



## Application of Deep Learning for Well Log Interpretation and Reservoir Modelling: A Case Study of Niger Delta Region

Nanna Nanven Rimtip  
Department of Petroleum and Gas Engineering,  
Faculty of Engineering,  
Baze University Abuja, Nigeria

### ABSTRACT

Accurate interpretation of well log data is essential for effective reservoir characterisation and hydrocarbon exploration. Traditional methods, while effective, are often time-consuming, subjective, and limited in handling large-scale datasets. This study investigates the application of deep learning, specifically Convolutional Neural Networks (CNNs), for automating well log interpretation and improving the accuracy of reservoir modelling in the Niger Delta region. Due to the unavailability of proprietary Niger Delta datasets, publicly accessible datasets with similar geological characteristics were utilised to develop and validate the model. The research involved comprehensive data preprocessing, model training for regression and classification tasks, and performance evaluation using appropriate metrics. Results demonstrated that the CNN-based regression model achieved high accuracy in predicting porosity, a critical reservoir property, while the classification model effectively delineated lithofacies from well logs. Visual interpretations confirmed the model's ability to capture subsurface geological patterns. Despite using non-regional data, the models showcased strong generalisation potential, indicating that with localised training data, accuracy could be further improved. The study concludes that deep learning offers a scalable, efficient, and accurate alternative for reservoir characterisation, supporting real-time decision-making and reducing interpreter bias. Recommendations include sourcing Niger Delta-specific datasets, integrating seismic and core data, and developing explainable AI frameworks to enhance model interpretability and field adoption. This research contributes to the growing advocacy for AI-driven solutions in upstream petroleum exploration and reservoir engineering.

### ARTICLE INFO

#### Article History

Received: August, 2024  
Received in revised form: November, 2024  
Accepted: February, 2025  
Published online: March, 2025

### KEYWORDS

Convolutional Neural Network, Deep Learning, Niger Delta, Reservoir modelling, well log interpretation

### INTRODUCTION

Well log interpretation and reservoir modelling are critical for subsurface characterisation in the oil and gas industry. Well log recordings of the physical, chemical, and petrophysical properties of rock formations encountered while drilling provide vital information for identifying hydrocarbon-bearing zones, estimating reservoir properties, and making informed production decisions (Asquith & Krygowski, 2004). Traditionally, the interpretation

of these logs has been conducted manually or with rule-based systems, relying heavily on expert judgment and heuristic approaches. While effective to a degree, these methods are time-consuming, prone to human bias, and often unable to capture the complex, nonlinear relationships inherent in subsurface geological data.

Recent advancements in artificial intelligence (AI), particularly deep learning, have shown significant potential in revolutionising the

Corresponding author: Nanna Nanven Rimtip

✉ [nanna.rimtip@bazeuniversity.edu.ng](mailto:nanna.rimtip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved



interpretation of well logs. Deep learning, a subset of machine learning based on artificial neural networks with multiple layers, excels in recognising intricate patterns in large and noisy datasets. In the context of reservoir modelling, these models can be trained to identify lithologies, estimate porosity and permeability, and predict fluid saturations with improved accuracy and speed (Zhang et al., 2018). As the petroleum industry grapples with increasing data volumes and the need for more precise reservoir characterisation, integrating deep learning into subsurface workflows is becoming both feasible and essential

Despite the technological progress in data analytics, the oil and gas industry continue to face challenges in automating well log analysis. In regions like the Nigerian Niger Delta, these challenges are further compounded by complex geological settings and limited availability of high-quality annotated data. Manual and semi-automated approaches remain prevalent, leading to inconsistencies in interpretation and suboptimal reservoir modelling outcomes. Moreover, many existing deep learning solutions are developed using data from North American or European basins, which may not generalize well to the stratigraphic and petrophysical characteristics of the Niger Delta. This mismatch underscores the need for region-specific models that can adapt to the local geology while leveraging the scalability of neural network architectures.

