundreds of miles per day. In recent times, there were several other devices which have been developed. This comprises the use of IR cameras to capture the effect of leak drops which are independent of the physical properties of the substances inside the pipeline. Research was conducted on the use of temperature sensors such as multi-sensor electrical cable and optical time domain reflectometry (Turner 1991).

Acoustic Devices. According to vocabulary.com, acoustic devices are those devices which are used for amplifying or transmitting sounds. When leaks occur, it generates noise as the fluid escapes from the pipeline. The gas escape with a wave speed that is affected by the physical properties of the fluid in the pipeline. The acoustic detectors are designed such that they detect the wave as well as the leak.

Sampling Devices. Vapor monitoring devices can also be used for the purpose of leak detection, as it helps to detect the vapor level of the hydrocarbon in the pipeline surroundings. All these are possible with the help of a gas sampling device.

Pressure Wave Detectors. The wave produced during leak is usually propagated from the upstream to the downstream at the leak site. When these waves travel with a speed of sound, Pressure transducers can be used to measure the pressure gradient with respect to time as stated by Turner (Turner 1991).

Software Based Methods for Leak Detection. The software-based methods, as stated by Turner (1991) and other researchers in the 90s, depend on some parameters of the gas or the pipeline. These parameters include pressure, temperature, flowrate of the gas through the pipeline and other data which are provided by SCADA (Supervisory Control and Data Acquisition) system. Bose and Olson (1993) classified the software-based technique into four categories as follows.

Flow or Pressure Change. This technique largely depends on the assumption that a high rate of change in flow or pressure at the upstream or downstream (inlet or outlet) sections of the pipeline signals the occurrence of a leak as stated by Mears.

Mass or Volume Balance. This method allows for the detection of leaks with low rate of change in pressure or flow. It works with the principle of changes with respect to either mass or the volume

Dynamic Model Based System. Dynamic models are mathematical models developed to account for the fluid flow within the pipeline. This involves measurement of several quantities and other physical equations that can help to achieve this fitness. Some equations include the equation of the conservation of mass, the equation of the conservation of momentum, the equation of conservation of energy, the equation of state, etc. There are several software packages which could be used to achieve this as well.

Pressure Point Analysis (PPA). This technique is largely based on the assumption that if there is a pressure drop in the pipeline, there is a probability of leaks occurring. Thus, it works with statistical correlations for the analysis of these measurements.

Intelligent Models for Leak Detection. Intelligent models are models which have computational intelligence, and which can learn specific tasks from either data or experiments. There exist several intelligent models which could be used for the different applications (Akinsete and Oshingbesan 2019).

Researchers have been on the scheme to improve the accuracy of the prediction of leak in a gas pipeline. Thus, the engagement of intelligent & artificial models which work with by training the computer to understand patterns in a dataset and make accurate predictions for response needed.

Five intelligent models have been explored to ascertain the possibilities in the prediction of leak accurately. The models they used were gradient boosting, decision trees, random forest, support vector machine, and artificial neural networks were used for the data stream. In their research, the results obtained showed that support vector machine and artificial neural networks are better regressors than others. Although, the random forest regressor and the decision trees can detect about 0.1% of the nominal flow in about 2hours. At the end of their experiment, they observed that the intelligent models performed comparatively well when other trade-offs are being considered (Akinsete and Oshingbesan 2019).

Santos et al. (2014) affirmed that the use of neural networks could be used to accurately predict leaks and their magnitudes. Still on the application of machine learning models, Alkhudhair et al. (2022) used machine learning models to predict anomaly that exist in the pipeline. In their research, they implemented five different machine learning models to predict occurrences which could be referred to as anomalies. The result of their experiment indicated that the use of support vector machine algorithm as well outperformed other models with an accuracy of 97.4% in detecting leakages in a pipeline. Some of the models applied for leak detection in a gas pipeline are reviewed below.

***K-Nearest Neighbor* (*KNN*)**. The KNN algorithm is a classification and regression problem model, which could be used to tackle both classification and regression tasks. It is an algorithm of the supervised learning machine type, which could also be used as outlier detection. It is a non-parametric learning algorithm; in that it does not assume anything about the underlying data. KNN works by memorizing positions in the dataset with the corresponding values for which it can make predictions after model training (Aniyom et al. 2022), thus it is very ease to implement and can be used for leak detection problems (Dakheel et al. 2019). As one of the algorithms applied in the research, they implemented this algorithm for the intrusion detection in gas pipeline as needed in the gas distribution industry. In their research, they discovered the algorithm performed better than other models with an accurate score of 97%. Although, may not perform optimally upon deployment due to the complex nature of gas distribution pipelines (Dakheel et al. 2019).

