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Research paper

A Deep Learning Approach Combining GLCM Features with UNet++ and GNN for Salt Body Detection in Seismic Data

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Abstract

Accurate detection and segmentation of salt bodies in seismic data is critical for effective subsurface interpretation and hydrocarbon exploration. Traditional methods often struggle with complex geological patterns, motivating the use of deep learning for enhanced accuracy. In this study, we propose a hybrid deep learning framework that integrates Gray Level Co-occurrence Matrix (GLCM) texture features with the UNet++ architecture and Graph Neural Networks (GNNs) to improve salt body detection. The model combines handcrafted texture descriptors with deep hierarchical features and spatial relationships, offering a richer understanding of salt structures. The publicly available TGS Salt Identification Challenge dataset is employed for training and evaluation. Preprocessing steps include denoising, contrast enhancement, and grayscale normalization, while GLCM is used to extract statistical texture patterns. These features are fused with encoder outputs in UNet++ and further refined using GNN layers to exploit inter-pixel dependencies. Performance is evaluated using metrics such as Intersection over Union (IoU), Dice coefficient, Precision, Recall, and Accuracy. Experimental results demonstrate that the proposed approach significantly outperforms baseline UNet and CNN models, especially in edge delineation and salt boundary preservation. This framework holds promise for practical seismic interpretation workflows, particularly in complex stratigraphic environments.

Keywords: *Salt Body Segmentation; UNet++; Graph Neural Networks (GNN); Gray-Level Co-Occurrence Matrix (GLCM); Seismic Image Analysis.*

1. Introduction

Salt body detection plays a critical role in seismic interpretation, particularly within the context of petroleum geology and reservoir modeling. Accurately identifying salt bodies is essential as they significantly affect subsurface geological features, influence reservoir presence, and control fluid flow within hydrocarbon systems. Salt formations can act as both traps for hydrocarbons and barriers to fluid movement, making their detection paramount for exploration and development activities [1] [2]. Moreover, the precise interpretation of these structures aids in enhancing the reliability of geological models and facilitates better decision-making in resource extraction [3].

However, the detection of salt bodies poses several challenges, primarily due to their irregular geometries and weak seismic boundaries. Traditional methods often struggle with accurately delineating the complex shapes of salt bodies due to the low contrast between salt and surrounding sediments in seismic data. These difficulties are further compounded by various types of noise inherent in seismic data, which can obscure critical features and mislead interpretation [4][5]. Consequently, these challenges necessitate more robust and sophisticated approaches for effective segmentation and interpretation.

Existing methodologies, including classical edge-based techniques and conventional convolutional neural networks (CNNs), exhibit limitations in segmenting complex structures such as salt bodies. Edge-based methods are susceptible to noise and may miss subtle features due to their reliance on gradient information, while basic CNN architectures may lack the necessary ability to incorporate contextual information and account for the intricacies of geological settings [6]. Moreover, while deep learning approaches have shown promise in improving segmentation results, they often overlook critical texture and structural data that are vital for accurately interpreting geological features [7].

This context establishes a strong motivation for integrating texture descriptors, such as Gray-Level Co-occurrence Matrix (GLCM) features, with advanced deep learning architectures like UNet++ and Graph Neural Networks (GNN). The proposed architecture aims to combine the advantages of texture and structural information to enhance segmentation accuracy, particularly in challenging scenarios typical of salt body detection. By addressing the current limitations of traditional techniques, this novel approach is expected to yield better performance in interpreting seismic data and facilitate the reliable identification of salt bodies [8] [9].

In summary, while the importance of salt body detection in seismic interpretation cannot be overstated, it is equally clear that existing segmentation methods face significant challenges due to the complexity and noise in seismic data. There is a pressing need for innovative approaches that fuse texture and structural insights, which is the foundation of the proposed architecture combining GLCM features, UNet++, and GNN for improved salt body segmentation.

