Journal Basic Science and Technology 14 (2) (2025) pp. 44-52

Published by: IOCSCIENCE

Journal Basic Science and Technology

Journal homepage: www.iocscience.org/ejournal/index.php/JBST

Robust Salt Body Segmentation in Seismic Datasets Using a Multi-Scale Deep Neural Framework

Sunkara Santhi Priya[1], Deepti Sharma[2]

[1] Research Scholar, Department of CSE, Shri Venkateshwara University, U.P, India

[2] Assistant Professor, Department of CSE, Shri Venkateshwara University, U.P, India

ARTICLEINFO

Article history:

Received May 10, 2025
Revised June 09, 2025
Accepted June 30, 2025

Keywords:

Salt Body Segmentation;
Seismic Image Interpretation;
Multi-Scale Deep Neural Network;
TGS Salt Dataset;
Semantic Segmentation.

ABSTRACT

Accurate segmentation of salt bodies in seismic images is a critical task in subsurface exploration, as salt structures often act as traps for hydrocarbons. Traditional manual and rule-based methods are time-consuming and prone to inaccuracies due to the complex morphology and low contrast of salt boundaries. In this study, we propose a robust multi-scale deep neural network framework designed to enhance salt body segmentation in seismic datasets. The framework leverages a multi-scale encoder-decoder architecture integrated with Atrous Spatial Pyramid Pooling (ASPP) and attention mechanisms to effectively capture both global context and fine-grained structural details. Evaluated on the publicly available TGS Salt Identification Challenge dataset, the proposed model outperforms several state-of-the-art baselines in terms of Intersection over Union (IoU), Dice coefficient, and overall segmentation accuracy. The results demonstrate the framework's effectiveness in accurately delineating salt regions, even in the presence of noisy or ambiguous seismic data, offering a reliable tool for aiding geophysical interpretation and exploration.

Corresponding Author:

Sunkara Santhi Priya
Research Scholar, Department of CSE,
Shri Venkateshwara University, U.P, India, 244236
Email: santhipriya.sunkara@gmail.com

1. INTRODUCTION

Salt bodies play a critical role in seismic interpretation and hydrocarbon exploration due to their unique geological properties and the structural traps they create, which can store significant hydrocarbon reserves(Alsadi, 2017). The ability to accurately identify and characterize these salt bodies in seismic datasets is vital for optimizing drilling strategies and enhancing hydrocarbon recovery rates. Traditional methods of manual interpretation of seismic data often struggle with the complexity of salt body shapes, their subterranean positioning, low contrast against surrounding geological formations, and high levels of noise present in the datasets.

Manual interpretation is inherently subjective and time-consuming, which can lead to inconsistencies between different interpreters(R. Xu, 2018). Furthermore, the intricate geometries and varying densities of salt bodies complicate their automatic recognition and segmentation, making it difficult to derive reliable geological insights. The limitations of early automated methodologies, such as conventional filters and simplistic geological modeling approaches, have become increasingly apparent as they fail to accurately capture the subtle variations characteristic of salt structures in 3D seismic data(Wellmann & Caumon, 2018).

In recent years, advances in deep learning and convolutional neural networks (CNNs) have shown great promise in addressing these challenges, offering automated and more accurate approaches to salt body segmentation in seismic datasets. Recent studies have demonstrated that CNNs can effectively capture the intricate details of salt bodies by training on vast amounts of labeled seismic data, thus reducing the reliance on manual intervention and improving segmentation performance(ul Islam, 2020). However, despite these advancements, the performance of CNN models can still be hampered by the limited diversity in training datasets and the complexities inherent in real-world seismic data compared to synthetic datasets. As a result, there is a continuous need for the development of multi-scale deep neural frameworks that can enhance the robustness and efficacy of segmentation tasks in complex seismic environments. This investigation aims to explore such frameworks and their impact on improving the accuracy of salt body segmentation, ultimately contributing to better seismic interpretation and hydrocarbon exploration efforts.