Random Forest. Random Forest is a machine learning algorithm which is most times regarded to as an ensemble learning method which can be used for classification and regression problem and for other task operations (Akinsete and Oshingbesan 2019). It is made up of n-collections of decision trees and it is largely based on the bootstrap aggregation concept, which helps reduce the variances experienced in the datasets. It computes the average number of leaf nodes for improved performance accuracy (Ekeopara et al. 2022).

Support Vector Machine.The support vector machine (SVM) is primarily defined by the separating hyperplanes. It can be used for predictions across classification and regression problems. It aids in the distinguishing between instances of different categories where the separating line (hyperplane line) finds the optimal separating plane between points in the different classes. It allows for hard and soft margins which reduces errors and other biases (Aniyom et al. 2022). When applying SVM for regression problems, it adopts the loss function for the penalization of the loss function which most times lead to sparse representation of the rule.

Methodology

This research applies to the machine learning algorithms for the prediction of leak pressure and location at several intervals of a natural gas pipeline. There exist several intelligent models which can be used for predictive analysis with machine learning. But machine learning as a field of study is largely classified into broad groups.

Supervised Machine Learning Model. Supervised learning machine model is an approach of creating an intelligent model by training the model on input data which have labels or targets inclusive. Thus, it is that form of machine learning model which works on structured dataset (data in rows and columns) with well-defined features. Here the computer is fed with a structured dataset and allowed to learn through the data, then predictions are made with respect to the trained data. this approach is only valid for datasets with the labels (Dakheel et al. 2019). The supervised ML is further classified into two methods: regression and classification methods. These are used for solving problems associated with any of the categories (Aniyom et al. 2022).

Unsupervised Machine Learning Model. This approach is used to uncover the hidden patterns that are resident in a data. The dataset used in this approach does not have the target variable or the label. It can either be structured or unstructured. The widely used approach for solving unsupervised kind of problems is the clustering algorithms (Ekeopara et al. 2022).

Model Development

In this study, gas pipeline X data was obtained for the analysis and the regression prediction of leak on gas pipeline. Figure 1 shows the workflow for the methodology, it also shows the steps that were followed to the actualization of the predictions respectively. The procedure for model development involves the following.

Data Description Ingestion. The data used for the training of this model is a gas pipeline X dataset from the Niger Delta region in Nigeria. The data was obtained from SCADA measurements of pressure, temperature and flowrate for inlet and outlet conditions of the gas pipe. In the ingestion of the data, both Microsoft Excel and Python were used to understand the dataset and for the performance of other analysis necessary for the prediction of leak. The field data was used to validate and measure the performance of the models. The data represents 542 leak case pipeline which has been recorded with the following features of the pipe being recorded.

Data Wrangling. This entails the modification of data for the machine learning models to appreciate it and to perform better. This was done visually with the use of Microsoft Excel, here the assessment of the dataset was done by scanning eyes through the dataset and the use of Python to programmatically access it as well. Here, the errors related to the datasets were corrected with all visualizations. This section also involves the computation and analysis of data with python and its dependent libraries.