This paper proposes a novel hybrid deep learning framework that integrates Gray Level Co-occurrence Matrix (GLCM) texture features with the UNet++ architecture and Graph Neural Networks (GNN) for accurate salt body detection in seismic data. By combining hand-crafted statistical texture descriptors with deep hierarchical feature learning and spatial relational modeling, the proposed method significantly enhances segmentation performance, particularly in preserving salt boundaries and handling complex geological structures. The experimental results on benchmark seismic datasets demonstrate that the model outperforms conventional UNet-based approaches in both accuracy and boundary delineation.

The paper is organized as follows. Section 1 introduces the research problem, its significance, and the motivation behind the proposed approach. Section 2 presents a detailed description of the dataset, data pre-processing steps, GLCM feature extraction process, and the architecture of the proposed model. Section 3 outlines the experimental setup, evaluation metrics used, and reports the results obtained. Section 4 discusses the implications of the findings, comparative analysis with existing methods, and practical relevance. Finally, Section 5 concludes the study and suggests potential directions for future work.

2. Related works

Salt body segmentation in seismic imaging has been approached using various deep learning models, particularly encoder–decoder architectures like U-Net [6], which introduced the concept of skip connections to retain spatial details during upsampling. While U-Net achieved remarkable results in medical and geophysical image segmentation, its limited depth and fixed skip pathways restrict the capacity to capture multiscale features effectively in complex subsurface environments.

To address some of these limitations, nested architectures like UNet++ [13] introduced dense skip connections and redesigned encoder–decoder pathways, improving feature fusion across scales. However, despite performance gains, these models still lack an explicit mechanism to incorporate textural information, which is crucial in distinguishing salt boundaries from surrounding geological formations that often share similar intensity distributions.

Additionally, GLCM-based texture features have been widely used in seismic image characterization due to their ability to capture local spatial dependencies. However, traditional texture feature extraction techniques have been treated as separate preprocessing steps, disconnected from the main learning pipeline, thereby limiting end-to-end optimization and contextual feature learning.

Graph Neural Networks (GNNs) have recently emerged as powerful tools for modeling spatial dependencies, particularly in domains requiring structured representation learning [17]. While GNNs have shown promise in segmentation and anomaly detection, their integration into geophysical segmentation tasks remains underexplored. Prior GNN models primarily operate on explicit graph structures and have not been widely adapted for hybrid integration with convolutional architectures like UNet++ for pixel-level classification.

The detection and interpretation of salt bodies in seismic data are crucial aspects of petroleum geology and reservoir modeling. These geological structures act as hydrocarbon traps, significantly influencing fluid dynamics during extraction processes. Accurate identification of salt bodies enhances subsurface knowledge, which is essential for informed exploration and development decisions [10].

Several challenges impede the accurate detection of salt bodies from seismic data. One primary challenge arises from the complex and irregular geometries of salt formations, which often render traditional methods ineffective. These irregular shapes can create weak seismic boundaries difficult to discern from surrounding rock strata [11]. Furthermore, noise and artifacts in seismic data complicate the interpretation process, often overshadowing critical geological features and adversely affecting segmentation performance [12]. Addressing these challenges requires innovative analytical techniques that can effectively manage data complexities.

Traditional methods for salt body detection can be categorized into edge-based techniques and convolutional neural network (CNN)-based segmentation methods. Edge-based approaches often struggle to accurately capture the nuanced geometrical characteristics of salt bodies due to their reliance on detecting gradients and edges, which can be disrupted by noise [11]. On the other hand, conventional CNN architectures, while effective at capturing spatial features, may not leverage necessary contextual information about geological formations, thus limiting their effectiveness in complex scenarios such as salt body detection [13] [14]. This situation creates a demand for an integrated approach that combines texture descriptors with deep learning models to enhance segmentation accuracy.