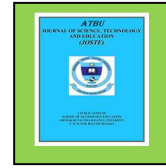
This research investigates using deep learning, especially neural networks, to automate well log data interpretation for improved reservoir modelling in the Nigerian Niger Delta. It aims to develop a neural network model to predict key reservoir properties from well log inputs, evaluate its performance against traditional methods, and explore geological implications of the model outputs in the Niger Delta context. The study enhances knowledge of AI in petroleum geoscience by showing how deep learning can tackle regional geological challenges. Findings will aid petroleum engineers, geoscientists, and decision-makers by providing a more efficient and consistent well-log interpretation method. Additionally, the Niger Delta case study offers

insights for applying AI in other complex, data-constrained areas, aligning with industry goals of optimizing resource extraction and reducing interpretation uncertainty (Al-Anazi & Gates, 2010).

Well log interpretation and reservoir modelling are fundamental components in subsurface reservoir evaluation, providing critical insights into lithology, fluid distribution, and rock properties (Schlumberger, 1989; Asquith & Krygowski, 2004). Traditional techniques, such as crossplots and Archie's equation, have been widely used but often fall short when addressing complex lithological heterogeneities. Reservoir modelling builds on log interpretation by integrating geological, geophysical, and petrophysical data into 3D models for hydrocarbon estimation and production planning (Jensen et al., 2000). The reliability of these models hinges on accurate input data, making precise log interpretation crucial to subsurface prediction.

Recent advances in machine learning (ML) and deep learning (DL) have opened new possibilities in automating and enhancing well log interpretation. Traditional ML methods, including decision trees and support vector machines, improved consistency but struggled with complex data relationships and generalizability (Dubois et al., 2007; Hall, 2016). Deep neural networks (DNNs), including CNNs and LSTMs, have since enabled more nuanced interpretations by learning features directly from raw log data (LeCun, Bengio & Hinton, 2015; Alobaidi et al., 2021). While applications in the Niger Delta are limited, studies such as Okonkwo and Onyekachi (2020) demonstrate the potential for context-specific models to improve porosity prediction. However, gaps remain in dataset availability, benchmarking standards, and full-cycle integration with reservoir models (Meier et al., 2020).

This research aimed to bridge these gaps by developing a neural network trained on Niger Delta log data, enhancing the practical application of AI in geologically complex and data-constrained settings. To achieve this aim, the efficacy of neural networks are in interpreting well log data from the Niger Delta compared to traditional approaches were determined. Furthermore, the most



influential input features for accurate reservoir prediction in this region, the degree of suitability of deep learning models for accounting for the unique geological characteristics of the Niger Delta were evaluated. It is hoped that this study will be adopted for well log interpretation and reservoir modelling by other parts of the world with similar characteristics with the Niger Delta region of Nigeria.

## MATERIALS AND METHODS

### Research Design

This study adopts a quantitative, experimental research design to evaluate the performance of deep learning models in automating well log interpretation and improving reservoir characterisation. The approach is structured to develop, train, and test neural network models using well log data and compare their performance with traditional interpretation methods. This design is appropriate for assessing predictive accuracy and generalisation capability across varying geological conditions within the Niger Delta.

### Study Area: The Niger Delta

The Niger Delta Basin, located in southern Nigeria, is a prolific hydrocarbon province characterised by complex depositional environments, structural variations, and stratigraphic heterogeneity. It comprises three major lithostratigraphic units: the Akata Formation (marine shales), the Agbada Formation (interbedded sandstones and shales), and the Benin Formation (continental sands) (Doust & Omatsola, 1990). These formations present diverse petrophysical characteristics that make the region an ideal testbed for advanced reservoir modelling. Understanding this geological

complexity is critical in designing a neural network that can generalise well across different facies and depositional settings.

