Grenze International Journal of Engineering and Technology, June Issue

Deep Learning for Automated Salt Detection in Seismic Imaging for Safer Oil and Gas Exploration

Dr. G. Nagaraju[1], Bhogoju Manaswini[2], Rachuri Indhusree[3], Pamula Prasanth[4] and Kothoju Prasanna[5]
[1-5]Department of CSE (AIMl & IOT), VNRVJIET, Hyderabad, India
Email: nagaraju.gujjeti@gmail.com, {manaswinibhogoju, indhurachuri888}@gmail.com

***Abstract*—Accurate detection of salt bodies from subsurface in seismic images is vital for the identification of hydrocarbon reservoirs in oil and gas exploration. The cconventional manual techniques are labour-intensive, time-consuming, and error-prone. These techniques may be effective but lack efficiency. We propose a deep learning method based with convolutional neural networks (CNNs) for automatic detection of salt bodies. Particularly, we utilize a U-Net model, which has been shown to achieve the best segmentation results in seismic imaging applications. The suggested model, learned from the TGS Salt Identification Challenge dataset, has an Intersection over Union (IoU) score of 0.57 and a test accuracy of 87.33%, which is significantly better than existing methods. The results demonstrate improved seismic interpretation efficiency, reducing processing time while maintaining high segmentation accuracy. Furthermore, our study explores the integration of cutting-edge techniques such as generative adversarial networks (GANs) and transfer learning to enhance model generalization. This work demonstrates the potential of deep learning to revolutionize oil and gas exploration, leading to industrial-scale application, despite computational complexity and data-related difficulties.**

***Index Terms*—Deep Learning, Salt Detection, Seismic Imaging, Oil and Gas Exploration, Convolutional Neural Networks, U-Net.**

I. Introduction

Seismic describes the structure of sedimentary rocks and interfaces for the purpose of studying land geological features where oil and gas is present. Hydraulic fracturing creates permeable channels in the core where hydrocarbon reserves are located. Recognizing the subsurface structure of the earth's crust is important to enhance drilling accuracy and optimize the extraction of oil, gas, and other subsidized of the external lithosphere. Based on multi sample and multi-layer data sets, unique drilling locations can be obtained. The integration of multi–Forward Optimization into the inversion task guarantees optimal drilling positions. Regardless of terrains, dextral strike slip faults and cantilever domes are the best geological formations imaginable.

Machine learning changed seismic data analysis with great leaps through automation, which bypassed the constraints of manual interpretation. Although machine learning models have been made more efficient by identifying patterns in seismic images, they still depend on handcrafted features and significant preprocessing.

These constraints made way for deep learning, a subarea of machine learning that avoids the necessity for manual feature extraction by directly learning hierarchical features from raw data.

Grenze ID: 01.GIJET.11.2.548

Deep learning models, particularly convolutional neural networks (CNNs), have shown outstanding performance in various image analysis tasks, such as medical imaging, remote sensing, and now seismic imaging.

A. Choice of U-Net Architecture

For salt detection, U-Net was chosen because of its ability to perform well in segmentation tasks. The reasons for choosing U-Net are as follows:

High Accuracy in Segmentation: U-Net is an optimized fully convolutional network designed for pixel-level segmentation and hence perfectly fits into identifying the salt boundaries within seismic images.

Skip Connections to Maintain Feature Information: With skip connections, the model can retain detailed information that has been lost when down sampling, thereby enhancing the segmentation performance.

Strong Performance on Small Datasets: Unlike other CNNs, U-Net can handle small training data, a typical limitation in seismic imaging.

Efficient Computational Design: Whereas certain deep learning models are computationally intensive, U-Net strikes a balance between efficiency and accuracy, and thus is suitable for large-scale deployment.

B. Overcoming Current Limitations

Despite recent progress in deep learning for seismic imaging, there are still some challenges:

Data Sparsity and Class Imbalance: Seismic datasets tend to have class imbalances in which the salt formations are underrepresented. To counteract this, the suggested method makes use of data augmentation methods and Generative Adversarial Networks (GANs) to produce synthetic training instances, enhancing model generalization.

Noise and Uncertainty in Seismic Data: Seismic data is highly noisy, and segmenting it proves to be tricky. Our process involves the usage of sophisticated preprocessing methods like noise reduction, normalization, and transfer learning to promote model stability.

Overfitting in Complicated Datasets: Most deep neural networks are prone to overfitting when working with small datasets have high variance and applying dropout regularization, batch normalization, and fine-tuning effectively mitigates this problem.