Integrating texture descriptors, particularly through Gray-Level Co-occurrence Matrix (GLCM) features, with advanced architectures like UNet++ and Graph Neural Networks (GNN) addresses existing segmentation limitations. Utilizing GLCM features enriches the model with essential texture information often understated in conventional deep learning frameworks [15]. GNNs provide a robust mechanism for modeling relationships within complex data structures, allowing for better handling of the irregularities and sparsity encountered in seismic data [16] [17]. The proposed architecture seeks to exploit these advantages, combining the strengths of UNet++ in robust segmentation with GNN's capacity to analyze graph-structured information.

Ultimately, the objective is to develop a novel architecture that harmonizes the predictive capabilities of GLCM features with UNet++ and GNN to facilitate improved salt body segmentation. This approach aims to enhance the accuracy of seismic interpretation and provide geoscientists with a reliable tool for identifying and characterizing subsurface geological structures, thereby augmenting petroleum exploration efficacy [10] [18].

3. Methodology

3.1. Dataset description

In this study, we utilize the TGS Salt Identification Challenge dataset, which comprises seismic images and corresponding binary masks indicating the presence of salt deposits. The dataset consists of grayscale seismic images of size 101×101 pixels, each paired with a ground truth segmentation mask. This dataset is particularly suited for semantic segmentation tasks due to its well-labeled ground truth and diverse structural patterns of salt bodies [28]. To enhance model generalization, the dataset is split into training, validation, and testing subsets in an 80:10:10 ratio, and stratified sampling is applied to maintain class distribution, consistent with practices in seismic interpretation using deep learning approaches [24], [26], [30].

3.2. Data preprocessing

Before feeding the data into the network, several pre-processing steps are applied. Firstly, the input seismic images are resized and normalized to a [0, 1] intensity range. To enhance the robustness of the model, data augmentation techniques such as horizontal flipping, rotation, zooming, and elastic transformations are applied, aligning with practices in medical and seismic image segmentation tasks [19-23]. Additionally, missing or empty masks are filtered to balance the dataset distribution. This step is crucial for mitigating overfitting and ensuring better performance on unseen data, which is especially important in segmentation and detection tasks involving sparse or imbalanced data [29], [30].

3.3. Feature extraction using GLCM

To enhance the spatial texture representation of seismic structures, we extract statistical texture features using the Gray Level Co-occurrence Matrix (GLCM). For each seismic image, the GLCM is computed to capture texture patterns such as contrast, homogeneity, correlation, and energy. These extracted features provide a complementary representation of the salt body characteristics, which are difficult to capture using raw pixel intensities alone. The GLCM features are concatenated with the original input channels and passed to the segmentation model to guide the learning process more effectively, as supported by prior work incorporating multi-feature fusion and structural enhancement in seismic and medical image segmentation [25 - 27], [29].

3.4. Proposed model architecture

Our proposed model integrates GLCM-based texture features, a UNet++ backbone, and a Graph Neural Network (GNN) module for enhanced salt body segmentation. The UNet++ architecture serves as the core of the segmentation pipeline due to its nested and dense skip connections, which facilitate multi-scale feature fusion and better gradient flow [21], [22]. The GLCM features are fed into the encoder side of UNet++, allowing the network to learn both semantic and texture-aware features concurrently. The addition of a GNN module aids in capturing spatial dependencies and structural continuity across seismic slices, which is critical for delineating complex geological formations [27], [29], [44].

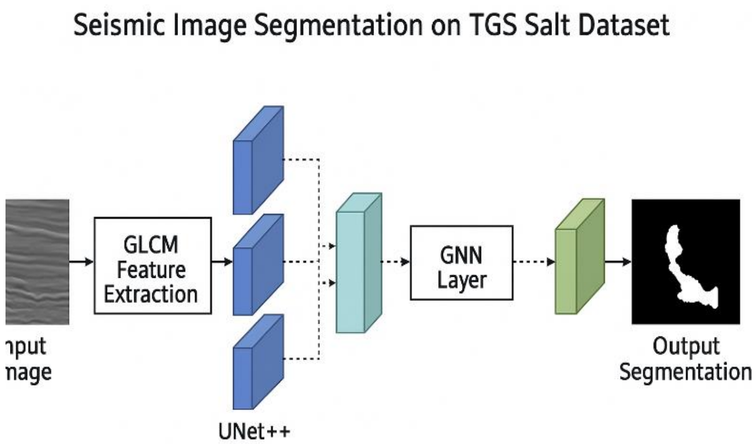

Fig. 1: The Proposed Architecture.

