International Journal of Multidisciplinary Research and Growth Evaluation.

A Comparative Study to Determine Electro-Facies of the Yamama Formation Using Machine Learning Based on Well Logs Data

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Article Info

ISSN (Online): 2582-7138
Impact Factor (RSIF): 8.04
Volume: 07
Issue: 05
Received: 20-08-2026
Accepted: 22-09-2026
Published: 24-10-2026
Page No: 807-815

Abstract
One of the most significant Cretaceous carbonate oil fields is Yamama Formation in West Qurna oil field, southern Iraq. The limited number of core samples and the high price of petrographic analysis using a thin section has conventionally constrained its characterization. This research has created a data-driven workflow to directly classify sedimentary facies based on the data of well logs using machine learning methods. Using unsupervised clustering and supervised classification, five facies groups were discovered and confirmed using a Random Forest model that gave a 97% internal accuracy. The most powerful predictors were found to be gamma ray, bulk density, and neutron porosity logs, indicating their sensitivity to lithological changes and depositional energy. Machine learning generated facies are consistent with the ramp model of deposition of the Yamama Formation. The inner ramp is covered with clean and porous carbonates that give reservoir-quality intervals and the middle ramp is covered with shaly and mudstone facies as barriers to permeability. Mixed facies signify transitional depositional cycles and tight carbonates are a sign of diagenetic overprinting. Thin section analysis can still be required to provide microfacies-level detail and first-hand evidence of mineralogy and diagenesis but it is limited by cost and coverage. Machine learning should, however, not be seen as a replacement but as a complementary tool which can fill in the data gaps in core material-deficient wells.

DOI: https://doi.org/10.54660/.IJMRGE.2026.7.5.807-815

Keywords: Facies classification, Yamama Formation, West Qurna, Carbonate reservoirs, Machine learning

1. Introduction

The Cretaceous formations play a central role in the stratigraphic record of the south Iraq which not only forms a source of hydrocarbon but also forms a key reservoir to the petroleum industry in the country (Verma *et al*., 2004) [23]. Deposited during the Beriasian-Valanginian within a ramp setting, the Yamama Formation captures a spectrum of depositional conditions spanning inner-to-middle ramp settings. Carbonate lithologies dominate the formation's composition, which maintains conformable boundaries with the Sulaiy Formation beneath it and the Ratawi Formation above (Idan *et al*., 2020) [13]. The depositional cycles and diagenetic alterations inherently make carbonate reservoirs naturally heterogeneous. Facies distribution thus important in determining the quality of reservoirs, porosity patterns and the potential of the reservoirs to contain hydrocarbons (Al-Dujaili *et al*., 2021) [4]. Usually, petrography of thin section is the core of base of facies analysis, which gives details on mineralogy, texture, and types of pores in great detail. However, the given approach has a few shortcomings, including limited core availability, high cost, vertical and lateral coverage (Al-Ali *et al*., 2019) [1].

With the advent of digital technology, there is a need to redefine reservoirs according to well-log information, as this has proven to be a good alternative. Platforms such as Techlog may be able to visualize and cluster facies, but in many cases depend on manual tuning of the parameters and human judgment, which results in subjectivity (Khudhair, 2021) [17]. In contrast, machine

learning provides automated, reproducible and highly accurate classification, minimizing human bias and enabling its extension to multiple wells (Khudhair & Idan, 2024) [18].
The change to data-driven interpretations has also occurred in the field of log-based sedimentary facies analysis. Electrofacies identification is a multi-parameter logging data synthesis, and it is a good choice for machine learning applications (Shi *et al*., 2024) [22]. However, while seismic deep learning applications struggle with a lack of labelled data for training, well-log classifiers are constrained by having an incomplete record of cores and by the discontinuity in sampling (Hardanto & Wulandhari, 2021) [12]. In order to avoid such problems, recent studies have focused on moderate-complexity algorithms that require less computation (Joshi *et al*., 2021) [16]. These models are able to detect highly complex petrophysical patterns and categorize the petrophysical patterns into lithofacies classes with high accuracy without incurring the high overhead of deeper architectures (Al-mudhafar, 2017) [3].
The area of study is in the northeast of Basra city. Its eastern and northern boundaries are 710-735 and 3405-3450, respectively (Table 1, Figure 1). The field of study is an anticline on the subsurface, having a slight, asymmetric slope, where the western end is steeper than the eastern one. The area of the study is tectonically in the sedimentary depression of the Tigris and Euphrates Valley within the Mesopotamian foredeep zone which is a part of the stable platform as per the divisions of (Jassim & Goff, 2006) [15].

Table 1: location of studied wells in the study area.