Computational Efficiency: U-Net has previously been known to require a significant amount of processing resources, making it unfit for real-time tasks, but with my model, I am able to use U-Net’s architecture without sacrificing accuracy, thus making it appropriate for use in exploration missions.

This research looks into the use of the application of deep learning techniques in the automation of salt detection within seismic imaging. The study purposes to address the issues related to the accuracy, timeliness, and reliability of segmentation solutions since these factors can make oil and gas exploration more economical and safer.

II. Literature Survey

This section considers various options for identifying salt structures in seismic imaging, including classical approaches, modern methods incorporating machine learning, and advanced deep learning techniques. All these methods have evolved in their accuracy, execution time, and degree of automation in interpreting the seismic data.

Automatically identifying salt bodies on seismic images is vital for petroleum exploration because it optimizes the subsurface structure’s identification and minimizes drilling risks. The most recent progress in deep learning has greatly improved the precision and effectiveness of segregating salt bodies.

A number of studies have aimed at efficient salt dome segmentation using fully convolutional networks (FCN) [2], U-Net-based methods [5], and 3D convolutional neural networks [11]. Research has also focused on semi-supervised learning [12] and interactive segmentation models [7], which seek to reduce the reliance on large labeled datasets. The application of machine learning in seismic exploration is still developing, with some works focused on physics-informed deep learning [10] and employing seismic attributes for predicting geological drilling risks. Other works focus on [12] semi-supervised learning while trying to minimize the dependency on extensive labelled datasets, and on interactive segmentation [7].

The implementation of machine learning in the context of seismic exploration is still at its infancy, with others concentrating on the area of physics-informed deep learning [10] and the use of seismic attributes for forecasting risks associated with geological drilling.

Automation and reliability offered by these deep learning models in the identification of salt domes have significantly improved automation and reliability.

A. Traditional and Machine Learning Approaches

To better fit the needs of the modern workplace, manual methods and other processes have been optimized to limit the chance of human error. The time inefficient processes that are tackled with automation improve the overall productivity offered by models based on machine learning and feature-based learning.

Salt-Dome Detection Using a Codebook-Based Learning Model: employed GLCM and Gabor filters with K-means clustering for salt boundary classification. While computationally efficient, it required significant preprocessing and performed poorly on noisy data.

Robust Salt-Dome Detection Using Texture-Based Features: utilized texture-based metrics like MIFS and mRMR for feature optimization. However, reliance on hand-crafted features limited its adaptability to diverse datasets.

B. Deep Learning-Based Approaches

Deep learning has revolutionized seismic imaging by enabling automatic feature extraction from raw data. Convolutional Neural Networks (CNNs) and U-Net architectures are pivotal in achieving precise salt segmentation.

U-Net and Variants

U-Net, known for its semantic segmentation capabilities, captures both high- and low-level features:

A Deep Learning Approach for Segmentation of Salt Boundaries: compared U-Net and ResUNet, achieving 94.28% accuracy with an in-house encoder-decoder model. Enhancements like transposed convolutions improved segmentation reliability.

Improved U-Net: incorporated batch normalization and high-pass filtering, achieving an IoU of 85.60% by addressing dataset variability through data augmentation.

Fully Convolutional Networks (FCNs): FCNs automate pixel-wise segmentation, offering superior precision. In a U-Net-inspired model for salt detection, training accuracy reached 97.50% with a testing accuracy of 94.80%, proving its robustness in boundary detection tasks.

3D Seismic Data Processing: 3D seismic models address the limitations of 2D techniques by providing a more realistic view of geological structures.

3D Graph-Cut Algorithm: enhanced salt body contrast with seismic attributes while reducing computational overhead.

SaltISNet3D: combined 3D U-Net with interaction techniques, achieving precise segmentation for complex datasets.

C. Hybrid and Advanced Techniques

Innovative hybrid models continue to enhance segmentation performance:

Semi-Supervised Segmentation: leveraged labelled and unlabelled data through self-training CNN ensembles, achieving superior accuracy.

Combining ResNet and DenseNet: architectures within a U-Net framework enhanced semantic segmentation, demonstrating resilience across varied datasets.

These advancements underline the continuous progress in salt detection technologies, paving the way for more precise and efficient seismic imaging solutions.