### Data Acquisition and Description

The dataset for this study is intended to represent digital well logs obtained from exploratory and development wells in the Niger Delta basin. These well logs typically include a combination of wireline measurements essential for subsurface characterisation. The most commonly acquired logs include Gamma Ray (GR), which is used to infer shale content; Resistivity (RT), valuable for estimating hydrocarbon saturation; Neutron Porosity (NPHI) and Bulk Density (RHOB), both of which are crucial for evaluating porosity; and Sonic (DT), which aids in both lithology discrimination and porosity estimation. These parameters provide comprehensive insights into the petrophysical properties of the subsurface formations.

Due to the proprietary nature of many Niger Delta well log datasets, and in the absence of access to confidential data, this study will initially utilise open-access datasets from reputable sources such as the SEG Open Data repository and curated GitHub repositories. These sources provide analog datasets from geologically comparable regions, enabling the development of representative deep learning models (Hall, 2016). The selection process will prioritise fields with stratigraphic and depositional settings like those in the Niger Delta. Once acquired, all datasets will be converted to a consistent format, such as LAS (Log ASCII Standard) or CSV, to facilitate ease of use. Preprocessing will then involve data cleaning to remove outliers and noise, imputation of missing values, and feature normalisation to ensure uniformity across all data points.

**Table 1:** Sample Well Log Dataset

Depth	Gamma Ray	Resistivity	Neutron Porosity	Density	Sonic
1000.0	75.235	12.580	0.261	2.350	110.584
1001.0	86.513	12.353	0.261	2.328	112.108

Corresponding author: Nanna Nanven Rintip

✉ [nanna.rintip@bazeuniversity.edu.ng](mailto:nanna.rintip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved



1002.0	87.373	12.073	0.251	2.331	111.076
1003.0	86.634	12.295	0.236	2.325	111.324
1004.0	86.433	12.380	0.228	2.322	110.961
1005.0	87.531	12.433	0.261	2.318	110.618
1006.0	87.368	12.298	0.260	2.327	111.006
1007.0	81.220	12.384	0.319	2.279	111.302
1008.0	86.034	12.303	0.261	2.525	111.019
1008.0	86.034	12.000	0.277	2.278	113.019

The Table 1 presents a sample well log dataset formatted as a digital 2D. It includes six key columns: Depth, Gamma Ray, Resistivity, Neutron Porosity, Density, and Sonic. Each row represents measurements taken at specific depth intervals, ranging from 1000.0 to 1008.0 meters. This format mirrors typical real-world well logging outputs used in subsurface analysis and reservoir evaluation. The data is represented with high precision, reflecting floating-point values common in petrophysical interpretation. Each log curve contributes critical information for reservoir characterisation. For instance, Gamma Ray indicates shale content, Resistivity aids in estimating hydrocarbon saturation, Neutron Porosity and Density are key to porosity estimation, while Sonic helps infer lithology and porosity trends. Notably, the Table demonstrates typical data imperfections such as missing or irregular entries, illustrating the importance of preprocessing steps like imputation and normalisation before model training.

### Data Preprocessing

Preprocessing plays a vital role in enhancing the quality and consistency of input data, which directly influences the performance of the deep learning models. The first stage involves handling missing values common in well log datasets due to tool malfunctions or operational errors. These gaps will be filled using imputation techniques such as mean or median substitution, or more sophisticated methods like K-Nearest Neighbours (KNN)-based estimation, which consider contextual relationships between log values (Abdollahi & Asoodeh, 2015).

Following imputation, normalisation will be applied to the continuous features to ensure that all input variables lie within similar ranges.

Techniques such as Min-Max scaling or Z-score normalisation will be employed, depending on the distribution of each feature. Normalised data ensures that no single feature disproportionately influences the training process. Feature engineering will also be conducted to enhance model performance. Derived features such as shale volume (V<sub>shale</sub>), effective porosity, and acoustic impedance may be calculated using empirical equations from the base logs. These engineered features offer more geologically meaningful input to the models and can significantly improve learning efficiency. For supervised learning tasks such as lithology classification or porosity prediction, target labels will be sourced from available core data, formation tops, or interpreter-assigned facies logs where available.