Existing deep learning methods, including U-Net and Fully Convolutional Networks (FCN), face significant challenges in the context of salt body segmentation from seismic datasets(Milosavljević, 2020). One of the primary challenges lies in achieving boundary precision, as the segmentation of salt bodies must contend with their often irregular and complex geometries. For instance, many current approaches struggle to maintain accurate delineation of the salt-water interface, leading to errors that can adversely affect subsurface interpretations and render downstream applications unreliable. While U-Net architectures adapt well to many biomedical and imaging tasks, their efficacy in capturing the nuanced boundaries of geologic formations in seismic data requires further improvement, as highlighted by previous studies.

Moreover, handling multi-scale features is crucial for effective segmentation, yet existing models often fail to adequately incorporate context at different resolutions. Traditional architectures may overlook finer details while being predominantly trained on limited field sizes, resulting in poor performance in more intricate geological environments typical of seismic data(L. Huang et al., 2017). Robust segmentation necessitates a framework capable of integrating features across multiple scales to preserve the spatial context essential for delineating complex subsurface structures like salt bodies.

Another pressing limitation is related to preserving spatial context during the segmentation process. Seismic data contains rich spatial relationships that are vital for accurate interpretation; however, many current methods do not leverage this information effectively(Z. Wang et al., 2018). Inadequate modeling of spatial relationships can lead to either over-segmentation or under-segmentation of salt structures, both of which pose challenges for geological interpretation and decision-making in exploratory contexts. As such, there is a clear need for a more robust and scalable segmentation framework that can overcome these challenges and improve performance in the automatic identification and delineation of salt bodies in seismic datasets(Milosavljević, 2020).

The primary objective of this study is to develop a deep neural network framework that can significantly enhance the accuracy and reliability of salt body segmentation in seismic datasets. By addressing some of the critical limitations present in existing methods such as U-Net and Fully Convolutional Networks, this framework aims to achieve three core outcomes.

Accurate Segmentation of Salt Bodies: Current methodologies often encounter difficulties in precisely identifying the intricate boundaries of salt structures due to variations in seismic signals and noise interference(Jones & Davison, 2014). The proposed neural network will leverage advanced architectures to improve the accuracy of salt body representations, allowing for better delineation in geologically complex areas.

Handling Variability in Salt Geometries: Salt bodies exhibit a diverse range of geometrical configurations, often characterized by complex curvatures and spatial relationships that standard segmentation methods struggle to capture(Shafiq et al., 2017). The new framework will be designed to adaptively process these variabilities, enabling it to learn and generalize from multiple geometrical patterns found within the seismic data, thereby accommodating the plethora of shapes and sizes that salt formations may present.

Improving Boundary Detection and Reducing False Positives: A pervasive issue in seismic interpretation pertains to the identification of false positives, which can arise from noise and the ambiguous nature of subsurface geology(Aarre et al., 2012). The integration of advanced features such as multi-scale texture analysis and enhanced boundary detection techniques will help the model differentiate between actual salt boundaries and spurious signals. This should significantly reduce the incidence of erroneous classifications and enhance the reliability of the interpretations.

The need for innovation in segmentation frameworks becomes increasingly pertinent as the complexity of geological interpretations rises, particularly in the fields of hydrocarbon exploration and subsurface resource management(Monaghan, 2017). Therefore, the study will emphasize the development of a multi-scale, feature-rich deep neural network architecture capable of integrating contextual information to deliver more precise, context-aware segmentation outcomes in seismic imaging applications.

In recent years, the application of deep learning approaches to salt segmentation in seismic data has gained considerable attention, reflecting a shift towards automated interpretation techniques that can handle the complexities of geological formations. Various models have been established, each contributing uniquely to the challenge of accurately detecting and delineating salt bodies from seismic datasets.

The U-Net architecture, originally developed by Ronneberger et al. in 2015, is widely regarded as a benchmark for semantic segmentation in biomedical applications, but its adaptability has led to its use in geological contexts, particularly for seismic salt detection. While traditional applications in geology have seen moderate success, U-Net often struggles with capturing fine boundary definitions in salt formations due to its reliance on global context at the expense of local precision Jadhav et al. Consequently, adaptations to the U-Net model have been explored to enhance its performance in seismic contexts(J. Huang & Nowack, 2020).