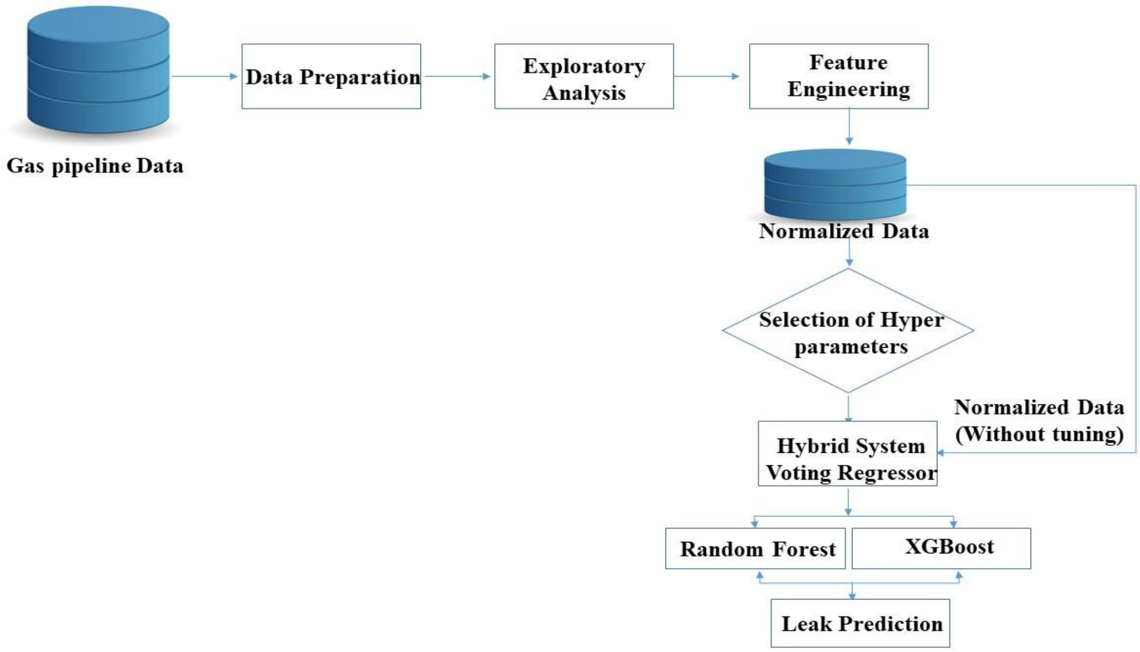

Figure 1—Model development workflow.

Feature Engineering. ***Standard Scaler.*** The features in the input variables were engineered for better performance of the models. The engineering done was the with the StandardScaler algorithm. The StandardScaler is used to resize the distribution of values so that the entire dataset will have a common means of observed values of 0 and standard deviation of 1. It was imported from the sklearn library for python.

Data Split. Data splitting is the process of dividing the dataset into two categories, the train and test dataset. The train dataset is used for the training of the model while the test dataset is used to test and predict the target variable. In this project, the split ratio used is 80:20 for train and test dataset respectively.

Hyper Parameter Tuning. Searching for optimal parameters for the models helps improve the performance of the models during predictions and validations of the model with test dataset. The two ML algorithms proposed to be embedded inside the voting regressor were subjected to hyper tuning to obtain the best parameters for the prediction.

The algorithm used for hyper parameter tuning is the GridSearchCV. GridSearchCV is the process of performing hyper parameters tuning to determine the optimal values for a given model. It has been observed that the performance of a model is largely dependent on the values of the hyper parameters. The GridSearchCV is a Scikit-learn (Sklearn) model_selection package, which was accessed using the 'import' keyword in python. The two models for which this algorithm was used upon are the Random Forest Regressor and the XGBoost Regressor.

Random Forest Hyper Parameters. The Random Forest Regressor was subjected to tuning to reduce the loss function and six parameters of the algorithm were tuned for the best performing values using the GridSearchCV and results are displayed in **Table 1**.

Table 1—Random forest hyper parameter and best value.

S/N	Hyper Parameter	Best Value
1	Bootstrap	True
2	Max_depth	1000
3	Max_features	Auto
4	Min_samples_leaf	1
5	Min_samples_split	2
6	N_estimators	1800

XGBoost Hyper Parameters. XGBoost algorithm was also tuned to obtain the best performing values of its parameters. This algorithm was tuned using the GridSearchCV tuning algorithm, and the manual tuning also was applied for optimal performance. The increase in performance shows the place of tuning in machine learning projects. After several hours of tuning, the model attained its optimal performance at the following parameters and values displayed in **Table 2**.

Table 2—XGBoost hyperparameter and best value.

S/N	Hyper Parameter	Best Value
1	N_estimators	1800
2	Max_depth	4
3	Eta	0.5
4	Subsample	0.4
5	Colsample_bytree	0.9

The tuning of the hyper parameters was done on the two single models only as they were embedded into the voting regressor and as such there was no need for the tuning of the voting regressor since these single models are expected to perform extremely well inside the voting regressor. After the tuning of the hyper parameters to be used for the building of the model, the actual process of the building of the single models was done with each of these models being trained independent of the other before the embedding itself was done. Thus, there was room for the measurement of the single models and the validation of these single models to ascertain the performance of the voting regressor as it was being built.

