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Salt Segmentation in Seismic Imagery Using Deep Learning Techniques

Prof. Pradnya D. Bormane[1], Pranav Mohite[2], Varun Patil[3], Om Ranasubhe[4], Sanjana Patil[5], Ms. Shalu Mahajan[6]

[1,2,3,4,5] AISSMS Institute of Information Technology, Pune, Maharashtra, India
[6] Kcloud Technologies, Noida.
Corresponding Author: Prof. Pradnya Bormane

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ABSTRACT

Identifying salt structures is crucial in hydrocarbon exploration, impacting global energy resource management due to the complex geometry of salt deposits. This study seeks to evaluate the effectiveness of the U-Net architecture in improving salt segmentation accuracy within seismic imagery, emphasizing deep learning advancements for detailed subsurface analysis. Our methodology includes a comprehensive review of recent U- Net implementations adapted for seismic data, evaluating architectural modifications, training strategies, and dataset variations. Comparisons with traditional methods highlight improvements in segmentation accuracy and computational efficiency, with a focus on various loss functions and their impact on complex salt structure delineation. Initial findings suggest that U-Net significantly outperforms traditional techniques, enhancing detail resolution and accuracy in interpreting salt deposits. Improved accuracy in salt segmentation leads to more efficient natural resource extraction, reducing environmental impact and enhancing energy sustainability.

KEYWORDS: Deep Learning, Salt Segmentation, Salt Structures, Seismic Imaging, U-Net Architecture

1. INTRODUCTION

Seismic imaging plays a pivotal role in exploring subsurface geology, crucial for identifying and delineating salt structures that are instrumental in hydrocarbon exploration. Salt structures, due to their impermeable nature, directly influence the trapping mechanisms of oil and gas reservoirs, making their accurate detection and interpretation essential for the petroleum industry. [1][3]

However, the interpretation of seismic images to identify salt structures presents significant challenges. Traditional methods, relying heavily on human expertise, are often constrained by the complexity and variability of salt body geometries as well as the quality of seismic data.[2][3] This has spurred interest in applying deep learning techniques, especially CNNs which has shown excellent in automating and enhancing the accuracy of salt segmentation. [1]

The U-Net architecture, known for its effectiveness in medical image segmentation, has been adapted to the geophysical realm due to its ability to handle the nuances of seismic data, offering improved segmentation accuracy over traditional methods. [1] This survey paper aims to explore various implementations of the U-Net architecture in seismic salt segmentation, addressing the challenges of data heterogeneity and model generalizability while benchmarking against traditional seismic interpretation methods. [2][3]

In essence, the need for advanced deep learning approaches in seismic salt segmentation is underscored by the increasing complexity of subsurface environments and the critical economic implications of accurate salt structure delineation. By harnessing the power of U-Net and its derivatives, this paper seeks to provide a comprehensive review of current methodologies, their developments, and future directions in the context of enhancing subsurface salt identification. [1][4]

2. LITERATURE SURVEY

[1] – They focus on addressing the challenge of salt segmentation in seismic images, an important task in oil and gas exploration as well as in agriculture, where identifying salt deposits can help optimize land use and drilling processes. The study employs two deep learning-based models. The first model combines ResNets within UNet as encoders for segmenting seismic data. The second model utilizes an ensemble approach, integrating UNet with ResNet-34, VGG16, and Inceptionv3 to further improve segmentation accuracy. Both models are trained on the TGS Salt

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Identification Challenge dataset, consisting of 4,000 labeled seismic images, augmented to mitigate data scarcity. The models use binary cross-entropy (BCE) and dice loss functions for optimization. Results show that the ensemble model has proved to be most effective with IoU metric score of 87.5%, outperforming individual models and demonstrating its potential for improving segmentation accuracy in identifying salt regions. This research suggests a significant enhancement in automated salt detection from seismic images, which can aid both in oil exploration and agricultural land management. [2]- They explore salt body segmentation in seismic images using a deep learning technique called Mask R- CNN. Traditional methods, such as edge detection and NCIS, were limited by computational inefficiency and low accuracy. To improve detection, the authors propose Mask R-CNN, leveraging its ability to classify and segment regions at the pixel level. The model uses ResNet101 for feature extraction and generates bounding boxes and masks for salt body areas. Experimental results, tested on a Kaggle seismic dataset, show that Mask R-CNN outperforms existing CNN models in precision, recall, and overall accuracy for salt body detection. This approach offers a more reliable and efficient solution for automated salt body detection, which is critical for petroleum exploration and geophysical studies.

[3] - They propose a novel approach in 3D Salt-HSM to improve salt body segmentation in 3D seismic data.. Traditional methods like edge detection and seismic attribute analysis face limitations in accuracy and efficiency. Recent deep learning methods, including CNNs, have improved segmentation but rely heavily on large labeled datasets. To address this, the authors propose a semi-supervised learning framework that combines pseudo-labeling and consistency regularization to leverage both labeled and unlabeled data. They also introduce multitask learning, incorporating edge detection and salt classification for better accuracy. The methodis more effective than state-of-the art, offering more precise and robust salt body segmentation.

[4] - They propose a hybrid approach for salt body segmentation in seismic images. Traditional methods, including edge detection and seismic attribute techniques, often struggle with noisy data and require manual intervention. Recent deep learning approaches, such as CNNs and U-net, improved automation but often produced incomplete or noisy results. The authors address this by integrating CNNs with human interaction points, transforming these into Euclidean distance maps (EDMs) to refine segmentation accuracy. Additionally, a graph cut algorithm is applied to further optimize salt boundary predictions. The proposed method outperforms existing techniques, providing more accurate segmentation on seismic datasets.