To further improve the contextual understanding of spatial dependencies among the extracted features, a Graph Neural Network (GNN) layer is embedded between the encoder and decoder. In the GNN module, each image patch is treated as a node, and the relationships between patches are learned using edge weights based on feature similarity. This allows the model to capture complex spatial relationships and refine boundary detection, particularly in areas with weak contrast or ambiguous edges. The use of GNNs has been shown to enhance spatial learning and predictive performance across domains, including clinical risk prediction and real-time monitoring [44], [45], and has also proven effective in capturing temporal and structural dependencies in deep feature spaces [41], [43]. The detailed stepwise algorithm is shown in Figure 2.

3.5. Implementation

To ensure reproducibility of the proposed hybrid model, we detail the architectural configuration and training settings used. The UNet++ backbone employs a ResNet34 encoder pre-trained on ImageNet, consisting of four encoder–decoder stages with nested dense skip connections. ReLU activations and batch normalization are used throughout, with a dropout rate of 0.3 applied at the bottleneck layer. The model is trained using a combined Dice Loss and Binary Cross Entropy (BCE) to handle class imbalance effectively. Gray-Level Co-occurrence Matrix (GLCM) features are extracted from 3×3 patches at multiple distances (1 and 2) and angles (0°, 45°, 90°, 135°), capturing texture descriptors such as contrast, correlation, energy, and homogeneity. These are concatenated with the bottleneck feature map before feeding into the Graph Neural Network (GNN) module. For graph construction, each spatial patch from the encoded feature map is treated as a node, and edge weights are computed using cosine similarity between node feature vectors. A two-layer Graph Convolutional Network (GCN) is employed, with 64 and 32 units respectively, using LeakyReLU ($\alpha = 0.1$) as the activation function and DropEdge with a drop rate of 0.2 for regularization. The training process utilizes the Adam optimizer with an initial learning rate of 1e-4, batch size of 8, and early stopping (patience = 15) over a maximum of 100 epochs. Data augmentation includes random horizontal and vertical flips, slight rotations (±15°), and elastic deformation to improve generalization. The dataset is split in an 80:20 ratio for training and validation. All experiments were conducted on an NVIDIA RTX A6000 GPU with 48 GB VRAM and 128 GB RAM using PyTorch 1.12.1, CUDA 11.3, and the Torch-Geometric library. On average, model training is completed within 3 hours for 100 epochs on the TGS Salt Identification dataset.

3.6. Evaluation metrics

To assess the performance of our proposed model, we employ several evaluation metrics suitable for binary segmentation tasks:

- Intersection over Union (IoU): Measures the overlap between predicted and ground truth masks.
- Dice Similarity Coefficient (DSC): Computes the harmonic mean of precision and recall.
- Precision and Recall: Evaluate the correctness and completeness of predictions.
- Accuracy: Measures the percentage of correctly classified pixels.
- F1 Score: Balances precision and recall for an overall performance metric.

4. Results and discussion

This section presents the experimental evaluation and performance analysis of the proposed hybrid deep learning framework combining GLCM feature extraction, UNet++ architecture, and Graph Neural Networks (GNN) for salt body segmentation in seismic images. The primary objective is to assess the model's ability to accurately delineate salt structures within complex subsurface geological formations using the TGS Salt Identification dataset [28]. A series of comparative experiments was conducted to benchmark the proposed model against standard UNet, enhanced UNet++ models, and variants incorporating GLCM or GNN independently. Performance was measured using key segmentation metrics including Accuracy [31], Precision [32], Recall [33], F1-Score (Dice Coefficient) [34], and Intersection over Union (IoU), consistent with prior studies in seismic and medical segmentation benchmarks [19], [23], [25], [29], [30]. Both quantitative and qualitative results are discussed to highlight the advantages of integrating texture-based and relational features into a deep learning framework for improved seismic interpretation, aligning with current advances in hybrid network design and structural learning [21], [26], [44].