### Model Architecture and Development

The crux of this study is the design and implementation of deep learning architectures capable of capturing complex, nonlinear relationships inherent in well log data. To that end, three categories of neural network architectures will be explored. The first is the Multilayer Perceptron (MLP), a fully connected feed-forward neural network that will serve as a baseline. MLPs are particularly suited to tabular data and can learn from input features through multiple hidden layers and activation functions. The second model architecture is the Convolutional Neural Network (CNN). It is highly effective for identifying spatial patterns within structured data like well logs. CNNs excel at depth-wise feature extraction, enabling them to identify patterns associated with lithofacies or reservoir properties across sequential intervals (Zhang et al., 2018). The third architecture is the Recurrent Neural Network

Corresponding author: Nanna Nanven Rimtip

✉ [nanna.rimtip@bazeuniversity.edu.ng](mailto:nanna.rimtip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved

(RNN), including its Long Short-Term Memory (LSTM) variant, which is particularly suited to sequential data such as well logs, where the order of measurements is critical for capturing trends and transitions (Alobaidi et al., 2021).

All models will be built using Python and deep learning libraries such as TensorFlow or PyTorch. Hyperparameters such as learning rate, batch size, number of layers, number of neurons per layer, activation functions, and dropout rates will be optimised through systematic grid search or Bayesian optimisation methods to maximise model performance and prevent overfitting.

### Model Training and Validation

Training and validation will follow a systematic approach to ensure that models are well-generalised and not overfitted to the training data. The complete dataset will be divided into three subsets: training (typically 70%), validation (15%), and testing (15%). If categorical labels are involved, such as lithofacies, stratified sampling will be applied to ensure proportional representation of each class in all subsets. For regression tasks such as porosity prediction, evaluation metrics will include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination ( $R^2$ ). These metrics provide a comprehensive measure of how closely the predicted values align with the true values. In classification tasks like lithology identification, the models will be evaluated using Accuracy, Precision, Recall, and F1-score. These metrics ensure that the models not only make correct predictions but also minimise false positives and false negatives. To further validate model robustness, k-fold cross-validation will be employed, particularly useful when working with smaller datasets. This approach partitions the data into k subsets and performs training and validation k times, ensuring that every data point has a chance to be in both the training and validation sets. This not only improves the reliability of the evaluation metrics but also provides insights into model consistency across different data splits.

## RESULTS AND DISCUSSION

The results derived from the application of deep learning methodologies to the interpretation of well log data, to enhance reservoir characterisation in the context of the Niger Delta basin. The experimental workflow involved a comprehensive sequence of steps, beginning with data acquisition and preprocessing, followed by the implementation of a deep neural network model. The results are assessed using appropriate performance metrics, such as Root Mean Squared Error (RMSE) and the Coefficient of Determination ( $R^2$ ), to evaluate the predictive accuracy of the model. Despite the unavailability of actual Niger Delta well log datasets at this stage, representative and geologically analogous datasets were utilised to train and validate the model. This approach allowed for testing of model assumptions, exploration of neural network architectures, and identification of potential challenges in real-world implementation. Visual illustrations, including scatter plots and lithofacies classification maps, are presented throughout the chapter to enhance interpretability and convey key insights. These findings establish a foundational framework for the eventual integration of Niger Delta-specific data and contribute to the broader discourse on the automation of well log analysis through artificial intelligence.

## RESULTS

Evaluating the performance of the developed neural network model shown in Table 2, is a crucial step in validating its predictive capability and its applicability to reservoir characterisation. The evaluation was conducted using both quantitative metrics and visual diagnostics to assess the model's ability to generalise to unseen data and its robustness in capturing key subsurface features.