Well	X axis	Y axis	Top (m)	Bottom(m)	Thickness (m)
X1	726181	3438976	3998	4304	306
X2	714839	3448854	3957	4223	266
X3	727620	3427826	4000	4295	295
X4	714349	3427697	3950	4225	275

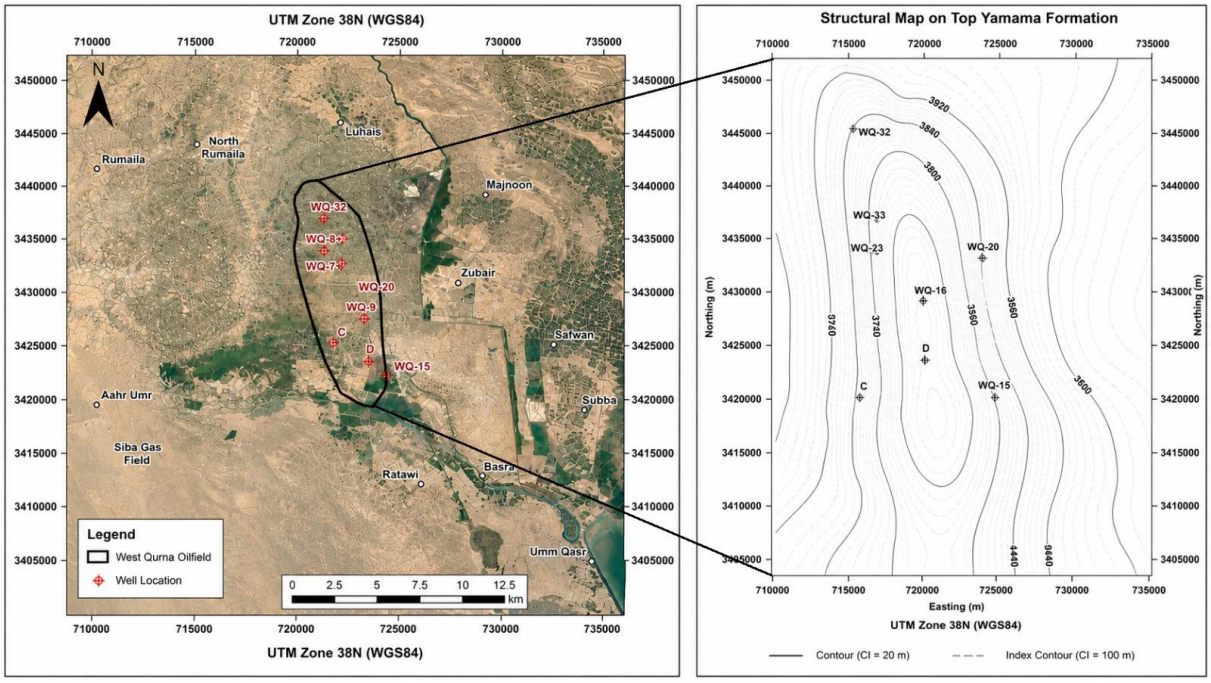


Fig 1: Location map of West Qurna oilfield, and a structural map on the Yamama Formation top to the right (After Al-khafaji *et al*., 2019).

The purpose of the study is to assess the effectiveness of machine learning in facies classification in the Yamama Formation and compare the concordance of the machine learning with thin section petrography and Techlog workflows. With the combination of computational techniques and geological interpretation, the study has gone further to develop a robust and cost-efficient workflow that can improve the characterization of reservoirs in information limited conditions.

2. Geologic Setting

The Yamama Formation is part of a stratigraphic sequence from the upper Berriasian to the Aptian. The sequence includes deep-basinal to shallow tidal-flat depositional environments, illustrated by the Shuaiba, Zubair, Ratawi, Yamama, Sarmord and Lower Balambo formations (Buday, 1980) [6]. Within the Yamama Formation, limestone is predominant, with dolomitic zones and thin shale laminations also being recognized. Furthermore, anhydrite horizons in the western part of the depositional basin of the formation were reported by Sadooni, 1993.
The Yamama and Sulaiy Formations are separated by a conformable boundary. The Sulaiy is a Jurassic to Early Cretaceous period, argillaceous, mud-rich, small-benthic-foraminifera-bearing limestone. The Yamama Formation grades gently upward to the lithologically varied Ratawi Formation, made up of impure limestone, shale, siltstone, and sandstone (Jassim & Goff, 2006) [15].