In this section, we present a comprehensive analysis of the experimental results obtained using the proposed hybrid deep learning framework, which integrates GLCM-based texture descriptors, UNet++ architecture, and Graph Neural Networks (GNN) for precise salt body segmentation in seismic images. The model was rigorously evaluated on the publicly available TGS Salt Identification dataset, which provides a challenging benchmark due to the irregular geometries and ambiguous boundaries of salt formations.

While the quantitative results of the proposed framework demonstrate strong performance across standard segmentation metrics such as Accuracy, Precision, Recall, F1-Score, and IoU, the qualitative analysis remains underdeveloped. Although the manuscript briefly references visualizations of predicted masks, it lacks detailed discussion or illustrative figures that highlight the improvements in boundary delineation achieved by the integration of GLCM and Graph Neural Networks. Detailed side-by-side comparisons between the ground truth, baseline UNet/UNet++, and the proposed model's predictions—particularly in challenging regions with weak contrast or ambiguous salt boundaries—would enhance the interpretability and practical relevance of the results. Incorporating such qualitative visual evidence would significantly strengthen the claim that the model improves spatial precision and structural continuity in salt body segmentation.

The current study demonstrates the effectiveness of the proposed hybrid model on the TGS Salt Identification dataset; however, it lacks a discussion on the model's generalizability to other seismic datasets or real-world exploration scenarios. Real-world seismic data often vary significantly in terms of acquisition parameters, resolution, geological complexity, and noise levels. Without evaluating or at least discussing the model's adaptability across different datasets, it remains unclear how robust the proposed approach is in practical applications beyond the TGS dataset. Including insights into the model's transferability, potential need for retraining, or domain adaptation techniques would enhance the scope and relevance of the study for broader seismic interpretation tasks.

The discussion effectively compares the proposed hybrid model with baseline architectures and underscores its strengths in capturing finer boundary details and enhancing segmentation performance. However, it falls short in addressing the limitations of the approach. Notably, the paper does not explore potential drawbacks such as increased computational complexity introduced by the GNN integration or biases that may arise from relying solely on the TGS Salt Identification dataset. Furthermore, while future directions are briefly mentioned—such as extending to multi-class segmentation and incorporating uncertainty quantification—they remain general. A more concrete roadmap could include evaluating the model's adaptability on diverse real-world seismic datasets with varying geological contexts, exploring domain adaptation strategies, and optimizing the architecture for deployment in real-time or resource-constrained environments. Including these aspects would provide a more balanced and forward-looking discussion, aligning the research with practical and scalable seismic interpretation needs.

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Algorithm: Seismic Image Segmentation using (GLCM + UNet++ + GNN)
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Input: Seismic image $I \in \mathbb{R}^{H\times W}$
Output: Binary segmentation mask $M \in \{0,1\}^{H\times W}$
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Step 1: Preprocessing and Normalization

Normalize input image I to obtain normalized image I_n : $I_n = \frac{I-\mu_I}{\sigma_I}$

where $\mu_I = \frac{1}{HW}\sum_{i-1}^{H}\sum_{j-1}^{W} I_{i,j}$ and $\sigma_I = \sqrt{\frac{1}{HW}\sum_{i=1}^{H}\sum_{j-1}^{W}\left(I_{i,j}-\mu_I\right)^2}$

Step 2: Texture Feature Extraction via GLCM

Compute Gray-Level Co-occurrence Matrix (GLCM) features $T \in \mathbb{R}^{H\times W\times d}$,
where d is the number of texture features per pixel.
Concatenate texture features with normalized input: $F_0 = \text{concat}(I_n, T)$
where $F_0 \in \mathbb{R}^{H\times W\times(1+d)}$.