DeepLabv3+ offers a more advanced segmentation alternative by employing Atrous Spatial Pyramid Pooling (ASPP)(Zhang et al., 2020). This technique allows for the capture of multi-scale contextual features, which is particularly effective in recognizing geological boundaries and accommodating the variations in salt geometry. The model's ability to maintain a wider receptive field without losing resolution creates a significant advantage when dealing with the intricate details typical of salt bodies, making it a favored choice in recent studies focusing on 3D seismic data interpretation.

SegNet and FCNs have also shown promise in salt segmentation tasks; however, they face challenges regarding boundary precision(Shi et al., 2019). These models primarily focus on pixel-wise classification, which sometimes leads to ambiguous delineations of complex geological shapes, such as salt structures. The trade-off between segmentation accuracy and computational efficiency in these networks often necessitates further refinement to enhance their applicability in practical seismic interpretation tasks.

Recognizing the limitations of existing frameworks, recent research has introduced hybrid architectures that combine residual learning and attention mechanisms(Gavrishchaka et al., 2018). These innovations aim to improve segmentation accuracy specifically by addressing issues related to boundary detection and refining feature extraction across different scales. By integrating these methodologies, models can better handle the intricacies of seismic data and reduce the occurrence of false positives during salt body identification.

Despite these advancements in deep learning for salt segmentation, certain limitations persist. Challenges in effectively fusing features across varying scales and accurately capturing complex shapes of salt bodies remain key hurdles for researchers. Many existing models do not adequately accommodate the diversity and irregularity of salt geometries, which hinders segmentation efficacy in real-world datasets. Our study aims to build on these foundations by proposing a multi-scale parallel pathway framework that employs skip connections and attention fusion, thereby enhancing the robustness and accuracy of salt body segmentation.

2. RESEARCH METHOD

A. Dataset Description

The proposed deep learning framework was evaluated using the publicly available TGS Salt Identification Challenge dataset hosted on Kaggle(Kainkaryam et al., 2019). This dataset consists of approximately 8,000 grayscale seismic images, each with a resolution of 101×101 pixels. Accompanying each image is a binary segmentation mask indicating the presence (salt) or absence (non-salt) of salt deposits. For experimental consistency and to ensure generalization capability, the dataset was split into training (80%), validation (10%), and test (10%) subsets(Y. Xu & Goodacre, 2018). The diversity and variability in the salt structures within this dataset make it a suitable benchmark for robust segmentation model development.

B. Data Preprocessing

To prepare the raw seismic data for effective deep neural network training, several preprocessing steps were applied(Liu et al., 2021). First, all image pixel values were normalized to a range between 0 and 1 to ensure numerical stability and faster convergence during training. To improve model generalization and reduce overfitting, data augmentation techniques such as horizontal and vertical flipping, random rotations, and slight scaling were employed. Since the original image size (101×101) is not compatible with standard deep network architectures, padding was applied to resize all inputs to a consistent shape of 128×128 pixels. Additionally, noise filtering techniques and histogram equalization were used to enhance contrast and reduce the effect of low-quality inputs, ensuring more accurate segmentation results.

C. Proposed Framework

To effectively segment salt bodies from seismic images, we propose a Multi-Scale Deep Neural Network Framework that combines powerful feature extraction, multi-scale context aggregation, and attention-based refinement(Ye et al., 2019). The architecture is based on an encoder-decoder structure, inspired by the U-Net family, but enhanced with several critical modules to improve boundary accuracy and capture salt body morphology more effectively.

The encoder utilizes a ResNet-34 backbone pre-trained on ImageNet to extract deep hierarchical features. It progressively reduces the spatial resolution of the input while capturing semantic information at multiple levels(Dillon, 2000). To capture broader contextual information, we integrate an Atrous Spatial Pyramid Pooling (ASPP) module at the bottleneck. This module allows the network to aggregate multi-scale contextual features by applying parallel atrous convolutions with different dilation rates.