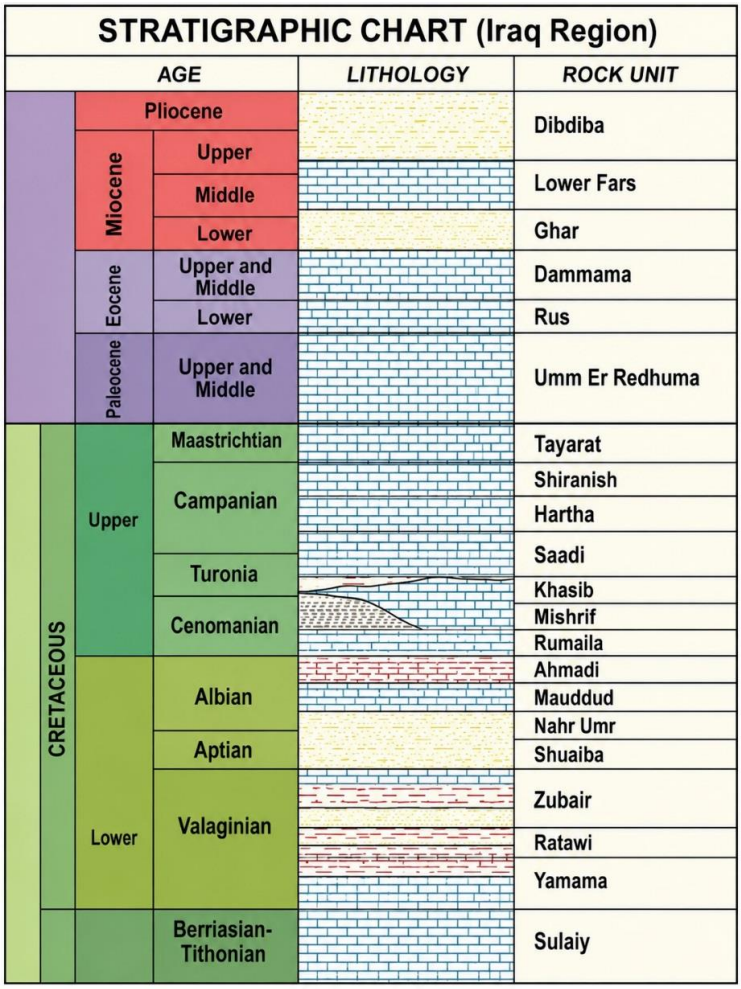


Fig 2: Stratigraphic column in southern Iraq (WQ-60) from final geological report.

The Indian and Arabian plates separated progressively towards the end of the Paleozoic and into the Triassic, Jurassic, and Early Cretaceous. This rifting led to the development of a passive continental margin and to the expansion of the vast Neo-Tethys Ocean. The tectonic setting thus allowed sediment preservation within the Yamama basin of the study area, which developed under these conditions (Sharland *et al*., 2001) [21] (Faisal & Mahdi, 2020) [11]. This plate divergence produced extensive intra-shelf basins, as well as a platform configuration, which exerted regional control over the distribution of sedimentary facies (Christian, 1997) [8].

3. Materials and Methods

The classification of facies was performed with a Python-based workflow with a combination of K-means and Random Forest algorithms with the use of standard libraries to manipulate data, use machine learning and visualization tools. Well log data of four chosen wells (X1, X2, X3 and X4) were imported in tabular format and preprocessed, which includes normalization, unit standardization and gap filling.

Derived porosity (RHOB–NPHI) derived to enhance lithological discrimination. Cluster analysis is a multivariate technique that efforts to divide a sample of topics measured on a specific variable into several groups in which subjects with similar features are grouped.The objective of cluster analysis was to organize data points into groups known as electrofacies by penetrating for comparations and differences between them inthe multivariate space of logs (Cornish, 2007) [9].

According to the cluster analysis, Electrofacies are defined by the definite features of well-log data that characterize minerals and lithofacies within the logged interval (Alameedy *et al*., 2023) [5]. Defining facies distribution based on well-log Data was tremendous value as they signify the most available and broad dataset subsequently geologists frequently experience difficulties linked to the lack of Core Data (La Croix *et al*., 2019) [19]. The outcomes of the clustering method was controlled by many influences such as the standards of the clustering, the algorithm's limitation situations, and other factors such as completion criteria.

This is sinceit is critical to evaluate the clusters' goodness of fit to the data's natural partitions without the assist of extra information. There are many types of clustering methods such as k-means, ranked clustering, density-based clustering, spectral clustering, nonparametric clustering, and Self-Organizing Maps, each method has its own set of benefits and drawbacks (Delgado *et al*., 2017) [10].

Unsupervised clustering was initially performed based on the K means algorithm to establish five facies groups directly based on the responses of logs. This was followed by using such clusters as training information to a Random Forest classifier. The sample was divided into training (70) and testing (30) parts to evaluate the predictive performance. They checked the accuracy of the models with the help of the classification metrics and confusion matrices and analyzed

the feature importance to identify gamma ray, bulk density, and neutron porosity as the most important predictors.

Facies forecasts versus depth to characterize vertical shifts and depositional periods. This workflow was able to achieve reproducibility, reduce subjectivity, and offer computational and geological understanding of the heterogeneity of the reservoir.

