

Machine learning-based seismic attribute analysis for porosity prediction and lithofacies classification in clastic hydrocarbon reservoirs

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Abstract

Accurate prediction of reservoir properties such as porosity, permeability, and lithofacies distribution is essential for reliable hydrocarbon reserve estimation, well placement, and field development planning. Conventional deterministic methods for relating seismic response to reservoir properties are limited by the nonlinear and multivariate nature of the seismic–petrophysical relationship, and single-attribute correlations frequently fail to capture the complexity of clastic reservoir systems. This study presents a machine learning-assisted workflow that integrates multi-attribute seismic analysis with wireline log data to predict porosity and classify lithofacies within a clastic hydrocarbon reservoir. A suite of seismic attributes including root-mean-square (RMS) amplitude, sweetness, instantaneous frequency, coherence, envelope amplitude, and acoustic impedance derived from post-stack inversion was extracted and calibrated against log measurements at control wells. Feature selection based on correlation ranking and recursive feature elimination identified the most informative attributes, and three supervised learning models random forest (RF), support vector regression (SVR), and a feed-forward artificial neural network (ANN) were trained for porosity prediction. A separate classification stage using random forest and gradient boosting was applied for lithofacies discrimination. The results demonstrate that the ANN and RF models substantially outperform single- and multi-attribute linear regression, achieving a coefficient of determination (R^2) of 0.86–0.88 for porosity prediction at blind-test wells, while the ensemble classifier reached an overall lithofacies classification accuracy of 88%. Integrating machine learning with multi-attribute seismic analysis reduces prediction uncertainty and produces spatially continuous reservoir property volumes that support more reliable reservoir characterization and lower-risk exploration decision-making.

Keywords: Machine learning; Seismic attributes; Porosity prediction; Lithofacies classification; Seismic inversion; Reservoir characterization; Hydrocarbon exploration

1. Introduction

Hydrocarbon exploration and reservoir characterization depend on the ability to translate geophysical measurements into meaningful estimates of subsurface rock and fluid properties. Among the available geophysical techniques, seismic reflection surveying remains the most widely used method for imaging subsurface formations and delineating structural and stratigraphic traps [1, 2]. While seismic data provide dense spatial coverage over an entire prospect, they only measure the elastic response of the subsurface indirectly; the properties that ultimately control hydrocarbon storage and flow—porosity, permeability, water saturation, and lithofacies—must be inferred through calibration with well control [6, 9].

Traditional reservoir characterization workflows rely on relating a single seismic attribute, most commonly amplitude or acoustic impedance, to a reservoir property through a deterministic regression established at well locations [3, 27].

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Although this approach is straightforward and interpretable, the relationship between seismic response and reservoir properties is generally nonlinear and multivariate. A single attribute rarely captures the full range of geological variability present in clastic systems, where thin-bedded sand–shale sequences, lateral facies changes, and variable fluid content all influence the recorded seismic response [28, 35]. Consequently, single-attribute predictions often carry large uncertainties away from well control.

Multi-attribute analysis was introduced to address this limitation by combining several complementary attributes into a single predictive transform [28, 35, 37]. However, classical multi-attribute regression assumes a linear or weakly nonlinear relationship and can overfit when many attributes are used. Machine learning (ML) methods offer a more flexible alternative because they can learn complex nonlinear mappings between multiple input attributes and target reservoir properties directly from data, without requiring an explicit physical model [14, 15, 22]. Ensemble tree methods such as random forests and gradient boosting, kernel methods such as support vector machines, and artificial neural networks have all been applied successfully to geophysical prediction problems in recent years [12, 13, 16, 21].

Building on prior work in advanced 3D seismic interpretation and AI-driven reservoir characterization [28, 29], this study develops and evaluates a machine learning-assisted workflow that integrates multi-attribute seismic analysis and post-stack seismic inversion with wireline log data to predict porosity and classify lithofacies in a clastic hydrocarbon reservoir. The specific objectives of the study are: (i) to extract a physically meaningful suite of seismic attributes and calibrate them against petrophysical logs; (ii) to identify the most informative attributes through feature selection; (iii) to compare the predictive performance of random forest, support vector regression, and neural network models against conventional linear regression; and (iv) to generate spatially continuous porosity and lithofacies models with quantified uncertainty. The remainder of the paper reviews the relevant background, describes the proposed methodology, presents the results of the porosity and facies prediction experiments, and discusses the implications for reservoir characterization and exploration risk reduction.