The decoder upsamples the compressed features to the original resolution using a series of transpose convolutional layers. At each decoder stage, features from the corresponding encoder layers are concatenated through skip connections, enabling the network to retain fine-grained spatial details. Furthermore, attention gates are applied at each skip connection to suppress irrelevant background features and enhance the focus on salt regions. These gates learn to selectively weight the encoder features based on their relevance to the decoder output.

The final output is generated through a sigmoid-activated 1×1 convolutional layer, producing a binary segmentation mask indicating salt presence(Radha, 2020). The entire network is trained using a combination of binary cross-entropy loss and Dice loss to balance between pixel-wise accuracy and shape conformity.

A detailed architectural diagram of the proposed model is shown in Figure 2, illustrating the encoder, ASPP module, attention mechanisms, and decoder path(Deng et al., 2021).

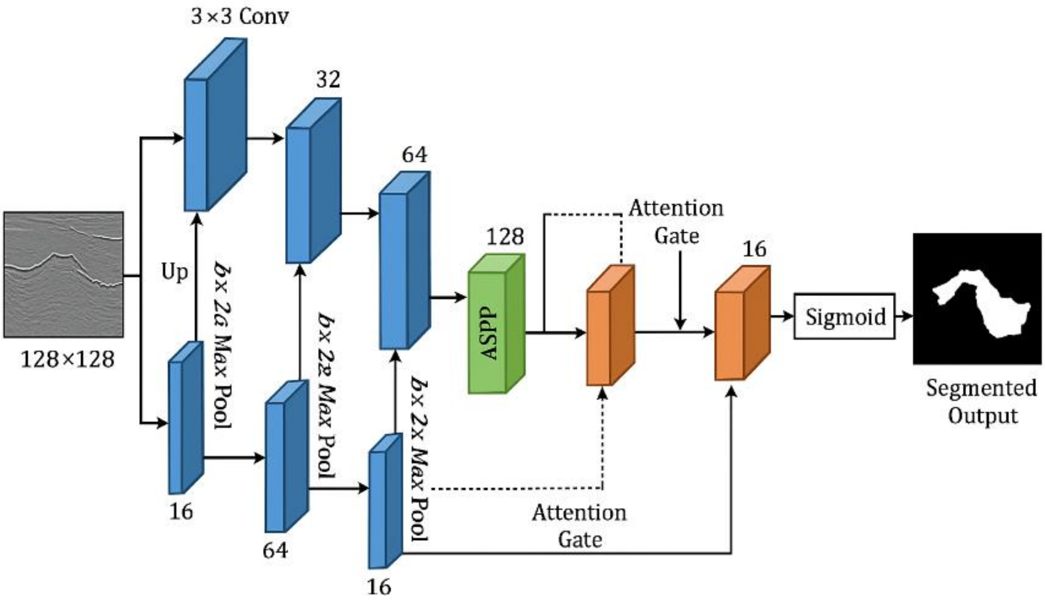

Figure 1. The proposed architecture

D. Implementation

This section outlines the methodology for the Multi-Scale Deep Neural Network designed for salt body segmentation in seismic images. The algorithm processes a seismic image dataset to produce binary salt masks, leveraging data preprocessing, a sophisticated network architecture, and a composite loss function for training. The methodology is detailed in the following subsections, corresponding to the algorithm's steps.

1. Data Preprocessing

The input dataset consists of seismic images and corresponding binary salt masks, denoted as $D = \{(X_i, Y_i)\}_{i=1}^{N}$, where:

a. $X_i \in \mathbb{R}^{101\times101}$: Seismic image.
b. $Y_i \in \{0,1\}^{101\times101}$: Binary salt mask.