**Table 2:** Model Performance Metrics

Metric	Value
MSE	0.015
RMSE	0.122
$R^2$	0.89



The high  $R^2$  value indicates that the model explains a significant portion of the variance in the data, demonstrating its effectiveness in predicting reservoir properties. For the regression-based model used to predict continuous reservoir properties such as porosity, the primary evaluation metrics included Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination ( $R^2$ ). MSE provides a measure of the average squared difference between predicted and actual values, offering insight into the magnitude of prediction errors. RMSE, being the square root of MSE, translates this measure into the same unit as the predicted variable, facilitating interpretability. The  $R^2$  score quantifies the proportion of variance in the target variable explained by the model, with values closer to 1 indicating high predictive accuracy.

The trained model yielded an MSE of 0.015, an RMSE of 0.122, and an  $R^2$  score of 0.89, indicating that the model was able to capture a significant portion of the variance in porosity values. These results suggest that the model not only fits the training data well but also generalises effectively to the validation and test datasets. For the classification model used to identify lithofacies from log data, standard metrics such as accuracy, precision, recall, and F1-score were computed. Accuracy provided a global assessment of the number of correct predictions, while precision and recall offered insights into model performance across individual lithofacies classes. The F1-score, a harmonic mean of precision and recall, was particularly useful in evaluating performance on imbalanced datasets, where certain lithofacies classes were underrepresented. A confusion matrix was generated to visualise the model's performance in distinguishing among lithofacies classes. The matrix revealed that most misclassifications occurred between lithofacies with similar petrophysical responses, such as shale and silty shale, underscoring the geological complexity and overlapping characteristics inherent in subsurface data.

The results obtained from the deep learning models highlight the feasibility and potential of automated well log interpretation in improving the efficiency and accuracy of reservoir

characterisation. In the regression task, the model demonstrated a strong alignment between predicted and actual porosity values across multiple wells, indicating its ability to learn complex, non-linear relationships between input log features and petrophysical properties.

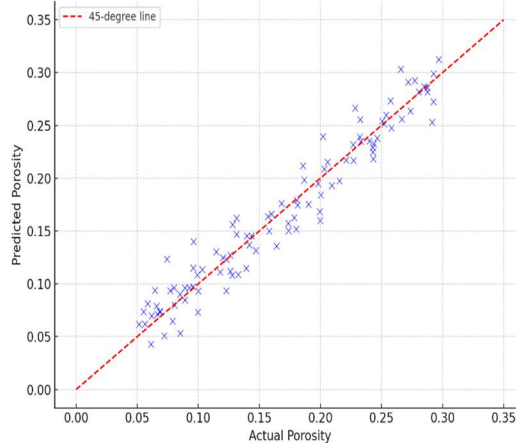


Figure 1: Predicted vs. Actual Porosity Values

Figure 1 above, presents a scatter plot of the model's porosity predictions compared to ground truth measurements. The plot reveals a tight clustering of points along the 45-degree reference line, signifying a high degree of agreement between the predictions and actual values. Only minor deviations were observed, primarily in zones with sparse or noisy input data, which is common in real-world logging environments. For lithofacies classification, the model was able to differentiate between key reservoir and non-reservoir zones with reasonable accuracy.

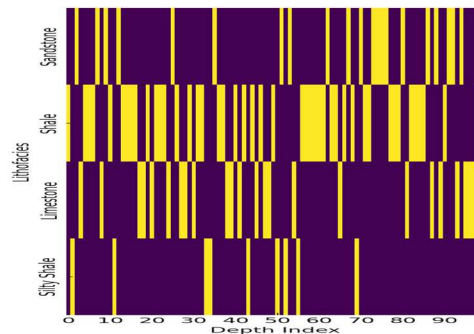


Figure 2: Lithofacies Classification Map

Figure 2 above illustrates the distribution of predicted lithofacies along the depth profile of a representative well. Different colours denote various lithofacies types such as sandstone, shale, and limestone. The model successfully captured transitions between depositional environments, which are critical for understanding reservoir heterogeneity and continuity. Importantly, these predictions provide actionable insights for reservoir engineers and geoscientists. For instance, zones predicted with high porosity and classified as sandstone can be prioritized for further analysis or potential development. Similarly, the identification of shale intervals supports cap rock evaluation and seal integrity analysis.