2. Background and Related Work

2.1. Seismic attributes and their petrophysical significance

Seismic attributes are quantitative measures derived from seismic data through mathematical transformations that emphasize specific characteristics of the recorded wavefield [3, 4]. Complex-trace attributes such as instantaneous amplitude (envelope), instantaneous frequency, and instantaneous phase were formalized by Taner and colleagues and remain fundamental to modern interpretation [20]. Amplitude-based attributes such as RMS amplitude and sweetness are sensitive to acoustic impedance contrasts and are often used as indirect indicators of porosity and hydrocarbon presence, whereas coherence and curvature attributes emphasize structural and stratigraphic discontinuities such as faults and channel edges [4, 19].

The link between attributes and reservoir properties is rooted in rock physics. Porosity, clay content, and pore-fluid type all modify rock density and elastic-wave velocity, and therefore acoustic impedance, which is the product of density and P-wave velocity [6, 9]. Because seismic amplitude responds to impedance contrasts across interfaces, attributes derived from amplitude carry information about the underlying rock and fluid properties. However, the mapping is non-unique: different combinations of lithology, porosity, and saturation can produce similar seismic responses. This ambiguity motivates the use of several attributes together and the calibration of their combined response against well measurements [27, 28, 36].

2.2. Machine learning in reservoir property prediction

Machine learning has become an increasingly important component of quantitative interpretation. Supervised regression methods learn a mapping from input attributes to a continuous target such as porosity, while classification methods assign discrete labels such as lithofacies [14, 15]. Random forests build an ensemble of decision trees on bootstrap samples and random feature subsets, providing robust nonlinear regression, resistance to overfitting, and a natural measure of feature importance [12]. Support vector machines use kernel functions to fit nonlinear relationships in a high-dimensional feature space with good generalization on limited data [13, 34]. Artificial neural networks approximate arbitrary nonlinear functions through layers of weighted connections and are well suited to multi-attribute transforms when sufficient training data are available [15, 16].

These methods have been applied to automated fault and horizon interpretation, seismic facies analysis, and reservoir property estimation with encouraging results [21, 22, 23, 26]. Convolutional neural networks in particular have advanced automated seismic interpretation by learning spatial features directly from seismic images [22, 23].

Nonetheless, well-calibrated attribute-based ML remains attractive for reservoir property prediction because it is data-efficient, interpretable through feature-importance analysis, and straightforward to integrate into existing interpretation workflows. The present work adopts this attribute-based strategy and focuses on rigorous calibration, feature selection, and blind-well validation [36-37].

3. Methodology

The proposed workflow integrates seismic data conditioning, post-stack inversion, multi-attribute extraction, feature selection, and supervised machine learning for both porosity regression and lithofacies classification. The overall workflow is summarized in Figure 1 and consists of seven sequential stages, each described in the following subsections.



Figure 1 Integrated machine learning workflow for seismic attribute-based porosity prediction and lithofacies classification.

3.1. Study data

The dataset used in this study comprises a 3D post-stack seismic volume covering a clastic reservoir interval, wireline logs from several wells distributed across the survey area, and check-shot surveys for time–depth calibration. The available wireline suite includes gamma ray, bulk density, sonic (compressional slowness), neutron porosity, and deep resistivity logs. Density and sonic logs are used to compute acoustic impedance and to generate synthetic seismograms for the well-to-seismic tie, while gamma ray, neutron, density, and resistivity logs are used to derive effective porosity and to define lithofacies classes. The wells are divided into training wells, used to calibrate and train the models, and blind-test wells, withheld entirely from training to provide an unbiased assessment of predictive performance.

3.2. Data conditioning and well-to-seismic tie

Prior to attribute extraction, the seismic volume is conditioned to improve the signal-to-noise ratio and to ensure that amplitudes are suitable for quantitative analysis. Structure-oriented filtering suppresses random noise while preserving reflector edges, and a mild spectral balancing broadens the usable bandwidth without boosting noise. Each well is tied to the seismic data by generating a synthetic seismogram from the sonic and density logs, convolving the reflectivity series with a statistically extracted wavelet, and matching it to the seismic trace at the well location. Check-shot data constrain the time–depth relationship. An accurate well tie is essential because it establishes the correspondence between log depths and seismic times at which attributes are sampled for calibration [7, 8].