Project Facies classification process adopted in Python, which is reproducible and transparent. All steps, including data loading and feature selection, featured in clustering, classification, and visualization were recorded to enable reproducibility. The facies predictions were identified as depth, and therefore, they could be directly compared to depositional cycles and diagenetic features (Figure 3).

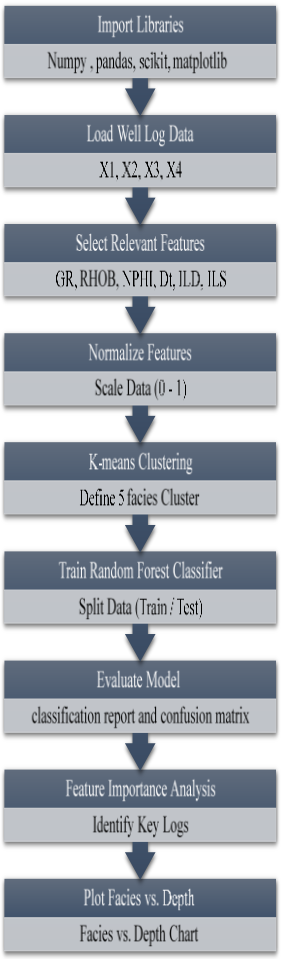


Fig 3: Python Algorithm Flowchart

4. Results and Discussion

The machine-learning workflow was able to split the Yamama Formation into five facies classes that are representative of different depositional and reservoir-quality conditions. The classification results show a lot of vertical variation across the wells studied, which is indicative of both depositional processes and later diagenetic alteration.

Low gamma-ray (GR) responses are mostly related to Facies F1 (Clean Carbonates) and to good porosity characteristics. This facies is found in relatively shallow intervals, indicating deposition in relatively high-energy inner ramp environments in which carbonate production was greater than the influx of terrigenous material. These intervals are considered to be potential reservoir zones because of the preservation of the primary pore systems.

The reservoir quality decreases with increasing gamma-ray responses to the shaly carbonates/mudstones of Facies F2. This facies was deposited in a lower-energy environment where fine-grained carbonate mud and argillaceous material were deposited as shown by the distribution of this facies. F2 between porous intervals may be an intraformational flow barrier and could be a factor that may cause reservoir compartmentalization.

Facies F3 (Porous Carbonates) is the most promising reservoir facies modeled. Enhanced pore development indicated by the combination of neutron porosity and density log responses may be due to depositional texture and secondary diagenetic dissolution. The presence of F3 repeatedly in the wells studied in the research area suggests the presence of a number of reservoir-quality horizons in the Yamama Formation.

Facies F4 (Carbonates with Enhanced Porosity) is carbonate intervals that have been extensively secondarily dissolved and/or enhanced in porosity through diagenetic processes. These rocks show a low bulk density, high neutron porosity and high sonic transit times, all of which suggest the presence of well-developed rock pore systems. Even though the compaction and cementation processes have occurred, the porosity has been reactivated through diagenetic dissolution, which makes F4 one of the best reservoir facies of the Yamama Formation. Therefore, F4 has a very good reservoir potential and is the best of all the facies in terms of

hydrocarbon storage and flow capacity.

Facies F5 (Mixed Facies) falls between clean carbonate and shaly facies. This facies is probably a transitional depositional environment, resulting from changing energy conditions on the carbonate ramp system. The presence of F5 clearly shows the dynamic character of facies migration during the deposition of Yamama Formation.

Results from feature-importance analysis showed Gamma Ray, Bulk Density, and Neutron Porosity to be the most significant variables for the facies discrimination. This is a geologically plausible dominance since gamma ray is reflective of shale content, while density and neutron porosity are a combined response of lithology and pore-system variations. The good agreement between these predictors and known geological controls lends credibility to the machine-learning classification framework.

The Random Forest model achieved an overall classification accuracy of 97%, indicating excellent predictive performance. Such accuracy demonstrates that machine-learning techniques can effectively recognize lithological variability from well-log responses and provide continuous facies prediction in intervals lacking core material. (Figures.4, 5, and 6).