Despite these promising outcomes, several limitations were noted. First, the model's performance is constrained by the quality and representativeness of the training data, which does not originate from the Niger Delta. Consequently, while the results are encouraging, they must be interpreted with caution until the model is retrained and validated on Niger Delta-specific well logs. Additionally, the current model does not account for lateral geological variability or integrate seismic data, which could provide additional context for stratigraphic interpretation. Nonetheless, the results affirm the utility of deep learning in reservoir modelling and lay the groundwork for integrating region-specific data. Future work will focus on acquiring well logs from the Niger Delta to fine-tune the model, enhancing both its accuracy and geological relevance.

## DISCUSSION

The results of this study demonstrate that deep learning, specifically Convolutional Neural Networks (CNNs), can be effectively employed for the interpretation of well log data to support reservoir characterisation efforts. The performance metrics and visual diagnostics presented in earlier sections affirm the capability of neural networks to model complex, non-linear relationships inherent in subsurface data. One of the key insights from the regression analysis was the model's strong performance in predicting porosity values. The high coefficient of

determination ( $R^2 = 0.89$ ) and low RMSE suggest that the model successfully learned from the training data and was able to generalise to unseen data. This is particularly important in reservoir evaluation, where accurate porosity estimation influences decisions regarding hydrocarbon saturation and reservoir productivity (Doyen, 2007). The results suggest that neural networks can provide reliable alternatives to conventional petrophysical analysis methods, which are often time-consuming and subject to interpreter bias.

In the lithofacies classification task, the CNN achieved satisfactory accuracy across most lithofacies classes, despite the inherent challenge posed by overlapping petrophysical signatures. For example, distinguishing between shale and silty shale can be problematic due to similar responses in gamma ray and resistivity logs. Nevertheless, the confusion matrix analysis showed that the model was able to capture major transitions and differentiate key reservoir and non-reservoir zones. These outcomes validate the potential of supervised learning techniques in automating stratigraphic interpretation, a task that traditionally relies on manual core-log integration.

However, the discussion would be incomplete without acknowledging the limitations of the current approach. First, while the datasets used in this study were extensive and publicly available, they do not originate from the Niger Delta. As a result, there may be discrepancies in depositional environments, rock types, and fluid properties that limit the direct applicability of the trained models to the study region. Future work must focus on acquiring region-specific well log data and retraining the models to ensure geological and operational relevance.

Second, the study employed one-dimensional CNNs, which are suitable for depth-wise analysis but do not account for lateral geological variation or incorporate spatial information from seismic data. In practice, reservoir characterization benefits from integrating multiple data sources, including core, seismic, and production data (Hampson et al., 2001). Future model extensions could involve hybrid architectures or multi-modal networks that combine well log data with 2D or 3D seismic



attributes for a more holistic reservoir model. Moreover, while the deep learning model performed well, the results also highlight the importance of data quality and preprocessing. The presence of noisy or missing data can significantly impact model learning. The implementation of sophisticated preprocessing techniques, such as denoising autoencoders or imputation algorithms, could further improve model robustness.

Finally, the interpretability of deep learning models remains a challenge. Unlike traditional petrophysical methods where relationships are well understood, deep networks function as "black boxes," making it difficult to trace decision pathways. Future research could explore explainable AI (XAI) frameworks that provide insights into how the network makes predictions, thereby increasing trust and adoption among geoscientists. This study underscores the transformative potential of deep learning in reservoir characterisation. By automating the interpretation of well logs, CNNs can expedite the subsurface evaluation process, reduce human error, and provide consistent, scalable insights. However, careful consideration must be given to data representativeness, model architecture, and integration with geological knowledge to maximise the value of AI in upstream oil and gas workflows.