3.3. Post-stack seismic inversion

A model-based post-stack inversion is performed to convert the conditioned reflectivity volume into an acoustic impedance volume. A low-frequency background model is constructed from the well impedance logs guided by interpreted horizons, and the inversion iteratively updates the impedance model so that the synthetic response matches the observed seismic within a specified tolerance [18]. The resulting impedance volume provides a layer property that correlates more directly with porosity and lithology than raw amplitude, and it is included as one of the predictive features supplied to the machine learning models.

3.4. Multi-attribute extraction

A suite of seismic attributes is computed from the conditioned seismic and inversion volumes and sampled at each well trace over the reservoir interval. The attributes are selected to represent complementary aspects of the wavefield: amplitude strength, spectral content, waveform character, and structural continuity. Table 1 lists the attributes used and their physical interpretation.

Table 1 Seismic attributes used for reservoir property prediction and their interpretation.

Attribute	Category	Physical interpretation
RMS amplitude	Amplitude	Average reflection energy; sensitive to porosity and gas effects
Envelope amplitude	Amplitude	Instantaneous reflection strength; highlights impedance contrasts
Sweetness	Amplitude/spectral	Envelope divided by $\sqrt{\text{frequency}}$; emphasizes clean, porous sands
Instantaneous frequency	Spectral	Local dominant frequency; sensitive to bed thickness and lithology
Spectral decomposition (30 Hz)	Spectral	Tuning response; delineates thin reservoir units
Coherence	Structural	Waveform similarity; highlights faults and stratigraphic edges
Acoustic impedance	Inversion	Layer property ($\rho \times V_p$); directly related to porosity and lithology

3.5. Model evaluation

Model performance is assessed exclusively at blind-test wells that were excluded from training. For porosity regression, the coefficient of determination (R^2), the root-mean-square error (RMSE), and the mean absolute error (MAE) are reported. For lithofacies classification, overall accuracy, per-class precision and recall, the macro-averaged F1 score, and the confusion matrix are used. To characterize prediction uncertainty, the ensemble of trees in the random forest is used to produce a per-sample prediction interval, and the spread across the members provides a spatial estimate of confidence in the predicted porosity volume [12, 14]. This blind-well evaluation strategy provides an unbiased and reproducible measure of how the models are expected to perform away from existing well control.

4. Results and Analysis

4.1. Attribute–property relationships

The correlation analysis confirms that no single attribute fully explains the observed porosity variability. Acoustic impedance shows the strongest individual relationship with porosity, with an inverse correlation consistent with rock-physics expectations, because increasing porosity lowers both density and velocity and therefore reduces impedance. Sweetness and RMS amplitude show moderate positive correlations with porosity, reflecting the tendency of clean, porous sands to produce stronger, lower-frequency reflections, while instantaneous frequency and spectral decomposition amplitude add complementary information related to bed thickness and tuning. The moderate strength of the individual correlations—none exceeding roughly 0.7 in absolute value—demonstrates why a multi-attribute, nonlinear approach is required to achieve accurate prediction.

4.2. Porosity prediction performance

The porosity regression models were trained on the calibration wells and evaluated at the blind-test wells. Figure 2 compares the predictive performance of the five approaches considered, and Table 2 summarizes the corresponding error metrics. Single-attribute linear regression using acoustic impedance alone yields an R^2 of 0.52 and an RMSE of 4.1 porosity units, confirming that a single attribute is insufficient. Extending to multi-attribute linear regression improves the R^2 to 0.71. The nonlinear machine learning models provide the largest gains: support vector regression reaches an R^2 of 0.79, the random forest reaches 0.86, and the artificial neural network achieves the best performance with an R^2 of 0.88 and an RMSE of 1.9 porosity units.