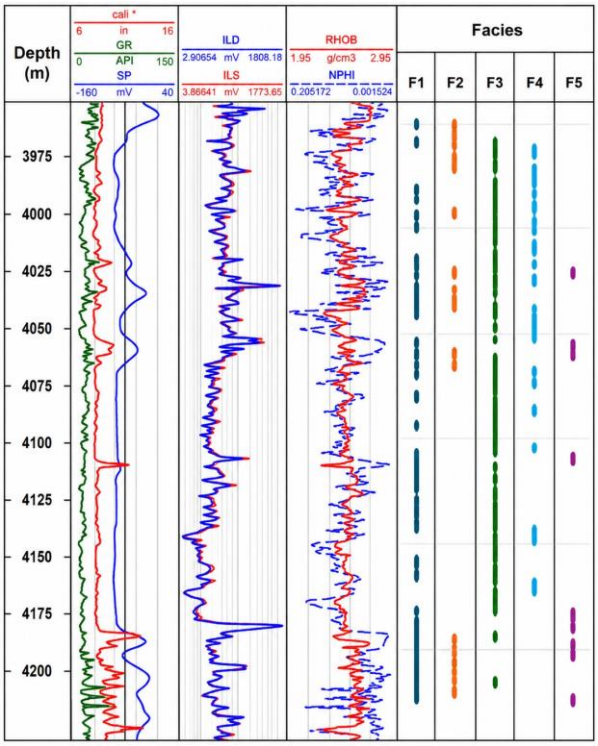


Fig 4: Facies – Depth relationship among X1 well.

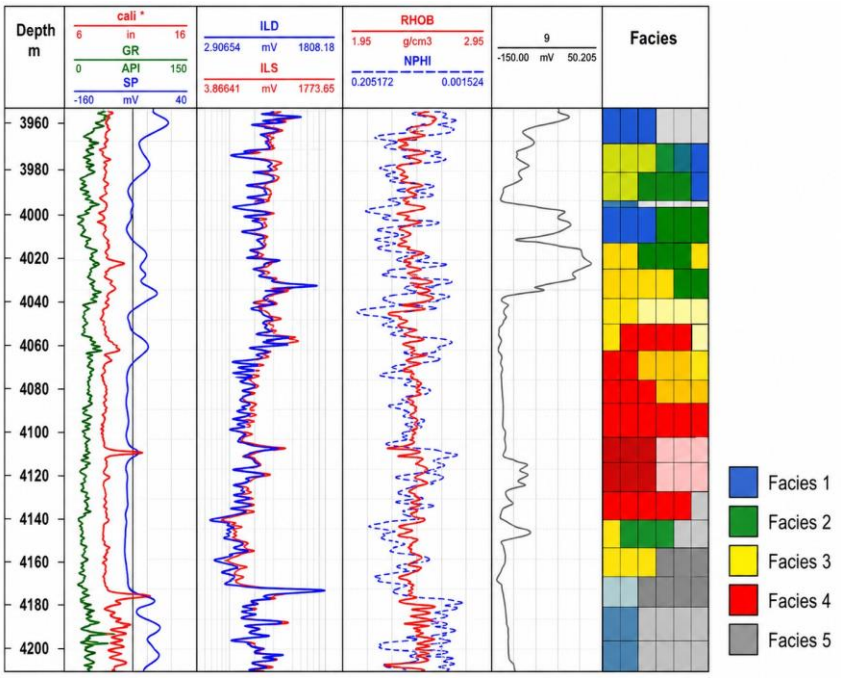


Fig 5: Facies – Depth relationship among X2 well.