Leak Detection Models Performance Metrics. After the models were successfully trained and predictions made, it was important to evaluate the performance of the models to estimate the loss function of the model. During model training the aim is to reduce the loss function to the minimum point. The metrics used for this study are as follows.

i. Mean Absolute Error (MAE)
ii. Mean Square Error (MSE)
iii. Root Mean Square Error (RMSE)
iv. Coefficient of Determination Score (R2 score)

Mean Absolute Error. It is a measure of errors between paired observations expressing same phenomenon. It is the amount of error that exists in a measurement, which shows the difference between true value and predicted values. **Eq. (1)** shows the mathematical equation for MAE.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}, \quad (1)$$

where, MAE is mean absolute error; y_i = predicted value; x_i = true value; n = total no. of data points.

Mean Square Error. It measures the average of the squares of the errors, i.e. it measures the average of the squares of the errors. It accounts for the number of errors in mathematical and statistical models, it basic mathematical principle is shown in **Eq. (2)**.

$$\mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\mathrm{Y_i} - \hat{\mathrm{Y}}_\mathrm{i}\right)^2 \quad (2)$$

where, MSE is mean square error;n = total no. of data points; Y_i is rue or observed values;$\hat{Y}_i$ is predicted values.

Root Mean Square Error (RMSE). This is the square root of the mean of the square of all of the error. It is considered an excellent general purpose error metric for numerical predictions. It is a frequently used measure of the differences between values predicted by the model and values observed. It is given by **Eq. (3)**.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2}{N}} \quad (3)$$

where, RMSE represents root mean square error; n is total no. of data points; Y_i is true or observed values; $\hat{Y}_i$ is predicted values.

Coefficient of Determination Score. This is known as the R-Squared score. It is the proportion of the variation in the dependent variable that is predicted from the independent variable. The best possible score is 1.0 and it can be negative (since some models can be arbitrarily worse). It can be represented by **Eq. (4)**.

$$R^2 = 1 - \frac{RSS}{TSS}, \quad (4)$$

where R^2 is coefficient of determination; RSS is sum of squares residuals; TSS is total sum of squares.

Results And Discussion

Also, a visualization to show the relationship between the leak and output pressures versus the pipeline length, to understand the flow nature and the point where the leak occurred.

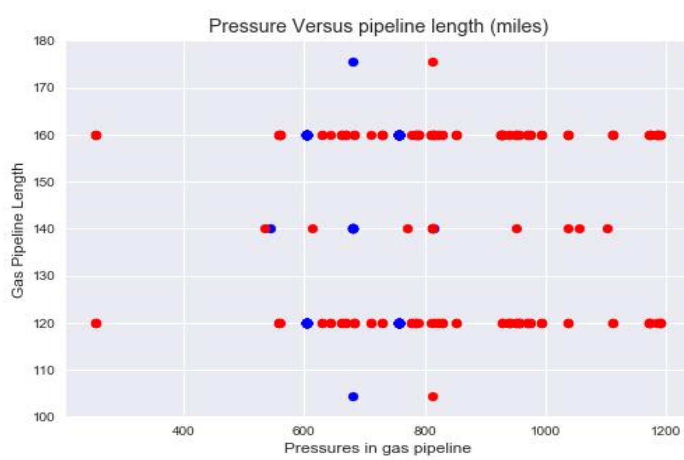

Figure 2—Pressures versus pipeline length (miles).

Model Validation. Validation of the model was done using the test data, after the predictions of the leak were executed. **Figures 3** through **5** show the regression plots for the single models that were used for the assemble voting regressor. The regression plots show how the models were fitted towards the regression line which depicts the accuracy level of the models in predicting the leak as against the actual field data.

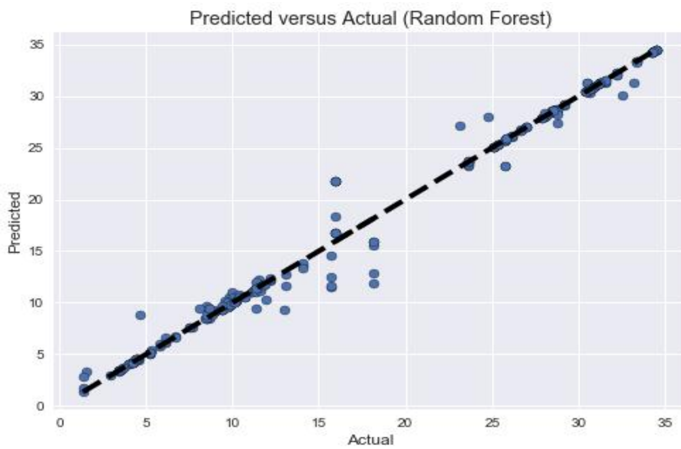

Figure 3—Regression for random forest.

