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Optimized LSTM Model Using Artificial Bee Colony Algorithm for Crude Oil Production Forecasting in Nigeria

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Abstract- In the oil and gas sector, economic planning and decision-making depend heavily on forecasting crude oil production. Crude oil production has been predicted using a variety of methods. Techniques based on deep learning show promise because they have been successfully implemented in many industries and can be used at many phases of the oil exploration and production process. Still, the oil industry needs more work in this regard. This study proposes an optimized Long Short-Term Memory model by Artificial Bee Colony ABC for oil production prediction. The methodology employed is the CRISP-DM methodology (Data Mining) for a structured approach. The proposed model was applied using real data from 323 oils that were developed and 265 oil wells from flow stations. The model was developed in a Google Colab environment, trained, tested, and evaluated well. The result of the model prediction is 1,428,751 barrels of crude oil production per month, the LSTM model was optimized using the Artificial Bee Colony Algorithm successfully and all three regression models namely the GA-GB model, Bagging Regressor, and KNN had lower scores when compared with the optimized model. Further studies suggest exploring novel techniques and methodologies to enhance model interpretability and scalability using robust real-life data

Keywords Artificial Bee Colony (ABC), Machine Learning, Data Mining, LSTM, Deep Learning, GA-GB model, Bagging Regressor, and KNN

I. INTRODUCTION

The process of locating and obtaining natural gas and petroleum from the subterranean is known as oil and gas exploration. Nigeria's oil and gas exploration process involves several phases, including seismic survey, exploratory drilling, appraisal, and development. The first step involves mapping subsurface structures using seismic data. If oil or gas is found, more wells are drilled to assess the reservoir's size and commercial potential. Once commercially feasible, the field is developed and production infrastructure is erected. After Angola, Nigeria is Africa's second-largest producer of gas and oil. Nearly 90% of Nigeria's export value and 9% of its GDP come from the oil and gas sector. Nigerian oil and gas exploration is dealing with several problems [1]. Handling large volumes of data generated during exploration and production can be challenging. Traditional methods may not fully exploit the potential insights from this data. Oil spills, gas flaring, pipeline vandalism. Security threats and social unrest from militant groups, local communities, and oil thieves poses a challenge to the oil sector. The delay in passing the Petroleum Industry Bill has created regulatory uncertainty and fiscal instability. The high costs and technical difficulties associated with the exploration and development of deep-water and unconventional resources [2]. Data analytics, deep learning, and machine learning can offer appropriate answers for these contemporary problems by, optimizing the drilling, production, and well stimulation operations utilizing real-time data and predictive analytics. Improving the precision and effectiveness of seismic data interpretation, reservoir characterization, and geological modeling. Using IoT sensors and anomaly detection to improve the upkeep and dependability of infrastructure and equipment. Predictive maintenance, regulatory compliance, environmental monitoring, reservoir management, and infrastructure optimization are among the applications of machine learning algorithms. They can foresee equipment breakdowns, identify security risks, and streamline extraction procedures by analyzing sensor data. In addition, they can support the optimization of infrastructure operations, regulatory compliance, and production trend prediction. All things considered, machine learning algorithms can lessen investor uncertainty, increase operational efficiency, and decrease downtime [3].