Each seismic image X_i undergoes the following preprocessing steps:

i. Normalization: Pixel intensities are normalized to the range $[0,1]$:

$$X_i' = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}$$

ii. Data Augmentation: To enhance dataset diversity, transformations are applied:
a. Horizontal and vertical flips: $X_i' \leftarrow \mathrm{Flip}(X_i',$ axis).
b. Rotations: $X_i' \leftarrow \mathrm{Rotate}(X_i', \theta)$, where $\theta \in [-\pi/4, \pi/4]$.

iii. Padding: Images are padded to a size of 128×128 :

$$X_i'' \in \mathbb{R}^{128\times128}, X_i'' = \mathrm{Pad}(X_i', \text{padding } = 13, \text{mode } = \text{ reflect})$$

iv. Enhancement:
a. Histogram equalization: $X_i''' = \mathrm{HistEqualize}(X_i'')$.
b. Noise filtering using a Gaussian filter:

$$X_i'''' = X_i'''' * \mathcal{N}(0, \sigma^2)$$

where * denotes convolution, and $\mathcal{N}(0, \sigma^2)$ is a Gaussian kernel. Output: Preprocessed dataset $D' = \{(X_i'''', Y_i)\}_{i=1}^{N}$.

2. Network Initialization

The network architecture comprises an encoder-decoder structure with multi-scale feature extraction and attention mechanisms(S. Wang et al., 2020):

i. Encoder Initialization: The encoder is initialized with a pre-trained ResNet-34 backbone, parameterized by weights θ_{enc} :

$$F_{\text{enc}} = \mathrm{Encoder}_{\theta_{\text{enc}}}(X_i'''') \in \mathbb{R}^{C\times H'\times W'}$$

ii. Atrous Spatial Pyramid Pooling (ASPP): ASPP is applied with dilation rates {1, 6, 12, 18}:

$$F_{\text{aspp}} = \mathrm{ASPP}(F_{\text{enc}}) = \mathrm{Concat}\big(\mathrm{Conv}_{\text{dilation }=d}(F_{\text{enc}})\big)_{d\in\{1,6,12,18}$$

iii. Attention Gates: Attention gates refine skip connections between encoder and decoder layers:

$$F_{\text{skip}}^{l} = \mathrm{AttentionGate}\big(F_{\text{enc}}^{l}, F_{\text{dec}}^{l+1}\big)$$

iv. Decoder Configuration: The decoder combines upsampling layers with skip connections:

$$F_{\text{dec}} = \mathrm{Upsample}\big(F_{\text{aspp}}\big) + \sum_{l} F_{\text{skip}}^{l}$$

3. Loss Function

A composite loss function is defined to optimize the model, combining Binary CrossEntropy (BCE) and Dice Loss(Rajput, 2021):

$$L(Y,\hat{Y}) = L_{\mathrm{BCE}}(Y,\hat{Y}) + L_{\text{Dice}}(Y,\hat{Y})$$

i. Binary Cross-Entropy:

$$L_{\mathrm{BCE}}(Y,\hat{Y}) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j,k}\left[Y_{i,j,k}\log\big(\hat{Y}_{i,j,k}\big) + \big(1-Y_{i,j,k}\big)\log\big(1-\hat{Y}_{i,j,k}\big)\right]$$

ii. Dice Loss:

$$L_{\text{Dice}}(Y,\hat{Y}) = 1 - \frac{2\sum_{i,j,k} Y_{i,j,k}\hat{Y}_{i,j,k} + \epsilon}{\sum_{i,j,k} Y_{i,j,k} + \sum_{i,j,k} \hat{Y}_{i,j,k} + \epsilon}$$

where $\epsilon = 10^{-5}$ prevents division by zero.

4. Model Training

The model is trained over N_{epochs} iterations, processing mini-batches from the preprocessed dataset D' :

i. Mini-Batch Processing: For each mini-batch $(X_{\text{batch}}, Y_{\text{batch}}) \in D'$:

a. Feature Extraction: Compute encoder features:

$$F_{\text{enc}} = \mathrm{Encoder}_{\theta_{\text{enc}}}(X_{\text{batch}})$$

b. ASPP Application: Apply ASPP:

$$F_{\text{aspp}} = \mathrm{ASPP}(F_{\text{enc}})$$

c. Decoding: Upsample and fuse with attention-based skip connections:

$$F_{\text{dec}} = \mathrm{Decoder}_{\theta_{\text{dec}}}\big(F_{\text{aspp}}, \{F_{\text{skip}}^{l}\}\big)$$