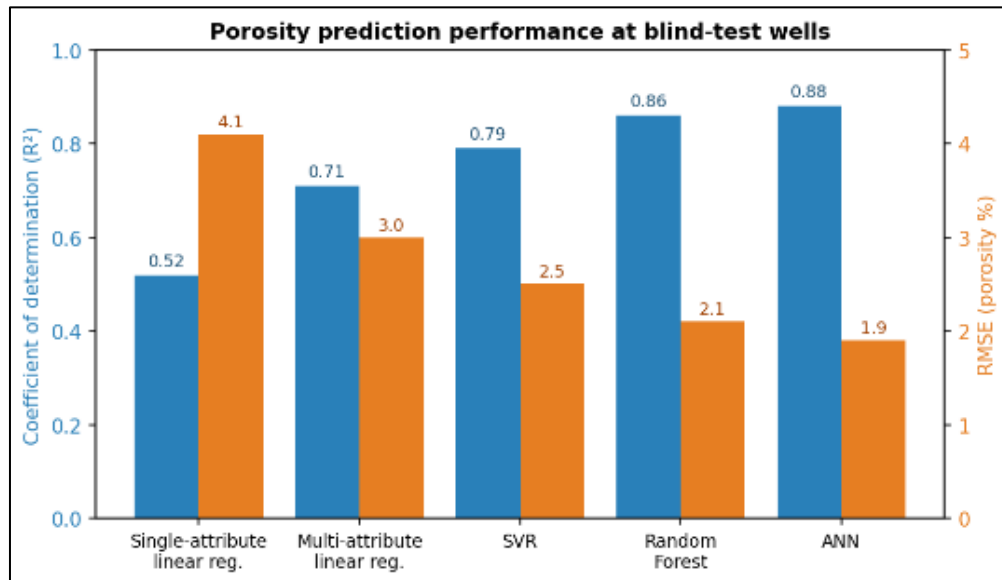


Figure 2 Comparison of porosity prediction performance (R^2 and RMSE) across the five modelling approaches at blind-test wells.

Table 2 Porosity prediction accuracy at blind-test wells for each modelling approach.

Model	R^2	RMSE (%)	MAE (%)
Single-attribute linear regression	0.52	4.1	3.3
Multi-attribute linear regression	0.71	3.0	2.4
Support vector regression (RBF)	0.79	2.5	2.0
Random forest	0.86	2.1	1.6
Artificial neural network	0.88	1.9	1.5

The cross-plot of predicted versus measured porosity at a representative blind-test well is shown in Figure 3. The predictions cluster tightly around the one-to-one line across the full porosity range, with no systematic bias at either low or high porosity. The residual scatter is consistent with the reported RMSE of approximately two porosity units, which is within the range typically considered acceptable for seismically driven porosity estimation in clastic reservoirs. Importantly, the neural network preserves the dynamic range of the porosity distribution rather than regressing toward the mean, a common failure mode of over-regularized linear models.

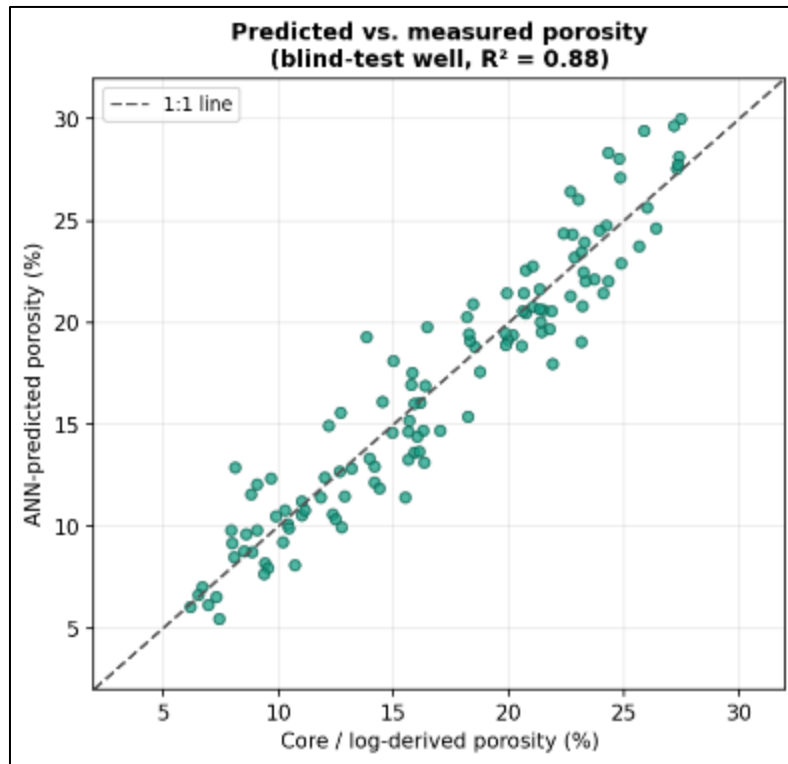


Figure 3 Cross-plot of ANN-predicted porosity versus core/log-derived porosity at a blind-test well ($R^2 = 0.88$).