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Many businesses began their drive toward ever-large quantity and quality of data when they recognized that the sheer volume of data, they already had exceeded the capacity, structure, capacity, and governance of their organizations [4]. These days, data is always being generated in a recurrently streaming manner due to inputs from various applications. These generated data can come from wired or wireless sensor networks, which are frequently employed in a variety of disciplines including geography, traffic, the internet of things (IOT), financial tickers, web2 and web3, e-commerce, social networks, and online communities [5]. This sharp increase in data traffic at the sensors from socialnetworks, e-commerce, and multimedia data streams is a new difficulty for businesses [6]. The oil and gas sector is currently living in the "Industry 4.0" age, along with the rest of the globe. As reservoirs are built, gauges and specific events provide an increasing number of both static and dynamic data (e.g., geological data, reservoir characteristic and fluid characteristics data, surveillance data, test data, experimental data, etc.). Making the most of this data has emerged as a new area of interest for researchers and technologists. The ability to estimate well performance quickly and accurately is becoming more and more crucial for optimizing and correcting development. Deep learning can be used to forecast performance more accurately thanks to advancements in artificial intelligence [7]. Decision-makers can benefit from accurate performance prediction results by having a strong foundation and trustworthy support. An essential component of the decision-making process for oil businesses is the capacity to forecast the production from oil wells. According to Ibrahim et al., Forecasting oil and gas production for hydrocarbon wells is challenging due to the time-consuming and resource-intensive nature of reservoir simulation software. A study suggests using machine learning and deep learning models to speed up forecasting, with XGBoost, ANN, and RNN models achieving high R2 scores [8]. Middle Eastern carbonate reservoir's production performance was predicted using a Long Short-Term Memory (LSTM) neural network model, incorporating gas injection effects. The model was trained and validated using historical data from the first 4000 days. The LSTM approach had an average inaccuracy of 43.75% less than conventional RNS, and only accounted for 10.43% and 36.46% of RNSs in CPU time and computational power consumption. Nigeria's oil and gas industry plays a major role in the nation's economy, contributing significantly to both its GDP and export revenue [7]. Nonetheless, the business has a lot of obstacles to overcome, such as problems with production optimization, pipeline security, and reservoir characterization. Its traditional data analysis methods often fall short in effectively harnessing the potential of this data due to its high dimensionality, non-linearity, and noise. Deep learning, a formidable branch of artificial intelligence, holds the key to transforming this industry's data processing and successfully tackling these issues [9].

II. LITERATURE REVIEW

This study explores the use of deep learning-based data analysis models in the oil and gas industry, highlighting their potential for 98% accuracy in forecasting production, subsurface drilling lost circulation severity classification, risk assessment, production forecasting, well-monitoring, and reservoir production forecasting.

A. Deep Learning Techniques in Data Analysis for the Oil and Gas Sector

Deep learning algorithms, such as GANs, RNNs, and CNNs, are being utilized in the oil and gas sector for tasks like reservoir characterization, anomaly identification, predictive maintenance, well-log analysis, production forecasting, fault detection, and drilling optimization [10]. The majority of the literature on data analysis applied to the oil and gas industry is not based on African datasets and domains, even though data analysis research has been booming [11]. A hybrid approach combining Vision Transformer and YOLOv5 computer vision techniques for pipeline fault detection, maintaining high precision and outperforming the YOLOv5 algorithm in classification accuracy [12]. This research proposes a unified cooperative inversion framework for geothermal, oil and gas, and mineral exploration data interpretation that blends conventional separate inversions with deep neural networks (DNNs). The DNN enhances the original deterministic inversion models, and the system exhibits strong generalization capabilities. The efficiency of the DL-based approach is confirmed by synthetic experiments, which show it to be more accurate and efficient than both cross-gradient-based joint inversion and traditional separate inversions. Applying it successfully to field data further demonstrates its efficacy [7].

B. Optimization Strategies for Deep Based Learning-Data Analysis

Researchers are enhancing the effectiveness of deep learning models in the oil and gas sector by customizing them for specific tasks, using regularization and hyperparameter optimization strategies [13]. As a new tool for improving deep learning models, another study generated the "Adaptive Gradient Rectification" (AGR) optimization technique [14]. a novel optimization technique for deep learning models called the "Adaptive Gradient Clipping" (AGC) algorithm [15]. The study presents a hybrid AI method that uses deep learning and multi-objective optimization to create a reservoir potential map, reducing optimization time by 82% and 95% [16]. An accurate oil production prediction model for Enhanced Oil Recovery (EOR) performance, combining Convolutional Neural Networks (CNN) and Gate Recurrent Unit (GRU) neural networks. The model outperforms common deeplearning techniques and a hybrid approach in two case studies [17].