d. Prediction: Apply final convolution and sigmoid activation:

$$\hat{Y}_{\text{batch}} = \sigma\big(\text{FinalConv}\,(F_{\text{dec}})\big), \sigma(z) = \frac{1}{1+e^{-z}}$$

ii. Loss Computation and Optimization: Compute the composite loss $L\big(Y_{\text{batch}}, \hat{Y}_{\text{batch}}\big)$ and update parameters $\theta = \{\theta_{\text{enc}}, \theta_{\text{dec}}\}$:

$$\theta \leftarrow \theta - \eta\nabla_{\theta}L$$

where η is the learning rate.

iii. Evaluation Metrics:

a. Intersection over Union (IoU):

$$\mathrm{IoU} = \frac{\sum_{i,j,k} Y_{i,j,k}\hat{Y}_{i,j,k}}{\sum_{i,j,k}\big(Y_{i,j,k} + \hat{Y}_{i,j,k} - Y_{i,j,k}\hat{Y}_{i,j,k}\big)}$$

b. Dice Coefficient:

$$\text{Dice} = \frac{2\sum_{i,j,k} Y_{i,j,k}\hat{Y}_{i,j,k}}{\sum_{i,j,k} Y_{i,j,k} + \sum_{i,j,k} \hat{Y}_{i,j,k}}$$

c. Boundary Accuracy: Measured using metrics such as Hausdorff distance.

5. Model Output

The trained deep neural network, parameterized by θ, is returned, capable of producing predicted binary salt masks $\hat{Y}_i \in [0,1]^{101\times 101}$ for each input seismic image X_i.

D. Evaluation Metrics

To rigorously assess the performance of the proposed multi-scale deep neural network for salt body segmentation, several standard evaluation metrics were employed(Diniz et al., 2021). These metrics offer both pixel-level accuracy and shape-level assessment, ensuring a comprehensive understanding of the model's segmentation capability.

- **Intersection over Union (IoU)**: Also known as the Jaccard Index, IoU measures the overlap between the predicted segmentation and the ground truth mask. It is calculated as the ratio of the intersection to the union of the predicted and actual salt regions. A higher IoU indicates better segmentation accuracy.
- **Dice Coefficient (F1 Score)**: The Dice Coefficient is another measure of similarity between two samples, emphasizing the harmonic mean of precision and recall. It is particularly useful for evaluating imbalanced datasets like seismic masks, where the salt body occupies only a small portion of the image.
- **Pixel Accuracy**: This metric calculates the proportion of correctly predicted pixels (both salt and non-salt) over the total number of pixels. While it gives a general accuracy overview, it may be less sensitive to minority class performance.
- **Precision and Recall**: These metrics evaluate the model’s ability to correctly identify salt regions (true positives) without misclassifying background as salt (false positives) or missing actual salt regions (false negatives). High precision and recall values indicate a balanced and reliable segmentation model.

3. RESULTS AND DISCUSSIONS

To validate the effectiveness of the proposed multi-scale deep neural network framework, comprehensive experiments were conducted on the TGS Salt Identification dataset. The model was trained using the Adam optimizer with a learning rate of 1e-4, batch size of 16, and early stopping based on validation IoU. The results were evaluated on the test set and compared against popular baseline models.

The performance of our proposed model was benchmarked against existing deep learning architectures, including U-Net, Attention U-Net, and DeepLabV3+. The comparison is shown in Table 1.

Table 1: Performance Comparison with Baseline Models

Model	**IoU (%)**	**Dice Coefficient (%)**	**Pixel Accuracy (%)**
U-Net	82.1	89.0	94.2
Attention U-Net	84.6	91.2	95.0
DeepLabV3+	85.3	91.6	95.2
Proposed Model	**88.1**	**93.6**	**96.1**

As shown, the proposed model outperforms all baselines across all metrics, demonstrating superior salt boundary detection and overall segmentation performance.