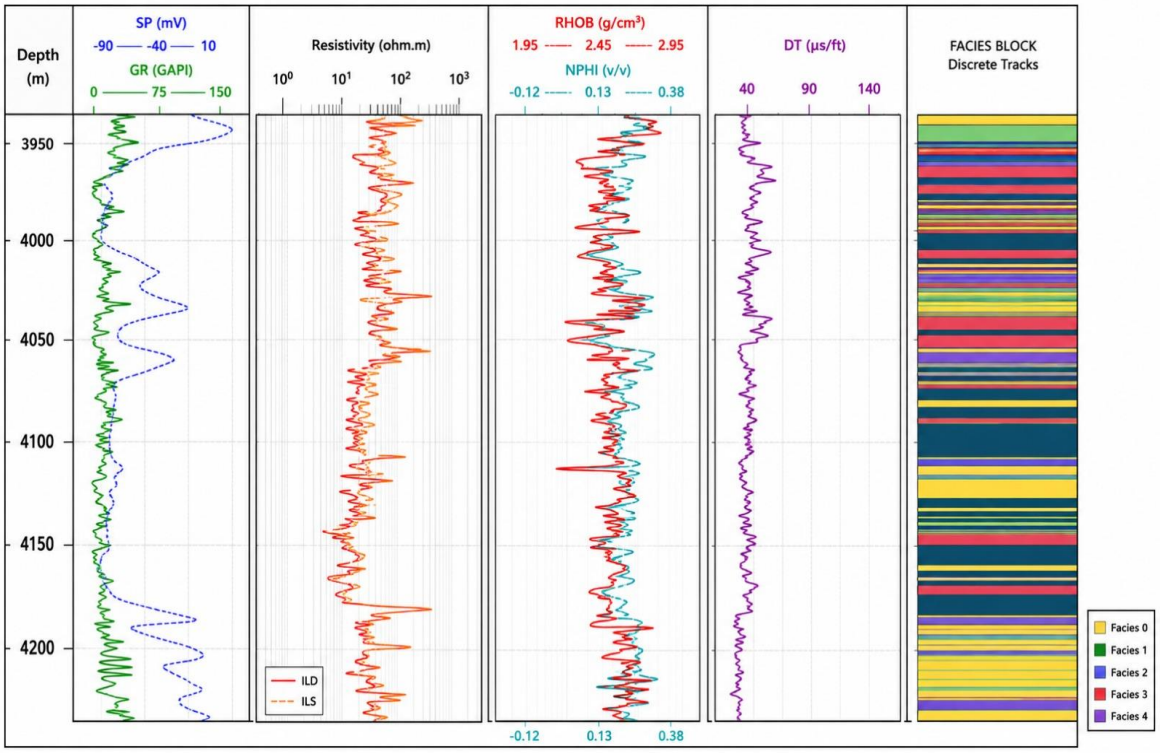


Fig 6: Facies – Depth relationship among X3 well.

Clean carbonates (F1) observed to dominate the higher intervals, which are high-energy inner ramp environments with desirable reservoir quality. F2 facies (shaly and mudstone) varied through the non-deepest sections, which were related to lower-energy deposition environments and put barriers to permeability. Porous carbonates (F3) occurred in deeper areas which are usually associated with reefal formation and diagenetic dissolution and are the most fruitful intervals of the reservoir. Carbonates of strong cementation and compaction (F4) were found to be non-reservoir facies, with mixed facies (F5) emphasizing conditions in between inner and middle ramp environments (Tables. 2, 3, Figure.7).

Table 2: Statistical Summary of the Identified Electrofacies in the Yammama Formation

Facies	Samples (n)	Percentage (%)	Mean GR (API)	Mean RHOB (g/cm³)	Mean NPHI (v/v)	Mean DT (µs/ft)	Interpretation	Reservoir Quality
F1	296	26.9	16.04	2.60	0.055	49.68	Clean carbonates deposited in relatively high-energy inner-ramp settings with limited shale influence.	Moderate
F2	108	9.8	30.86	2.66	0.049	48.67	Shaly carbonates and mud-supported facies characterized by elevated clay content and reduced pore development.	Poor
F3	463	42.1	15.05	2.50	0.102	53.35	Porous carbonate facies with favorable petrophysical properties and enhanced storage capacity.	Good
F4	176	16.0	15.26	2.42	0.148	57.75	Highly porous carbonates affected by secondary dissolution and diagenetic pore enhancement.	Very Good
F5	58	5.3	19.31	2.44	0.017	47.05	Dense and cemented carbonate intervals with limited effective porosity.	Very Poor
Total	1101	100	—	—	—	—	—	—

Table 3: Reservoir Quality Ranking of the Electrofacies

Rank	Facies	Reservoir Potential	Supporting Petrophysical Evidence
1	F4	Excellent	Lowest density, highest neutron porosity, and highest sonic transit time indicating enhanced pore development.
2	F3	Very Good	Moderate density and elevated neutron porosity reflecting favorable reservoir properties.
3	F1	Moderate	Clean carbonate intervals with limited shale content but moderate porosity.
4	F2	Poor	High gamma-ray values indicating shale-rich intervals and reduced reservoir quality.
5	F5	Very Poor	Extremely low neutron porosity and low sonic transit time indicating tight and cemented carbonates.