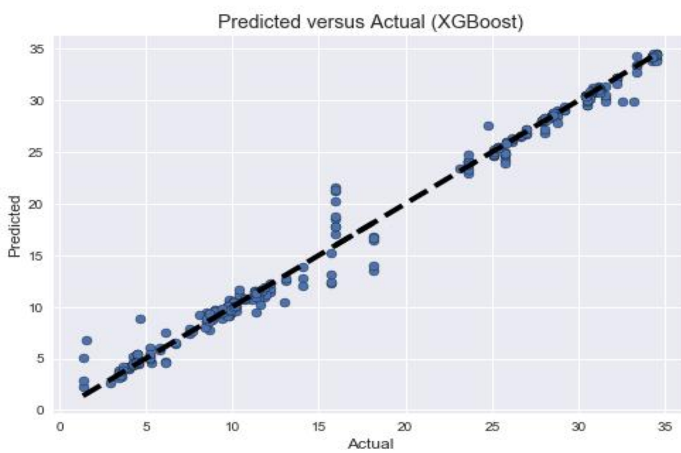

Figure 4—Regression for XGBoost.

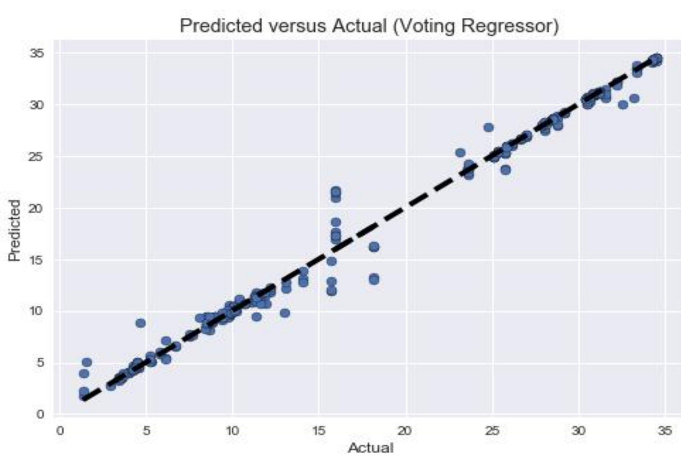

Figure 5—Regression for voting regressor.

Deviation from the regression line experienced in the regression plots from the models developed above are the because of irregularities and unconformities experienced in the dataset. It shows that 100% cannot be attained. The models all performed well by predicting over 90% of the leak experienced in the gas pipeline, with minimized errors of less than 2.0 in infinity range.

Figure 6 shows the statistical errors metrics which include Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). From the plot it is observed that the voting regressor algorithm had a minimal error, since the loss function was optimally reduced. With this minimal error experienced with the voting regressor, it is reliable upon deployment as it will perform better compared to the since models with almost complete reduction in the loss function.