C. Optimization and Hyperparameter Tuning

Researchers optimize deep learning models using grid search, evolutionary algorithms, and Bayesian optimization for oil and gas data analysis tasks, improving generalizability, accuracy, and resilience [18]. This paper presents an HPO technique that reduces wait times and computing needs in two steps. It evaluates a small portion of the training dataset for hyperparameters and reevaluates the best-performing models after training. This method has been used in up to 135 times faster neural network simulators for aerosol activation [19]. The paper enhances flood hazard mapping models in Ningxiang City, China, using hyperparameter optimization techniques. It considers 2064 flood locations and 19 pluvial factors, focusing on hybrid models and Bayesian optimization. Key factors include topography relief, rainfall intensity, river distance, and rainfall [20].

D. Optimized Deep Learning Architectures

This chapter introduces CoDeepNEAT, an automated technique for deep learning architecture optimization using volution, achieving object recognition and language modeling outcomes comparable to human designs, and highlighting its potential for future deep learning applications [21]. This study uses an enhanced version of the Chimp Optimization Algorithm to determine the ideal DCNN design, modifying the baseline in three ways. The model outperforms other benchmarks in 87 out of 95 studies, demonstrating autonomous DCNN architecture evolution [22]. Researchers are enhancing deep learning architectures like CNNs, RNNs, and LSTM networks to meet sector requirements, utilizing feature engineering, transfer learning, and ensemble learning [23].

E. Handling Complex and High-Dimensional Data

Seismic data and well-log data are two examples of the sophisticated, high-dimensional data that are used in the oil and gas industry. Deep learning models, such as autoencoders, variational autoencoders, and t-SNE, are utilized for dimensionality reduction and feature selection in the oil and gas industry [24]. A study suggests using a genetic algorithm known as GARS to quickly and precisely identify features in high-dimensional, multi-class datasets. GARS has superior performance compared to conventional filter-based and wrapper selection techniques, showcasing good classification accuracy and manageable computation times. If typical methods don't work for high-dimensional data analysis, this approach can help [25]. The proposed dimensionality reduction fusion technique accurately classifies lung cancer biomarkers using random forest, feature extraction, and neural networks, accurately identifying cancerous or noncancerous groups [26]. Researchers developed the Binary Enhanced Golden Jackal Optimization (BEGJO) metaheuristic FS method, which minimizes high-dimensional feature selection problems using Copula Entropy. The method, evaluated on high-dimensional benchmark datasets, ranks fourth in processing time and outperforms other algorithms in feature dimension and classification accuracy [27].

F. Performance Evaluation of Deep Learning-Based Data Analysis Model

Nesrine et al., found ensemble learning voting classifiers outperform other models in accuracy and prediction accuracy, surpassing deep learning predictions in both simulated and real datasets. Studies compare deep learning models in oil and gas industry, evaluating accuracy, efficiency, scalability, and interpretability[28]. Ensemble learning techniques outperform traditional methods [29].

III. METHODOLOGY

The study uses CRISP-DM methodology to develop and evaluate an optimized deep-learning model for oil prediction in Nigeria, utilizing data from various terminals and marginal fields to understand challenges in oil production.

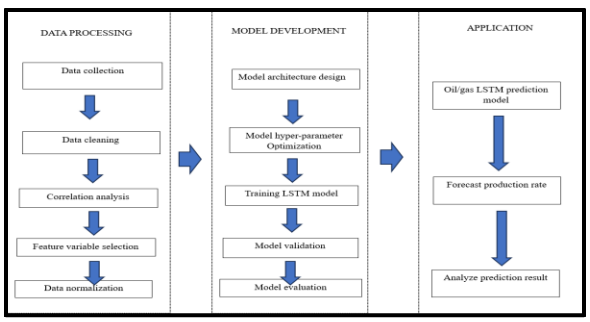

Fig. 2. Model workflow

A. Business understanding

Nigeria's oil output faces challenges such as corruption, waste, and efficiency issues. To improve the sector, it is crucial to understand the nuances of oil extraction, transportation, exploration, and market fluctuations. This knowledge can help reduce risks, streamline procedures, and make informed decisions for a more robust and successful sector [30].

B. Data understanding

Understanding Nigeria's oil industry requires examining the characteristics and limitations of current datasets, including production data. This includes analyzing oil output, reserves, exploration, and cost. Each dataset has its limitations, such as biases, incomplete values, or inaccurate data collection techniques. Examining relationships between features, such as oil output and global prices, is crucial [30].