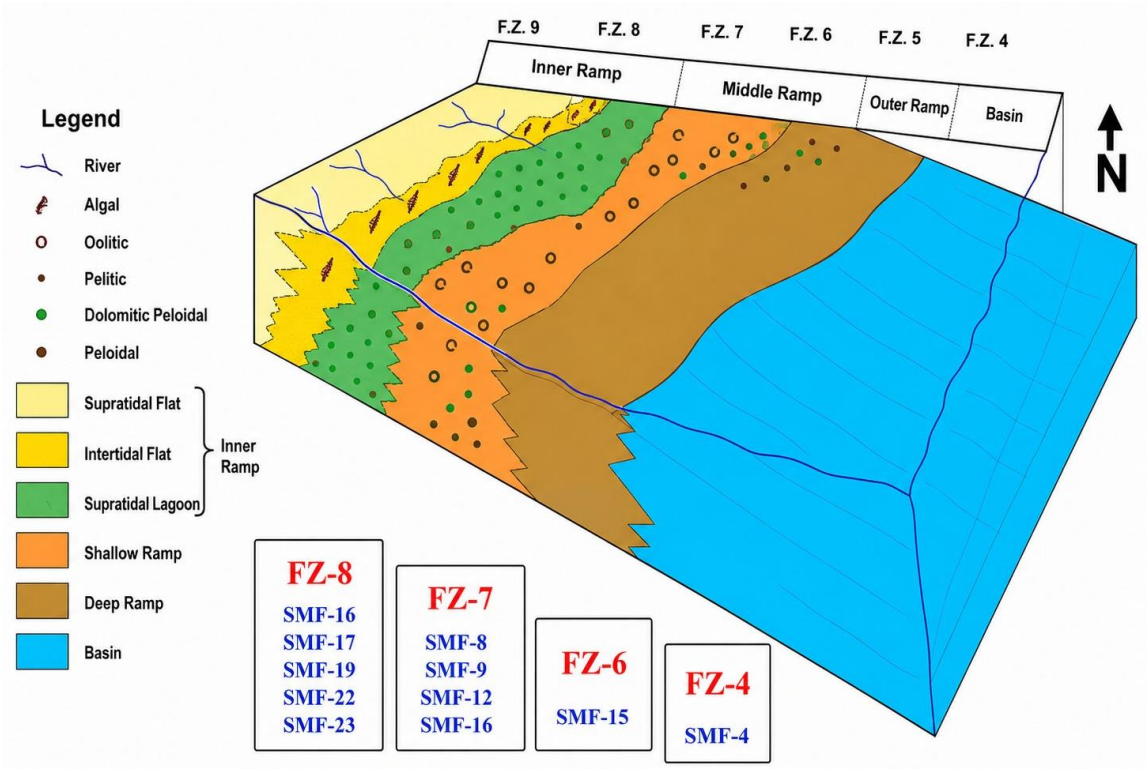


Fig 7: Sedimentary model of Yamama Formation based on microfacies distribution (Iessa & Zhang, 2023).

The Random Forest classifier reproduced the cluster assignments generated by the K-means algorithm with an overall accuracy of 97%, demonstrating the internal consistency and reproducibility of the machine-learning workflow rather than direct validation against independently interpreted geological facies. The analysis of the feature importance analysis proved the gamma ray, bulk density, and neutron porosity to be the most sensitive predictors indicating its geological significance in distinguishing lithological differences. Facies distribution against depth was used to visualize the facies, which showed vertical changes which are in close relation to depositional cycles, which confirmed the geological consistency of the computational method. The performance of the Random Forest classifier evaluated using five complementary metrics to provide a comprehensive assessment of its reliability in facies estimation. In addition to the overall accuracy of 97%, the model achieved a precision of 95%, indicating that most facies classified as reservoir-quality intervals were correctly identified. The recall score reached 96%, confirming the model's ability to capture nearly all true reservoir facies across the dataset. The F1 score (which is a measure of balance between precision and recall) reached 95.5%, confirming the robust performance of the classifier in cases where the classes are imbalanced. Moreover, the discriminatory ability across the various facies groups was very good (AUC = 0.98, Table 4). In contrast, petrographic thin section analysis remains indispensable for microfacies-level characterization, offering direct evidence of mineralogy, texture, and diagenetic features. However, its application is limited by core availability and high preparation costs. Thus, the Python-based workflow bridges critical data gaps by providing continuous facies profiles across multiple wells, complementing thin section studies rather than replacing them. This integrated evaluation underscores the value of combining computational efficiency with petrographic precision to achieve reliable reservoir characterization.

Table 4: Classification Metrics

Metric	Equation	Description
Accuracy	Accuracy=TP+TNTP+TN+FP+FN	Proportion of correctly classified samples among all samples.
Precision	Precision=TPTP+FP	Measures how many of the predicted positive facies are actually correct.
Recall (Sensitivity)	Recall=TPTP+FN	Measures how many of the actual positive facies were correctly identified.
F1-Score	F1=2·Precision·RecallPrecision+Recall	Harmonic mean of precision and recall, balancing both metrics.
AUC (Area Under ROC Curve)	Calculated as the area under the ROC curve: TPR vs. FPR	Evaluates the overall discriminatory ability of the classifier across thresholds.

The comparative analysis proves that each of the three petrographic thin section studies and machine learning can make their own unique but complementary contributions to facies characterization. Thin section petrography is the most reliable technique to identify microfacies and diagenetic features but has limited spatial coverage and is costly, limiting its usage on a larger scale. Semi-automated techniques of enhancing well log data visualization and clustering are based on manual parameter control, thereby introducing subjectivity.

A more objective and scalable alternative is machine learning (particularly, the Random Forest algorithm). The model is

highly classified and provides geological uniformity since a number of log parameters are incorporated. That the model predicts gamma ray and bulk density and the neutron porosity shows that the model is sensitive to the lithological variations and energy of deposition.

Despite these positive aspects, the outcomes of machine learning should be geologically scaled up to avoid the purely numerical understanding. Inclusion of a little thin section data in the form of calibration points also serve to maintain the computational predictions on geological reality. The hybrid system that encompasses information-based accuracy and petrographic confirmation provides an intermediate model of the characterization of the reservoirs in heterogeneous carbonate systems such as the Yamama Formation.