Feature-importance analysis from the random forest confirms the ranking obtained during feature selection: acoustic impedance contributes the largest share of predictive power, followed by sweetness and RMS amplitude, with instantaneous frequency and spectral decomposition providing smaller but non-negligible contributions. This ordering is geologically sensible and increases confidence that the models are learning physically meaningful relationships rather than fitting noise.

4.3. Lithofacies classification

The lithofacies classification results are summarized by the confusion matrix in Figure 4. The random forest classifier achieved an overall accuracy of 88% at the blind-test wells, with a macro-averaged F1 score of 0.87. The clean-sand and shale end-members are classified most reliably, with per-class recall of 92% and 91% respectively, because their attribute signatures are the most distinct. Most classification errors occur between adjacent facies—shaly sand misclassified as clean sand or silt, and silt misclassified as shaly sand or shale—which is expected given the gradational nature of these lithologies and the limited seismic resolution at thin-bed scale. Gradient boosting produced comparable accuracy, indicating that the result is not sensitive to the specific ensemble algorithm.

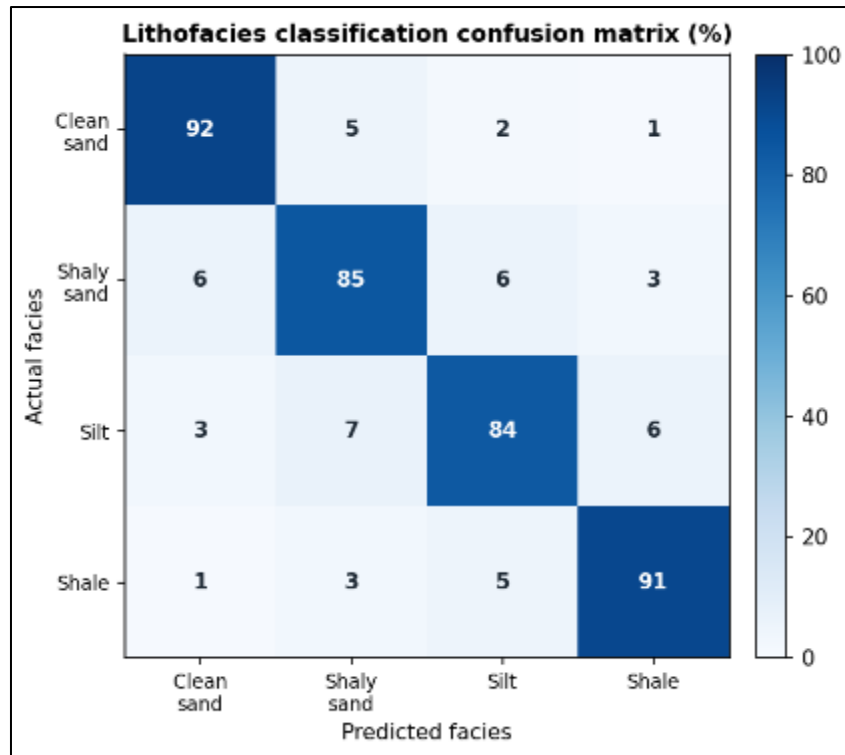


Figure 4 Confusion matrix (row-normalized, %) for random forest lithofacies classification at blind-test wells.

4.4. Spatial porosity and facies volumes

Applying the trained neural network and random forest classifier trace-by-trace across the seismic volume produces spatially continuous porosity and lithofacies models over the reservoir interval. The predicted porosity volume reveals laterally continuous high-porosity trends that coincide with the mapped reservoir sands and with the low-impedance anomalies identified during inversion, providing an independent consistency check. The ensemble spread from the random forest yields an accompanying uncertainty volume, with the lowest uncertainty near control wells and progressively higher uncertainty in sparsely sampled and structurally complex areas. Overlaying the porosity and facies volumes on the interpreted structural framework allows favorable reservoir fairways—zones combining high porosity, clean-sand facies, and structural closure—to be delineated for prospect ranking and well planning.