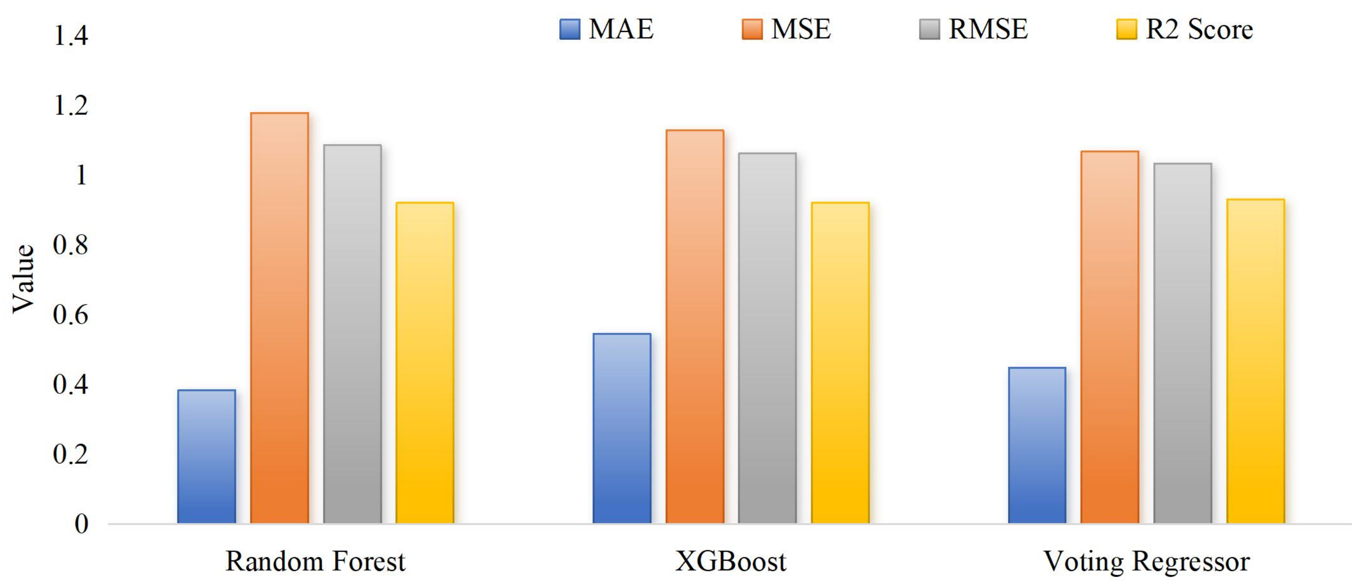

Figure 6—Error percentage plots.

The accuracy of the models was measured using the sklearn metric functions to evaluate the performance of the models with respect to the actual field data. The R-Squared metric was used for the evaluation of the performance of these models.

Table 3—Models' accuracy using statistical metrics.

	Random Forest	XGBoost	Voting Regressor
MAE	0.3836	0.5447	0.4478
MSE	1.1777	1.1275	1.0674
RMSE	1.0852	1.0618	1.0331
R2 Score	0.92	0.92	0.93
Accuracy on train	0.99	0.999	0.999
Accuracy on test	0.92	0.92	0.93

The R-Squared metric is a statistical measure that represents the proportion of the variance for a target variable which is explained by the input parameters. Table 3. shows the accuracy scores of the single models and that of the voting regressor. From the table it was observed that the voting regressor had the best performance of above 1% increase in the accuracy and the R^2 score. This implies that the voting regressor can predict leak in gas pipelines with higher accuracy than the single models.

Conclusion

Data analytics has gained more relevance in the oil and gas industry recently as the industry seeks to analytically use data for optimal productivity and reduction of cost/time management purposes. As data is growing in this industry, the ability of the industry to use this data alongside intelligent models to solve problems is very important and as well useful in the detection of leaks in oil and gas pipelines. In reservoir engineering and other disciplines in the oil and gas industry, history matching is often done, and futuristic predictions are made towards the prediction of either the optimal production rate or the oil in place in a particular reserve. The same is applied in the use of intelligent models to make predictions towards future occurrences in a gas pipeline, with respect to existing dataset recorded. Machine learning models are data driven models, and as such they make use of the basic gas pipeline operational parameters to make predictions of leaks and the locations for which the leak occurs. The problem of detecting leaks is a two-way solution, the first is a classification solution where the model is expected to predict if a leak will occur or not (a yes-or-no-target-solution). The other solution is the regression solution, where the model is expected to either predict the leak location or the leak pressure or both as the case maybe. The solution provided by this project is anchored on the latter to predict both the leak pressure and the leak location.

The results obtained from the models are impressive. The machine learning models perform when compared relatively with the transient models (in use in most gas industries). Because of the limitations in other models the data driven models are now seen to be more effective when it comes to leak detection. From the results obtained above the voting regressor performed better and will absolutely perform best upon deployment.

From the results, it is evident that machine learning models can be used for the predictions and of leaks in a gas pipeline with bigger data volumes. The result indicates that the machine learning models could be used alongside the transient models and leak alarms for effective detection of leaks across gas pipeline networks. Although these models have not been deployed in real time predictions, as such more research can be done in this regard and deployment executed in a pilot gas pipeline plant.