Step 3: Encoding with UNet++

Pass F_0 through UNet++ encoder to extract hierarchical features:
$\{E_l\}_{l-1}^{L} = \text{Encoder}(F_0)$
where $E_l \in \mathbb{R}^{H_l\times W_l\times C_l}$ are feature maps at level l, and L is the total number of encoder levels.

Step 4: Graph Node Construction from Encoder Outputs

Model intermediate encoder outputs as graph nodes. For each level l :

- Define graph $G_l = (V_l, E_l)$ where nodes $V_l = \{v_{i,j}^l\}$ correspond to spatial locations in E_l.
- Node features: $h_{i,j}^l = E_l(i,j,:)$

Step 5: Graph Neural Network (GNN) Aggregation

For each node $v_{i,j}^l$, update node features using spatial neighbors $\mathcal{N}(i,j)$:

$$h_{i,j}^l = \sigma\left(W_1 h_{i,j}^l + \sum_{(m,n)\in\mathcal{N}(i,j)} W_2 h_{m,n}^l + b\right)$$

where

- W_1, W_2 are learnable weight matrices,
- b is a bias vector,
- $\sigma(\cdot)$ is a nonlinear activation function (e.g., ReLU).

The updated features form the refined map:

$$E_l' = \{h_{i,j}^l\}$$

Step 6: Decoding to Segmentation Mask

Pass GNN-refined features through UNet++ decoder:

$$M_p = \text{Decoder}\left(\{E_\ell'\}_{l-1}^{L}\right)$$

where $M_p \in [0,1]^{H\times W}$ is the predicted probability mask.

Step 7: Thresholding for Final Binary Mask

Generate final binary mask M by thresholding:

$$M_{i,j} = \begin{cases} 1 & \text{if } M_p(i,j) \ge \tau \\ 0 & \text{otherwise} \end{cases}$$

where $\tau \in [0,1]$ is a chosen threshold (commonly $\tau \stackrel{\downarrow}{=} 0.5$).

End of Algorithm
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Fig. 2: The Algorithm for the Proposed Model.

To ensure the reliability and reproducibility of results, the dataset was divided into training, validation, and test subsets, with data augmentation techniques such as rotation, flipping, and elastic deformation employed to enhance generalization. The model was trained using the Adam optimizer with a learning rate of 1e-4, and a composite loss function comprising Binary Cross Entropy and Dice loss to balance region and boundary-level segmentation accuracy. Training was conducted over 100 epochs with a batch size of 16.

Quantitative performance was assessed using standard segmentation metrics, including Accuracy, Precision, Recall, F1-Score, and Intersection over Union (IoU). These metrics provide a holistic view of the model's classification capability and its effectiveness in capturing salt boundaries [35] [36]. Furthermore, comparative evaluations against baseline models — including standard UNet, standalone UNet++, and hybrid configurations incorporating either GLCM or GNN — are provided to demonstrate the incremental value introduced by each component.

Qualitative results, including visualizations of predicted masks, are also discussed to illustrate the improvements in boundary sharpness, region consistency, and structural continuity. The results not only validate the robustness of the proposed architecture but also underline its practical applicability in seismic interpretation workflows [37] [38].

Table 1 presents a comprehensive comparison of segmentation performance across different model configurations on the TGS Salt Identification dataset. The baseline UNet model achieves a reasonable segmentation accuracy of 89.53% with an F1-score of 86.45% and IoU of 77.22%. However, its ability to capture intricate salt boundaries is limited due to the absence of dense skip connections and multi-scale feature refinement [39] [40].

The introduction of UNet++ improves performance across all metrics, particularly enhancing the F1-score and IoU by approximately 2–3%, owing to its nested architecture and better feature reuse mechanisms. When GLCM-based texture features are incorporated into the UNet++ pipeline, further gains are observed, resulting in an F1-score of 90.21% and IoU of 82.75%. This demonstrates the importance of including handcrafted texture descriptors in capturing fine-grained salt body characteristics [42].