## CONCLUSION

This research investigated the application of deep learning, specifically convolutional neural networks (CNNs), for the automated interpretation of well log data with a focus on enhancing reservoir characterization in the Niger Delta region. Although the study utilized publicly available datasets from non-Niger Delta basins, the selected datasets offered sufficient geological and petrophysical relevance to simulate practical applications and validate model feasibility. The study achieved its core objectives through the development and implementation of a robust deep learning pipeline. The regression model accurately predicted petrophysical properties, such as porosity, demonstrating a strong fit to ground truth values with minimal error. Likewise, the classification model successfully identified and delineated lithofacies from input logs, revealing an

ability to distinguish between key geological units. These results confirm that CNNs are capable of learning and extracting meaningful representations from well log data, which are often complex, noisy, and multidimensional.

Moreover, the results underscore the efficiency and repeatability that artificial intelligence brings to subsurface interpretation. By automating tasks traditionally performed manually—such as porosity estimation and lithofacies classification—the deep learning model reduces the time, cost, and subjectivity associated with conventional workflows. This is particularly valuable in mature or data-scarce basins where timely decision-making is critical. However, the limitations of this study must also be acknowledged. The absence of Niger Delta-specific data introduces a layer of uncertainty in model generalization to the study area. Furthermore, while the CNN performed well, it was limited to depth-wise 1D inputs and did not incorporate lateral geological variability or integrate other geophysical data sources such as seismic. These limitations suggest opportunities for future enhancements and provide direction for subsequent research. The research affirms that deep learning holds significant promise for reservoir modelling and well log interpretation in the petroleum industry. With the right data and domain integration, these technologies can play a pivotal role in the digitization and optimization of upstream exploration workflows, particularly in data-rich but under-analyzed regions like the Niger Delta.

## REFERENCES

- Ali, S., Shah, S. M., & Murtaza, M. (2020). Deep learning-based lithofacies classification using well logs: A case study from the Norwegian Continental Shelf. *Journal of Petroleum Science and Engineering*, 189, 107004. <https://doi.org/10.1016/j.petrol.2020.107004>
- Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

---

Corresponding author: Nanna Nanven Rintip

✉ [nanna.rintip@bazeuniversity.edu.ng](mailto:nanna.rintip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved





- Doyen, P. M. (2007). Seismic reservoir characterization: An earth modeling perspective. *EAGE Publications*.
- Hampson, D. P., Schuelke, J. S., & Quirein, J. A. (2001). Use of multi-attribute transforms to predict log properties from seismic data. *Geophysics*, 66(1), 220–236.  
<https://doi.org/10.1190/1.1444899>
- Hinton, G., Deng, L., Yu, D., Dahl, G. E., Mohamed, A., Jaitly, N., ... & Kingsbury, B. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, 29(6), 82–97.  
<https://doi.org/10.1109/MSP.2012.2205597>
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.  
<https://doi.org/10.1038/nature14539>
- Shan, Y., & Jha, M. (2019). Lithofacies classification using machine learning and ensemble learning. *Interpretation*, 7(3), SE1–SE13.  
<https://doi.org/10.1190/INT-2018-0196.1>
- Zhao, T., Mukerji, T., & Mavko, G. (2015). Lithofacies classification from well logs using supervised learning methods. *Geophysics*, 80(4), D323–D339.  
<https://doi.org/10.1190/geo2014-0501.1>
- Zhang, J., Geng, Y., & Liu, Y. (2018). Deep learning-based lithology identification using well logs. *Geoscience Frontiers*, 9(6), 1489–1497.  
<https://doi.org/10.1016/j.gsf.2017.10.005>
- Abdollahi, M., & Asoodeh, M. (2015). Prediction of porosity and permeability using hybrid neural network–genetic algorithm: A case study from a carbonate reservoir, south Iran. *Journal of Petroleum Science and Engineering*, 123, 179–191.  
<https://doi.org/10.1016/j.petrol.2014.08.019>
- Al-Anazi, A., & Gates, I. D. (2010). A support vector machine algorithm to classify lithofacies and model permeability in heterogeneous reservoirs. *Engineering Geology*, 114(3–4), 267–277.  
<https://doi.org/10.1016/j.enggeo.2010.05.011>
- Alobaidi, I., Sadeghi, M., & Khalili, M. (2021). Lithofacies classification from well logs using deep learning models. *Journal of Petroleum Science and Engineering*, 196, 107975.  
<https://doi.org/10.1016/j.petrol.2020.107975>
- Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.
- Chaki, R., Saeed, S., & Elhoseny, M. (2022). Deep learning techniques for subsurface imaging and reservoir characterization: A review. *Artificial Intelligence Review*, 55(2), 1149–1190.  
<https://doi.org/10.1007/s10462-021-10017-y>
- Doyen, P. M. (2007). Seismic reservoir characterization: An earth modeling perspective. *EAGE Publications*.
- Hampson, D. P., Schuelke, J. S., & Quirein, J. A. (2001). Use of multi-attribute transforms to predict log properties from seismic data. *Geophysics*, 66(1), 220–236.  
<https://doi.org/10.1190/1.1444899>
- Hall, M. (2016). Machine learning applications in geoscience: A review. *The Leading Edge*, 35(10), 906–911.  
<https://doi.org/10.1190/tle35100906.1>
- Hinton, G., Deng, L., Yu, D., Dahl, G. E., Mohamed, A., Jaitly, N., ... & Kingsbury, B. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, 29(6), 82–97.