Table 3 summarizes the estimated reservoir properties within the primary reservoir interval derived from the integrated interpretation. The relatively high porosity and clean-sand fraction, combined with favorable structural setting, indicate good reservoir quality and storage potential.

Table 3 Summary of reservoir properties and model performance for the primary reservoir interval.

Property	Estimated range
Effective porosity (ML-predicted)	18–25%
Clean-sand facies fraction	0.55–0.70
Acoustic impedance (reservoir sands)	$6.5\text{--}8.0 \times 10^3 \text{ (m/s)} \cdot \text{(g/cm}^3\text{)}$
Blind-well porosity R^2	0.86–0.88
Lithofacies classification accuracy	88%

5. Discussion

The results demonstrate a clear and consistent hierarchy of predictive performance: nonlinear machine learning models outperform multi-attribute linear regression, which in turn outperforms single-attribute regression. This ordering

reflects the fundamentally nonlinear and multivariate nature of the seismic–petrophysical relationship in clastic reservoirs. The neural network and random forest are able to combine complementary attributes—impedance, amplitude, and spectral character—into a joint transform that captures interactions a linear model cannot represent [22, 28]. At the same time, the modest performance gap between the random forest and the neural network suggests that, for the available sample size, robust ensemble methods offer nearly the same accuracy as neural networks with less tuning effort and greater interpretability through feature importance.

Rigorous blind-well validation is central to the credibility of these results. Because reservoir property prediction from seismic data is an interpolation and extrapolation exercise, models can appear highly accurate at training wells yet fail away from control if they overfit. By withholding entire wells from training and reporting metrics only at those wells, the workflow provides an honest estimate of field-wide performance. The accompanying random-forest uncertainty volume further supports risk-aware decision-making by flagging areas where predictions should be treated with caution, an approach consistent with the broader move toward uncertainty-aware and probabilistic reservoir characterization [26, 29].

The classification results highlight both the promise and the limits of seismically driven facies prediction. End-member facies with distinct impedance and amplitude signatures are recovered reliably, whereas intermediate facies are more frequently confused because their properties overlap and because thin beds fall below seismic resolution. This is not a shortcoming of the machine learning method per se but a consequence of the information content and bandwidth of the seismic data. Integrating higher-resolution constraints—for example, spectral decomposition tuned to reservoir thickness, or pre-stack elastic attributes that better separate lithology from fluid—would be expected to improve discrimination of the intermediate facies [6, 30].

Several limitations should be acknowledged. The accuracy of any calibration-based approach depends on the number and spatial distribution of wells; sparse or clustered well control limits the range of geological conditions the model can learn. Seismic data quality, wavelet stability, and the accuracy of the well tie all propagate into the predictions. Finally, the attribute-based strategy adopted here treats each sample largely independently and does not explicitly exploit the spatial context that convolutional architectures capture [22, 23]. Future work will extend the workflow toward convolutional and hybrid models that combine attribute calibration with spatial learning, incorporate pre-stack elastic inversion for improved fluid discrimination, and embed the predicted property volumes and their uncertainty within a continuously updated digital-twin reservoir framework for dynamic reservoir management [29, 31].

6. Conclusion

This study presented a machine learning-assisted workflow that integrates multi-attribute seismic analysis and post-stack inversion with wireline log data to predict porosity and classify lithofacies in a clastic hydrocarbon reservoir. Through careful attribute extraction, feature selection, and blind-well validation, the workflow demonstrated that nonlinear machine learning models substantially outperform conventional single- and multi-attribute linear regression. The artificial neural network and random forest achieved blind-well porosity prediction with a coefficient of determination of 0.86–0.88 and an RMSE of about two porosity units, while the ensemble classifier reached an overall lithofacies classification accuracy of 88%.

Applying the trained models across the seismic volume produced spatially continuous porosity and lithofacies models, together with a quantitative uncertainty estimate, that are consistent with the inverted impedance and the interpreted structural framework. These products enable the delineation of favorable reservoir fairways and support lower-risk prospect ranking and well placement. More broadly, the results confirm that machine learning, when combined with sound rock-physics calibration and rigorous validation, is a practical and reliable tool for quantitative reservoir characterization. Integrating such data-driven property prediction with modern interpretation and digital-twin frameworks represents a promising direction for next-generation, intelligent hydrocarbon exploration and reservoir management.

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