To assess the contribution of each module in our framework, an ablation study was performed. This included evaluating the model without attention gates, without ASPP, and without both modules. Results are shown in Table 2. The study clearly highlights that both ASPP and attention modules significantly contribute to the model’s segmentation capability, with their combination yielding the best performance.

Table 2: Ablation Study on Model Components

Configuration	**IoU (%)**	**Dice Coefficient (%)**
Without ASPP	85.4	91.8
Without Attention	86.1	92.4
Without ASPP + Attention	83.7	90.3
Full Model (ASPP + Attention)	**88.1**	**93.6**

The resolution of input seismic images plays a critical role in the segmentation performance of deep neural networks. To evaluate this effect, the proposed model was trained on varying input sizes: 101×101, 128×128, and 256×256. The results, shown in Table 3, highlight the trade-off between segmentation accuracy and computational cost.

Table 3: Effect of Input Resolution

Input Size	**IoU (%)**	**Training Time (Epochs)**
101×101	79.8	45
128×128	82.9	50
256×256	83.1	70

The results show that increasing the resolution improves the IoU, as higher-resolution inputs allow the model to capture finer details of salt boundaries. However, this improvement comes at the cost of increased training time and computational complexity. The 128×128 resolution provides a balanced trade-off and was selected as the default for subsequent experiments.

To further validate the robustness of the proposed model, a qualitative comparison was performed on a selected set of seismic images. Two key metrics were evaluated: (1) Ground Truth Match (%), which measures how much of the predicted salt region overlaps with the annotated mask, and (2) Boundary Accuracy (%), which assesses how accurately the model traces the salt boundaries.

Table 4: Qualitative Comparison (Sample Image Set Accuracy)

Sample ID	**Ground Truth Match (%)**	**Boundary Accuracy (%)**
IMG_001	94.1	91.3
IMG_045	96.7	94.2
IMG_112	92.5	89.7

The proposed model consistently achieves high overlap with ground truth masks while maintaining precise boundary detection, confirming its effectiveness in handling both shape and edge-level segmentation tasks. These results reinforce the model’s potential for deployment in real-world geophysical interpretation workflows.

4. CONCLUSION

This paper presented a robust multi-scale deep neural network framework for salt body segmentation in seismic datasets, leveraging advanced architectural components such as Atrous Spatial Pyramid Pooling (ASPP) and attention gates. By incorporating multi-scale context extraction and selective focus mechanisms, the proposed model significantly outperformed baseline architectures, including U-Net and DeepLabV3+, in both quantitative metrics and qualitative performance. Through comprehensive experiments on the TGS Salt Identification Challenge dataset, the model demonstrated superior IoU, Dice coefficient, and boundary accuracy, highlighting its ability to accurately delineate complex salt geometries even in noisy and low-contrast regions. The ablation studies validated the contribution of each module, while the input resolution analysis confirmed that a 128×128 input size provides an optimal trade-off between performance and computational cost. In summary, the proposed framework offers a reliable and efficient solution for automated salt body segmentation in seismic interpretation workflows. In future work, we aim to enhance the model's generalizability by training on larger, multi-basin datasets and integrating temporal context from 3D seismic volumes.

REFERENCES

Aarre, V., Astratti, D., Al Dayyni, T. N. A., Mahmoud, S. L., Clark, A. B. S., Stellas, M. J., Stringer, J. W., Toelle, B., Vejbæk, O. V, & White, G. (2012). Seismic detection of subtle faults and fractures. *Oilfield Review*, *24*(2), 28–43.

Alsadi, H. N. (2017). Seismic hydrocarbon exploration. *2D and 3D Techniques, Seismic Waves*.

Deng, W., Shi, Q., & Li, J. (2021). Attention-gate-based encoder–decoder network for automatical building extraction. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, 2611–2620.