Conflicting Interests

The author(s) declare that they have no conflicting interests.

Reference

Akinsete, O. and Oshingbesan, A. 2019. Leak Detection in Natural Gas Pipelines Using Intelligent Models. Paper presented at the SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 5-7 August, SPE-198738-MS.

Alkhudhair, A. A., Aljubran, F., and Alzannan, R. M. 2022. An Anomaly Detection Model for Oil and Gas Pipelines Using Machine Learning. *Computation* **10**(138): 1-15.

Aniyom, E., Chikwe, A., and Odo, J. 2022. Hybridization of Optimized Supervised Machine Learning Algorithms for Effective Lithology. Paper presented at the SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 1-3 August. SPE-212019-MS.

Boaz, L., Kaijage, S., and Sinde, R. 2014. An Overview of Pipeline Leak Detection and Location Systems. Paper presented at the 2nd Pan African International Conference on Science, Computing and Telecommunications, Arusha, Tanzania, 14-18 July.

Bose, J. R. and Olson, M. K. 1993. TAPS's Leak Detection Seeks Greater Precision. *Oil and Gas Journal* **12**(2):123-135.

Chris, T. and Saguna, A. 2007. Pipeline Detection Techniques. *Annals Computer Science Series* **5**(1):1-17.

Dakheel, A. H., Dakheel, A. H., and Abbas, H. H. 2019. Intrusion Detection System in Gas-Pipeline Industry Using Machine Learning. *Periodicals of Engineering and Natural Sciences* **7**(3): 1030-1040.

Ekeopara, P., Odo, J., and Obah, B., et al. 2022. Hybridized Probabilistic Machine Learning Ranking System for Lithological Identification in Geothermal Resources. Paper presented at the SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 1-3 August. SPE-212015-MS.

Nicola, C. I., Nicola, M., and Hurezeanu, I. 2018. Pipeline Leakage Detection by Means of Acoustic Emission Technique. *Journal of Mechanical Engineering and Automation* **8**(2): 59-67.

Obibuike, U. J., Kerunwa, A., and Udechukwu, M., et al. 2020. Mathematical Approach to Determination of the Pressure at the Point of Leak in Natural Gas Pipeline. *International Journal of Oil, Gas and Coal Engineering* **6**(1):1-15.

Olawuyi, P. D. and Tubodenyefa, D. Z. 2019. Review of the Environmental Guidelines and Standards for the Petroleum Industry in Nigeria. In Institute for Oil, Gas, Energy, Environment and Sustainable Development (OGEES Institute), Afe BabalolaUniversity, Ado Ekiti, Nigeria.

Santos, R. B., Sousa, E. O., and De Silva, F. V., et al. 2014. Detection and On-Line Prediction of Leak Magnitude in a Gas Pipeline Using an Acoustic Method and Neural Network Data Processing. *Brazilian Journal of Chemical Engineering* **31**(1): 145-153.

Skalle, P. and Aamodt, A. 2020. Downhole Failures Revealed Through Ontology Engineering. *Journal of Petroleum Science and Engineering* **191**(3): 107-128.

Turner, N. C. 1991. Hardware and Software Techniques for Pipeline Integrity and Leak Detection Monitoring. Paper presented at the SPE Offshore Europe, Aberdeen, United Kingdom, 3-6 September. SPE-23044-MS.

Aniyom Ebenezer is a Petroleum Engineer and Data Science researcher specializing in energy systems and data-driven engineering solutions. He holds a B.Eng. in Petroleum Engineering from the Federal University of Technology, Owerri. Currently as a Graduate Trainee Engineer at Hydroserve Oil Services, he has also worked as a Data Science Intern at Qwasar and a Researcher at Elitar Consult. His research interests include machine learning applications in the oil and gas industry, digital transformation, and process optimization.

Anthony Ogbaegbe Chikwe is a Senior lecturer in the department of Petroleum Engineering, Federal University of Technology, Owerri. He holds both Bsc and Msc degree in Petrochemical Engineering from the University of Oil and Gas, Moscow. He also holds Post graduate Certificate in Advanced Studies in Academic practice from Newcastle University upon Tyne, UK and Ph.D degree in Petroleum Engineering from the Federal University of Technology, Owerri. His research interests are in production, reservoir, natural gas and drilling Engineering. He is also a fellow of the Higher Education Academy, UK.