C. Data collection

Gathering the data needed to train the model is the first stage. Numerous sources, including well logs, seismic data, and production logs, can provide this information. To eliminate any mistakes or discrepancies, the data must be cleaned, and pre-processed oil exploration [31].

D. Data preparation

Data preparation involves data cleaning, integration, and transformation to ensure model building quality. This process involves locating and correcting inaccurate or corrupt records, removing incomplete, imprecise, or irrelevant data. Tools like data wrangling can be used for interactive or batch cleansing. This includes seismic data normalization, geological feature integration, and resolving missing values and data imbalances[31].

E. Correlation analysis

Correlation analysis is a crucial step in model training, determining the relationship between candidate feature variables. It helps identify redundant variables, select relevant features, and understand data relationships. High positive correlations indicate a strong relationship, while low correlations indicate minimal linkage. Correlation analysis helps in identifying and understanding data relationships [32].

F. Feature Variable Selection

The next step involves extracting and converting relevant data into a model-friendly format, such as production logs, to build features like gas, water, and oil production rates. Feature variable selection aims to capture essential elements for forecasting, such as oil and gas production rates and reservoir parameters, for a precise prediction of Nigerian oil and gas exploration results [31].

G. Modelling

The LSTM model for oil and gas forecasting is refined using Artificial Bee Colony optimization, a nature-inspired metaheuristic technique. This iterative optimization reduces prediction error and increases accuracy. The model is developed using PyTorch frameworks, enhancing its predictive capabilities and robustness. The process includes several crucial steps.
1. Architecture Design: Model architecture design is the process of determining the architecture of a machine learning model, focusing on layers, types, and relationships. It involves considering factors like dataset size, problem type, and computing capacity. The architecture is customized to meet the unique demands of oil and gas prediction activities [32].

2. Hyperparameter Optimization: The Artificial Bee Colony optimization algorithm is used to explore the hyperparameter space of a LSTM model to optimize its predictive performance. This process involves tuning parameters like learning rate, dropout rate, batch size, and epoch number. The goal is to maximize predictive accuracy, model generalization, and efficiency [33].

3. Define Search Space: The first step is to define the search space for each hyperparameter. This includes specifying the range or set of values that each hyperparameter can take. For example, the learning rate may range from 0.001 to 0.1, while the batch size may vary from 16 to 128.

4. Select Optimization Technique: The ideal set can be located by searching the hyperparameter space using a variety of optimization approaches. Grid search, random search, Bayesian optimization, genetic algorithms, and evolutionary tactics are examples of common techniques.

5. Objective Function: Define an objective function that quantifies the model's performance on a validation dataset for a given set of hyperparameters. This could be a loss function such as mean squared error (MSE) mean absolute error (MAE), or any other relevant metric.

6. Hyperparameter Tuning: Evaluate the objective function for various hyperparameter configurations by iteratively exploring the hyperparameter space using the optimization technique of your choice. The best-performing model is indicated by the combination of hyperparameters that minimize the value of the objective function.

7. Validation and Evaluation: The optimized LSTM model in Nigeria is tested on a separate dataset to assess its generalization ability and performance. The optimization process enhances the model's predictive accuracy, robustness, and reliability, contributing to informed decision-making and resource allocation [33] (Nwulu and Lekan, 2021).

H. Model Training: The prepared dataset is used to train the optimal LSTM model, which uses past data to uncover underlying patterns and correlations. The model iteratively modifies its parameters during training to reduce prediction error and enhance predictive power using the input-output pairs that are supplied. Once the features are engineered, the model may be trained. To accomplish this, the relationships between the features and the target variable must be found using a deep learning method. The goal variable, such as the future rate of oil production, is the variable that the model is trying to predict [31].

I. Validation and Evaluation: After training, the model needs to be evaluated to see how well it performs. This can be done with a holdout dataset that was not used to train the model. The trained LSTM model is validated and evaluated using held-out data or cross-validation techniques to assess its generalization ability and predictive accuracy. Various metrics, such as mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R-squared), are used to quantify the model's performance [31] (Alfares 2023).