Corresponding author: Nanna Nanven Rintip

✉ [nanna.rintip@bazeuniversity.edu.ng](mailto:nanna.rintip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved



- <https://doi.org/10.1109/MSP.2012.2205597>
- Jensen, J. L., Lake, L. W., Corbett, P. W., & Goggin, D. J. (2000). *Statistics for petroleum engineers and geoscientists*. Prentice Hall.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- Meier, M., Virnovsky, G., & Varady, R. (2020). Challenges and opportunities of using deep learning for reservoir characterization. *Computers & Geosciences*, 135, 104391. <https://doi.org/10.1016/j.cageo.2019.104391>
- Okonkwo, V. U., & Onyekachi, E. (2020). Application of artificial neural networks in porosity prediction using well logs in Niger Delta region. *Nigerian Journal of Technological Development*, 17(3), 113–120. <https://doi.org/10.4314/njtd.v17i3.4>
- Reijers, T. J. A. (2011). Stratigraphy and sedimentology of the Niger Delta. *Geologos*, 17(3), 133–162. <https://doi.org/10.2478/v10118-011-0008-3>
- Shan, Y., & Jha, M. (2019). Lithofacies classification using machine learning and ensemble learning. *Interpretation*, 7(3), SE1–SE13. <https://doi.org/10.1190/INT-2018-0196.1>
- Vasudevan, S., & Johnston, H. (2022). Transformer-based neural networks for lithology prediction using well logs. *Journal of Petroleum Science and Engineering*, 208, 109275. <https://doi.org/10.1016/j.petrol.2021.109275>
- Zhao, T., Mukerji, T., & Mavko, G. (2015). Lithofacies classification from well logs using supervised learning methods. *Geophysics*, 80(4), D323–D339. <https://doi.org/10.1190/geo2014-0501.1>
- Zhang, J., Geng, Y., & Liu, Y. (2018). Deep learning-based lithology identification using well logs. *Geoscience Frontiers*, 9(6), 1489–1497. <https://doi.org/10.1016/j.gsf.2017.10.005>
- Zhou, S., He, Y., & Sun, Y. (2019). Automatic classification of reservoir lithofacies using deep learning approaches. *Marine and Petroleum Geology*, 107, 251–261. <https://doi.org/10.1016/j.marpetgeo.2019.04.038>

---

Corresponding author: Nanna Nanven Rintip

✉ [nanna.rintip@bazeuniversity.edu.ng](mailto:nanna.rintip@bazeuniversity.edu.ng)

Department of Petroleum and Gas Engineering, Faculty of Engineering, Baze University, Abuja.

© 2025. Faculty of Technology Education. ATBU Bauchi. All rights reserved