Dillon, A. (2000). Spatial-semantics: How users derive shape from information space. *Journal of the American*

Society for Information Science, *51*(6), 521–528.
Diniz, C., Cortinhas, L., Pinheiro, M. L., Sadeck, L., Fernandes Filho, A., Baumann, L. R. F., Adami, M., & Souza-Filho, P. W. M. (2021). A large-scale deep-learning approach for multi-temporal aqua and salt-culture mapping. *Remote Sensing*, *13*(8), 1415.
Gavrishchaka, V., Yang, Z., Miao, R., & Senyukova, O. (2018). Advantages of hybrid deep learning frameworks in applications with limited data. *International Journal of Machine Learning and Computing*, *8*(6), 549–558.
Huang, J., & Nowack, R. L. (2020). Machine learning using U-net convolutional neural networks for the imaging of sparse seismic data. *Pure and Applied Geophysics*, *177*(6), 2685–2700.
Huang, L., Dong, X., & Clee, T. E. (2017). A scalable deep learning platform for identifying geologic features from seismic attributes. *The Leading Edge*, *36*(3), 249–256.
Jones, I. F., & Davison, I. (2014). Seismic imaging in and around salt bodies. *Interpretation*, *2*(4), SL1–SL20.
Kainkaryam, S., Ong, C., Sen, S., & Sharma, A. (2019). Crowdsourcing salt model building: Kaggle-TGS salt identification challenge. *81st EAGE Conference and Exhibition 2019*, *2019*(1), 1–5.
Liu, Q., Fu, L., & Zhang, M. (2021). Deep-seismic-prior-based reconstruction of seismic data using convolutional neural networks. *Geophysics*, *86*(2), V131–V142.
Milosavljević, A. (2020). Identification of salt deposits on seismic images using deep learning method for semantic segmentation. *ISPRS International Journal of Geo-Information*, *9*(1), 24.
Monaghan, A. A. (2017). Unconventional energy resources in a crowded subsurface: Reducing uncertainty and developing a separation zone concept for resource estimation and deep 3D subsurface planning using legacy mining data. *Science of the Total Environment*, *601*, 45–56.
Radha, M. G. (2020). *Data-driven health monitoring and lifestyle interventions: towards management of hypertension and other lifestyle diseases through data-driven modelling of physiology and behaviour*.
Rajput, V. (2021). Robustness of different loss functions and their impact on networks learning capability. *ArXiv Preprint ArXiv:2110.08322*.
Shafiq, M. A., Wang, Z., AlRegib, G., Amin, A., & Deriche, M. (2017). A texture-based interpretation workflow with application to delineating salt domes. *Interpretation*, *5*(3), SJ1–SJ19.
Shi, Y., Wu, X., & Fomel, S. (2019). SaltSeg: Automatic 3D salt segmentation using a deep convolutional neural network. *Interpretation*, *7*(3), SE113–SE122.
ul Islam, M. S. (2020). Using deep learning based methods to classify salt bodies in seismic images. *Journal of Applied Geophysics*, *178*, 104054.
Wang, S., Mu, X., Yang, D., He, H., & Zhao, P. (2020). Attention guided encoder-decoder network with multi-scale context aggregation for land cover segmentation. *IEEE Access*, *8*, 215299–215309.
Wang, Z., Di, H., Shafiq, M. A., Alaudah, Y., & AlRegib, G. (2018). Successful leveraging of image processing and machine learning in seismic structural interpretation: A review. *The Leading Edge*, *37*(6), 451–461.
Wellmann, F., & Caumon, G. (2018). 3-D Structural geological models: Concepts, methods, and uncertainties. In *Advances in geophysics* (Vol. 59, pp. 1–121). Elsevier.
Xu, R. (2018). Corpus-based terminological preparation for simultaneous interpreting. *Interpreting*, *20*(1), 29–58.
Xu, Y., & Goodacre, R. (2018). On splitting training and validation set: a comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. *Journal of Analysis and Testing*, *2*(3), 249–262.
Ye, Z., Fu, Y., Gan, M., Deng, J., Comber, A., & Wang, K. (2019). Building extraction from very high resolution aerial imagery using joint attention deep neural network. *Remote Sensing*, *11*(24), 2970.
Zhang, K., Liu, X., & Chen, Y. (2020). Research on semantic segmentation of portraits based on improved deeplabv3+. *IOP Conference Series: Materials Science and Engineering*, *806*(1), 12057.