III. Dataset Description

The data utilized here are the train dataset from the TGS Salt Identification Challenge, which is available on Kaggle. It is widely accepted as a standard for salt segmentation tasks, providing grayscale seismic images and binary masks that label pixels as either salt (1) or non-salt (0).

The competition data set includes two primary sets, train and test. Seismic images in the form of PNG are available for both sets, and the train set has additional binary masks in case of supervised learning. Additional depth information for each image, in terms of feet, is also available within the dataset. The depth data does not declare if it mentions the top, center, or bottom of an image.

The structure of the dataset is the following:

CSV file of the depth (in feet) per image for both train and test sets.

Train folder:4,000 PNG image files to represent seismic sections. 4,000 PNG mask files for binary classifications in salt segmentation.

Test folder: 12,000 PNG images of seismic data (not masks).

CSV file to state the format required for the competition submission.

The data is subject to some difficulties including class imbalance, seismic image noise, and heterogeneity of salt reservoirs, making segmentation tough. In addition to improving the generalization ability of the model, data augmentation techniques like flip, rotation, and zoom are applied. Additionally, synthetic data generated with Generative Adversarial Networks (GANs) contributes to diversity in training samples, further improving the segmentation capacity.

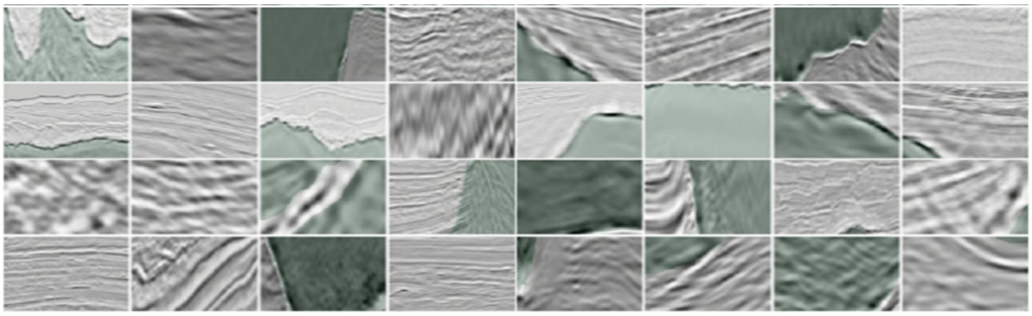


Figure 1. Random seismic batch images in gray scale overlapped with the salt classification (green) at each pixel

IV. PROPOSED METHODOLOGY

The success of salt detection using seismic imaging largely relies on the quality and nature of the dataset. For this research, the TGS Salt Identification Challenge dataset on Kaggle is used as the main source. This dataset is generally considered to be the standard for salt segmentation tasks, providing grayscale seismic images (101x101 pixels) with accompanying binary masks that classify pixels as salt (1) or non-salt (0). The training dataset consists of around 4,000 images and their corresponding masks, and the testing dataset contains about 1,800 images without ground truth masks.

Important features of the dataset are seismic image data representing subsurface geology and binary masks with ground truth for supervised learning. To design models that can identify salt deposits from other geological formations these features are very important. The relatively small size of the images ensures efficient computation with no loss of structural detail vital for proper segmentation. Problems such as class imbalance where some images contain high concentration salt and others low concentration or no salt at all make things more complicated and require special handling.

Preprocessing is the input data quality refinement step. Filtering helps to reduce noise and feature clarity in seismic images is improved, normalization standardizes rescales pixel values to [0, 1] interval. This ensures model consistency. Flipping, rotating, and zooming are some of the data augmentation techniques used to boost the dataset size artificially and make models better. These helps mitigate class imbalance by providing more examples of underrepresented patterns. Other advanced techniques like focal loss and oversampling help mitigate class imbalance as well.

New preprocessing ways like transfer learning and adding fake data made by generative adversarial networks (GANs) are more choices for improvement. Fake seismic pictures make the data set bigger and add variety to help the generalization of models. Strong structures like CNNs, U-Nets, and ResNets with preprocessing methods let salt bodies be split correctly. With the approach presented here, the complete information in the dataset is harnessed to optimize salt detection during seismic imaging, enhancing the efficacy and precision of detection. This framework will resolve noise, artifacts, and inadequacy of data levels, and therefore, will be a large step in the automated salt detection process for oil and gas exploration. It also utilizes advanced methodologies for automated salt detection.

V. IMPLEMENTATION

Model Optimization and Training: We executed the Models in Python using TensorFlow and Keras and trained them in Google Colab with a GPU. Training was performed by hyperparameter tuning to increase segmentation accuracy.