J. Fine-tuning and Iteration: To enhance its performance, the LSTM model may go through more iterations and fine-tuning in light of the evaluation outcomes. In this iterative process, the model is retrained, the architecture is improved, and the hyperparameters are adjusted until the desired outcomes are obtained. The objective is to create a reliable and precise predictive model for oil and gas exploration in Nigeria through the utilization of Artificial Bee Colony optimization and Long Short-Term Memory networks. The Nigerian oil and gas industry might greatly benefit from this model's ability

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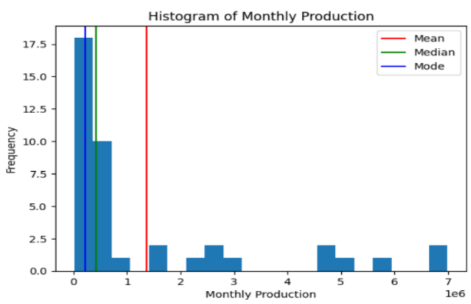
to enhance decision-making procedures, resource allocation plans, and overall exploration efficiency [31](Alfares, 2023).

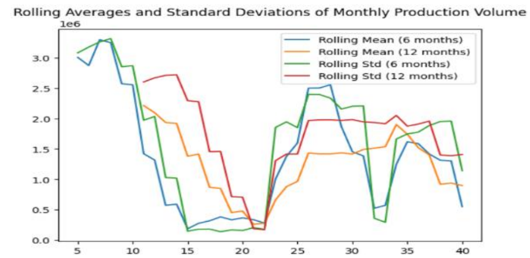
IV. RESULT AND DISCUSSION

Our main objective is to address the unique difficulties faced by Nigeria's oil and gas sector and give stakeholders useful information. The study's main conclusions, takeaways, and ramifications for Nigeria's oil and gas industry are presented in the parts that follow. After identifying and analyzing the trends and patterns in oil production, we move on to the creation and improvement of the LSTM model. In conclusion, we assessed our model's performance and compared it with current model.

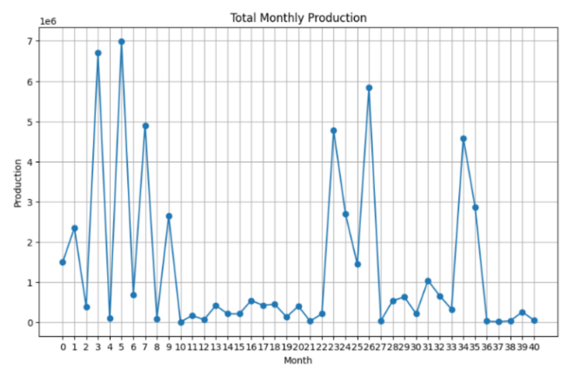
A. Identification and Analysis of Trends



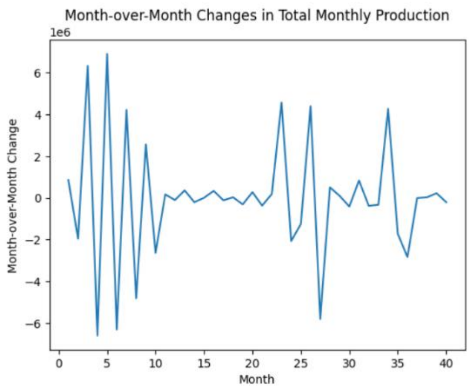
The mean production volume in the dataset is 1,360,601. This indicates an average monthly production volume of around this value, with a significant increase in high production values. The median production volume is 423,567, with half of the monthly volumes below this value and half above it. The median production value is lower than the mean, suggesting a right-skewed distribution. The mode production volume is 214,168, indicating the most frequent production volume in the dataset. The standard deviation of 1,978,452.41 indicates that monthly production quantities deviate by 1.98 million units from the mean output, affecting forecasting and planning processes. The monthly production levels within the dataset are around 6,983,202, indicating significant fluctuation in output quantities over time. This variation in output volumes is noteworthy when compared to industry benchmarks. The mean production volume is significantly higher than the median and mode, suggesting a right-skewed distribution.