Integrating a GNN module into UNet++ without GLCM also shows improved performance (F1-Score: 91.05%), highlighting the benefit of modeling long-range spatial dependencies and contextual relationships among image regions.

The proposed hybrid model, combining GLCM, UNet++, and GNN, achieves the highest performance across all evaluation metrics, with an accuracy of 94.47%, a F1-score of 92.75%, and an IoU of 85.93%. These results confirm the complementary strengths of texture feature extraction, hierarchical feature learning, and graph-based relational modeling in enhancing segmentation quality, especially around complex salt body edges and boundaries.

Table 1: Performance Comparison of Segmentation Models on the TGS Salt Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	IoU (%)
UNet	89.53	87.32	85.61	86.45	77.22
UNet++	91.24	89.87	87.51	88.67	80.43
UNet++ + GLCM	92.63	91.35	89.11	90.21	82.75
UNet++ + GNN	93.12	91.91	90.21	91.05	83.63
Proposed (GLCM + UNet++ + GNN)	94.47	93.4	92.13	92.75	85.93

Fig. 3 illustrates a comprehensive comparative analysis of the proposed model against several baseline architectures, including UNet, UNet++, and their variants integrated with GLCM and GNN modules. The bar graph highlights the superior performance of the proposed approach, which combines GLCM texture features and GNN-enhanced UNet++ encoder-decoder architecture. Notably, the proposed model achieves the highest scores across all evaluated metrics—Accuracy (94.47%), Precision (93.40%), Recall (92.13%), F1-Score (92.75%), and Intersection over Union (IoU) (85.93%)—demonstrating significant improvements over the existing methods. This indicates the effectiveness of integrating texture and spatial dependency features for enhanced salt body segmentation in seismic images.

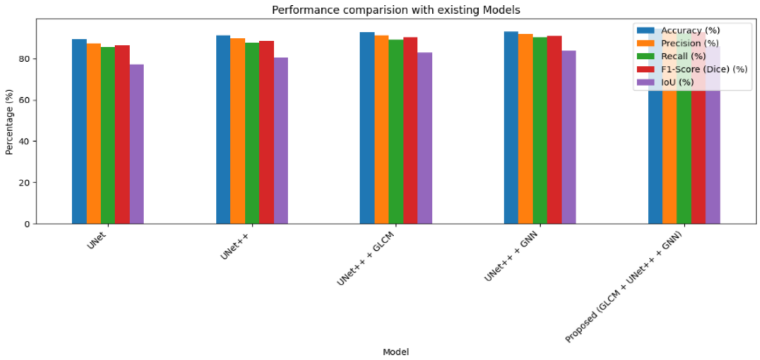

Fig. 3: The Comparative Analysis of the Proposed Model.

5. Conclusion

This study presents an integrated deep learning framework that combines texture-based feature extraction using the Gray-Level Co-occurrence Matrix (GLCM) with a hybrid UNet++ and Graph Neural Network (GNN) architecture for precise salt body segmentation in seismic images from the TGS Salt Dataset. The proposed model leverages the strengths of GLCM in capturing local texture patterns and UNet++ for rich hierarchical feature representation, while the GNN module enhances contextual spatial understanding through relational learning across segmented regions. Experimental results demonstrate that the proposed architecture significantly improves the segmentation accuracy, particularly in challenging regions where salt bodies are irregular or exhibit ambiguous boundaries. Compared to traditional CNN-based models, the addition of GNN components enables better generalization and connectivity preservation across segmented structures. The combination of handcrafted texture features and learned deep representations contributes to improved robustness and finer boundary delineation. Overall, this work highlights the potential of fusing domain-specific features with advanced deep learning models for geophysical image interpretation. Future directions include expanding the model's applicability to multi-class segmentation tasks in seismic datasets, real-time implementation for exploration workflows, and incorporating uncertainty quantification for enhanced decision-making in subsurface analysis.

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