2.1 Comparison Table

Table 1. Comparison of various methods of segmentation

Research paper Title	Year of publication & authors	Methodology adapted
Salt segmentation Identification in Seismic image using deep learning technique.	(ICEARS-2023). Authors: Lakshmi Devi N, Rajasekhar Reddy Bochu, and Naveen Kumar Buddha .	The authors used 4,000 seismic image patches to develop two deep learning models: a U-Net with ResNet-18/34 encoders and an ensemble combining U-Net, ResNet-34, VGG16, and Inceptionv3.
Salt SCG: Interactive salt Segmentation method based on CNN and graph Cut.	(May 2022 IEEE) Authors-Hao Zhang, Peimin Zhu, Zhiying Liao, Zewei Li	The method combines Euclidean distance maps (EDMs) with seismic images to train a modified U-Net with pyramid pooling, while a graph cut algorithm refines segmentation for better salt boundary detection.
Salt segmentation in seismic images using Mark R-CNN	(2022 IEEE) Authors: Arsha P V, Pillai Praveen Thulasidharan	The methodology utilizes Mask RCNN with a ResNet101 backbone for feature extraction, an RPN to generate candidate regions, and a process for creating segmentation masks.

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Accurate semantic segmentation of aerial imagery using attention ResU-net architecture.	(2024 IEEE) Sai kumar aduni, Rishindra maeti, LV Narsimha prasad.	The paper employs an Attention Res U-Net, combining attention and residual mechanisms to enhance feature extraction and segmentation accuracy in aerial images
A convolutional Autoencoder method for Simantaneous Seismic data Reconstruction and denosing.	(2022 IEEE) Haoran Ren, Jinsheng jiang , Meng Zhang.	The methodology involves a systematic literature review to identify key themes, synthesize findings, and highlight gaps in current research.
Deep learning Using synthetic Seismic data by Fourier domain adaption in seismic structure interpretation.	(2022 IEEE) Dekuan chang, Jinahu gao, Yihui wang.	The paper uses Fourier Domain Adaptation (FDA) to align synthetic seismic data with real data by replacing the synthetic amplitude spectrum, improving deep learning model performance on real-world scenarios.

3. METHDOLOG

Block diagram of proposed methodology is shown in Fig .1.

Initialization:
The model initializes the encoder based on the specified depth (34, 101, 152) for ResNet. Depending on the depth, different layers of the ResNet are used. Additional convolutional layers and blocks are initialized to handle the decoding part and the transition between encoder and decoder phases.

Forward Pass:
Input Adjustment: Adjust the input image through initial convolutional layers that match the input requirement of the chosen ResNet encoder.

Encoder: The image data is passed through several stages of the ResNet encoder. Each stage progressively increases the depth while reducing the spatial dimensions.

Bridge: The deepest representation is obtained at the end of the encoder.

Decoder: The decoder progressively recovers spatial dimensions while reducing depth, using skip connections from the encoder to retain spatial information lost during down-sampling.

Output Generation: In the final step, a convolutional layer reduces the output channels to match the number of classes needed for the segmentation task.

Deep Supervision: The model includes deep supervision layers at various stages of the decoder. These layers help in guiding the training process more effectively by introducing auxiliary loss functions at multiple scales.

Dropout: Dropout layers are optionally included in the decoder to regularize the model and prevent overfitting.

Concatenation of Features: In the decoder, features from the encoder are concatenated with upsampled features to provide context and detailed local information that helps in precise segmentation.

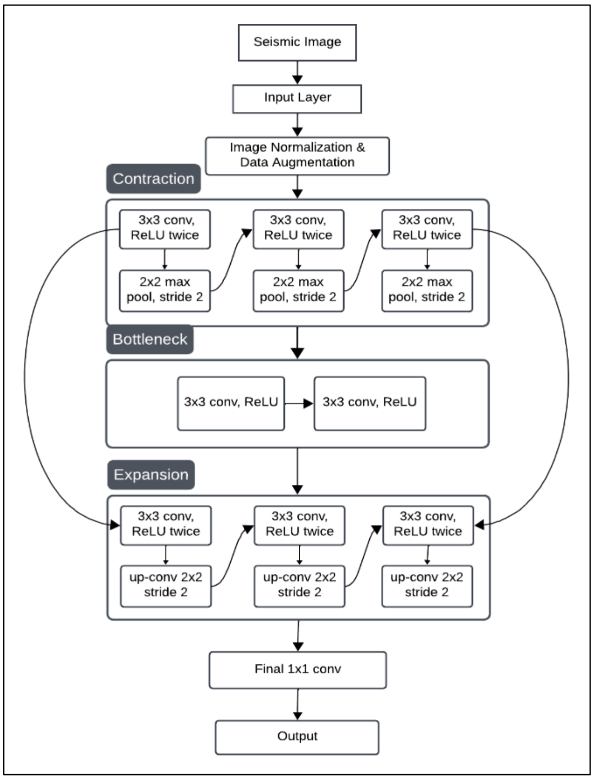

Fig. 1. U-Net Architecture for Seismic Image Segmentation

4. CONCLUSION

Leveraging deep learning models such as U-Net architectures utilizing enhanced ResNet encoders, has proven highly effective in the challenging task of salt segmentation from seismic imagery. The utilization of these sophisticated neural network models enables a significant enhancement in both the accuracy and efficiency of salt boundary detection, surpassing traditional methods that are often limited by the complexity of seismic data and the manual effort required. Through a series of encoder-decoder mechanisms and innovative use of skip connections and deep supervision, these models not only preserve crucial spatial information but also ensure detailed contextual interpretation, which is pivotal for accurate geological assessments. The integration of such advanced computational techniques holds great promise for the future of geophysical exploration, potentially revolutionizing how subsurface imaging performs in the oil and gas industry.

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