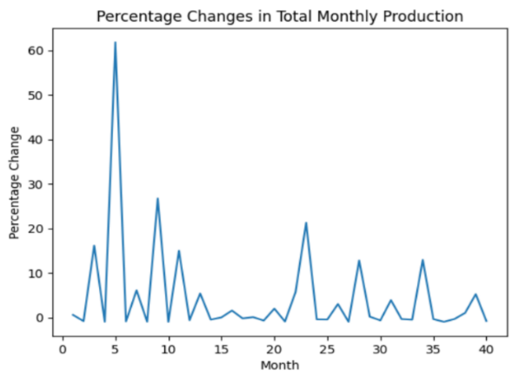


The average oil production over months was 1,411,930 barrels, with rolling averages indicating long-term trends. Monthly production showed high output volatility, possibly due to factors like security, market swings, operational adjustments, or external events. Low volatility intervals were represented by numbers like 10645.68, 62829.9, and 83229.39, with a relatively constant standard deviation indicating steady output levels. The data showed no discernible linear trend, instead exhibiting erratically fluctuating values, with no discernible linear trend.



The plot displays monthly production values over time, indicating potential trends like unstable levels and seasonal fluctuations. The zigzag pattern suggests irregular fluctuations, possibly due to seasonal variations, changes in production processes, or external economic influences. Without more context, it's difficult to draw definitive conclusions. Further analysis, such as seasonal decomposition, time series forecasting, or correlations with other variables, could provide more insights into the underlying patterns and drivers of the production data.





The percentage changes vary significantly, ranging from a high of 61.82% increase to a low of -0.99% decrease. There seems to be no clear seasonal pattern or trend in the data without additional information. Some months experience large fluctuations (positive or negative), while others show more modest changes or remain flat.

B. Development and Optimization of LSTM Model

When the Artificial Bee Colony method was used to optimize the LSTM model, it showed encouraging results in tackling the problems that were found. Increased precision in output rate forecasting. increased effectiveness in decision support and risk assessment. Optimal hyperparameter tuning leads to improved resilience and dependability of the model.

The targeted hyperparameter that ABC is used to optimize is the learning rate. Start an artificial bee population from scratch. The bee locations are iteratively updated using the ABC method depending on model performance, or fitness. The LSTM model is evaluated using cross-validation with various hyperparameters. Update the best answer that the bees could find. The input size of the LSTM model is 115, the hidden layer size is 64, and the output size is 1. The mean square error (MSE) of the model was 95.9% overall. According to our prediction, the monthly oil output will be around 1,428,751 barrels.

C. Evaluation and Benchmarking

The obtained results were rigorously evaluated and benchmarked against recently reported models. Comparative analysis highlighted the effectiveness and competitiveness of our approach. When compared with three regression models, namely the GA-GB model, the Bagging regressor and KNN had 95.9%, 99%, and 98.2% R squared respectively, for the Mean Absolute Error (MAE) GA-GB 0.04, Bagging regressor 0.006, and KNN 0.009. lastly, Mean Squared Error (MSE) GA-GB 0.007, Bagging regressor 0.0003 and KNN 0.0005.

V. CONCLUSION

Our study achieves significant progress in developing an optimized deep-learning model for oil prediction in Nigeria. A new LSTM model with artificial bee colonies was developed to accurately predict oil output. The model was tested on oil production data from the Department of Petroleum Resources, revealing a monthly production of 1,428,751 barrels below the OPEC average. The manufacturing volume fluctuated erratically, and the LSTM-ABC model performed the best compared to the Novel models. We successfully identified and analyzed the current issues in oil production in Nigeria, providing valuable insights into the challenges faced by the industry. Our study effectively developed and optimized an LSTM model using the Artificial Bee Colony algorithm, showcasing significant improvements in predictive accuracy and robustness. The obtained results were thoroughly evaluated and benchmarked against recent models, affirming the effectiveness and competitiveness of our approach in the Nigerian context.

There are areas for improvement and future research. This includes further refinement and optimization of deep learning models to address evolving exploration challenges, integration of additional data sources, and exploration of advanced optimization techniques.

Continuous collaboration with industry stakeholders and ongoing innovation will drive the evolution of our approach and its application in the Nigerian oil sector.

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