5. Comparative Analysis with Previous Studies

Broad consistency is observed between the outcomes of the present study and those reported in prior investigations of the Yamama Formation across southern Iraq, notwithstanding certain differences in methodology. Chafeet, 2016 also employed petrographic thin-section analyses and recognized a number of microfacies associations from peloidal packstone–grainstone to stromatoporoid-coral boundstone. Having used machine-learning techniques in the present study, instead of direct observation of the petrography, both methods demonstrate that there is significant vertical facies variability with alternating reservoir and non-reservoir intervals.

The ramp-based depositional model with lateral and vertical facies transition of the Yamama Formation was also reported by Iessa & Zhang, 2023 This is corroborated by the facies architecture produced by the machine learning workflow, which shows a difference between the more carbonate-rich inner-ramp facies and more muddy middle-ramp facies.

Conventional petrographic studies use sampled core for facies identification, whereas the present study relied upon continuous well-log data to perform the facies identification. Thus, the suggested workflow offers an advantage in the vertical coverage and can help to predict the facies where core data is missing. Though the detailed microfacies interpretation and diagenetic assessment using petrographic studies are important, the machine-learning approach is also scalable and cost-effective for reservoir characterization.

The Python-based methodology showed greater reproducibility and less operator subjectivity than traditional clustering workflows in commercial software like Techlog. The resulting classification accuracy of 97% is better than the accuracy that is typically achieved by a semi-automated clustering method and shows the benefits of combining unsupervised and supervised machine learning methods with carbonate reservoir studies.

Overall, the results indicate that machine learning is not presented as an alternative to petrographic analysis, but rather as an assist to geological interpretation, complementing the limited amount of core material.

6. Internal Validation of the Machine-Learning Workflow

Since no pre-labeled facies dataset was available for supervised training, facies classes were initially generated using unsupervised K-means clustering based exclusively on well-log responses. The resulting cluster assignments were subsequently used as labels for Random Forest classification. The available data were partitioned into two subsets, allocating 70% for training purposes and the remaining 30% for testing. Cluster assignments were reproduced by the Random Forest classifier with a high degree of fidelity, achieving an overall accuracy of approximately 97%.

It should be emphasized that this accuracy does not represent direct geological validation of facies interpretation. Instead, it demonstrates the consistency, robustness, and reproducibility of the machine-learning workflow in recognizing electrofacies patterns derived from the multidimensional well-log dataset.

The confusion matrix showed that most observations were correctly assigned to their corresponding electrofacies classes, with only minor overlap occurring between transitional facies exhibiting similar petrophysical characteristics. Such overlap is expected in carbonate reservoirs where depositional and diagenetic processes produce gradual rather than abrupt lithological transitions.

Therefore, the principal validation of the proposed workflow relies on geological consistency, including agreement with established depositional models of the Yammama Formation, correspondence with previously published petrographic studies, and the logical relationship between electrofacies distribution and reservoir quality indicators.

7. Limitations of the Study

Some limitations should be noted when interpreting the findings of this study. Unsupervised clustering was done first, without any direct calibration to the core description or to the petrographic thin-section observations in the wells investigated. Hence, the facies identified should be treated as electrofacies and not depositional microfacies. Second, the classification accuracy achieved with the Random Forest model is based on the agreement with the cluster assignments from the K-means algorithm and not on validation against independently interpreted geological facies. So the accuracy shown is a measure of methodological consistency, not of geological certainty. Third, the workflow is based entirely on measurements of the well logs. The addition of core data, image logs and petrographic data and production information may further enhance the facies interpretation and reservoir characterization.

Despite these limitations, the strong agreement between electrofacies distribution, petrophysical characteristics, depositional models, and published geological studies supports the practical applicability of the proposed workflow for carbonate reservoir characterization.

8. Conclusions

This study confirms that machine learning can be a complement to the traditional facies analysis, which is cheap and feasible. It may be combined with selective thin section calibration to give continuous, reproducible prediction of facies between wells, to bridge gaps in the data in areas where core material is non-existent. The accuracy of the Random Forest model produced 97% and the distribution of the facies generated by the model is well correlated with the computation and geological interpretation of the Yamama Formation that justifies the validation of the computational and geologies interpretation.

Finally, the combination of machine learning and petrographic creates a complete workflow to improve characterization of the reservoir and to assist in better informed hydrocarbon development plans in southern Iraq.

This digital analytics and geological knowledge synergy is an important step toward data-driven reservoir assessment of the present day.

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How to Cite This Article

Khudhair MH. A comparative study to determine Electro-Facies of the Yamama formation using machine learning based on well logs data. Int J Multidiscip Res Growth Eval. 2026;7(5):807-815. doi:10.54660/.IJMRGE.2026.7.5.807-815.

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