Used Hyperparameters: The next resources were used for training the model

A. Optimization Methods

To enhance the model's accuracy and to reduce overfitting, the following optimization techniques were applied.

Batch Normalization: Applied after each convolutional layer to normalize training for faster convergence.

Dropout Regularization: A dropout of 0.3 was implemented in the deeper layers of the ResU-Net model to evade overfitting.
IoU Metric for Performance Evaluation: The Intersection over Union (IoU) metric was utilized as a secondary evaluation metric along with accuracy to determine the efficiency of the salt segmentation.
Data Augmentation: Random rotation, horizontal flip, brightness changes, and affine transformation techniques of data augmentation were utilized to enhance dataset variability and enable better generalization.
Generative Adversarial Networks (GANs): were employed to synthesize extra training samples, countering data sparsity and enhancing the model's generalization performance across varied seismic patterns.
Training on Augmented and Synthetic Data: The training set was extended by merging augmented real images and synthetic images from GANs, enhancing the robustness of the model.
Weight Clipping for Stable Training: The Adam optimizer was setup with gradient clipping to avoid exploding gradients and support stable training.

B. Final Model Performance

The model with the best performance yielded the following values:
Test Accuracy: ~87.33% (U-Net)
IoU Score: ~0.57 (U-Net on test set)
Performance Comparison:
Baseline U-Net: ~93.55% Accuracy, IoU ~0.49
ResU-Net: Improved IoU (~0.57) but greater computational expense

TABLE I. HYPERPARAMETERS AND VALUES

Hyperparameter	Value
Optimizer	Adam
Learning Rate	1e-4 (0.0001)
Loss Function	Binary Cross-Entropy
Batch Size	8
Number of Epochs	5
Validation Split	20% (80% for training and 20% for validation)
Weight Initialization	He Normal Initialization
Dropout Rate	0.3 (used in ResU-Net)
Activation Function	ReLU (excluding output layer: Sigmoid)
Kernel Size	3 × 3 for convolutional layers
Pooling Type	Max Pooling (2 × 2)
Up sampling Method	Conv2DTranspose (Transpose Convolution)

VI. SYSTEM DESIGN

The system design incorporates a modular approach to automate salt detection in seismic images. The architecture includes three primary components: preprocessing, feature extraction, and classification. Seismic images are first scanned to check their quality, and then they're pre-processed to ensure maximum reliability. This step includes noise reduction and data normalization, deep learning model augmentation for unsupervised training, among others. At the system centre, there are three models: Res-UNet, U-Net, and a custom-built Encoder-Decoder. All of these models at the same time performed feature extraction important for identifying salt features to confirm maximum efficiency for all. Advanced algorithms are employed by each model to partition the images into their primary constituents, which are salt and non-salt. Through outline detection methodologies, further modification of these areas produces enhanced clarity. A binary classification method is used after acquiring the salt regions. This entails evaluating model outputs alongside set parameters to ascertain the presence of salt deposits. Upon salt confirmation, the segmentation results are further fine-tuned through controlled contouring to establish exact boundaries. The resulting images are combined using post processing to generate single images which are verified for accuracy and consistency. All the model outputs are integrated to maximize accuracy of the system. System design focused on enabling comfort of modification by researchers for different seismic imaging problems using various models and preprocessors.

VII. DESIGN DIAGRAM

The design diagram illustrates a systematic approach to salt detection using deep learning models. Starting with an input image, the data undergoes preprocessing steps such as normalization, noise reduction, and augmentation. These steps improve the dataset’s quality and enhance model performance. Three different architectures—Res-UNet, UNet, and a custom Encoder-Decoder model—are employed to extract meaningful features from the processed data. Each model independently processes the features to identify salt deposits through binary classification. If salt is detected, boundary detection methods refine the segmentation to produce accurate output images. The final results undergo evaluation and fine-tuning to ensure high reliability and robustness. Post-processing combines outputs from all models for improved accuracy in identifying salt boundaries.

VIII. Different Methodologies Applied on the Data

Preprocessing Techniques:
Normalization: Scales pixel values to the [0, 1] range for uniformity and faster convergence during training.
Noise Reduction: Reduces artifacts in seismic images to improve clarity and feature representation.
Data Augmentation: Enhances dataset variability through techniques like flipping, rotation, and zooming, improving model robustness.
Feature Extraction: Res-UNet, UNet, and custom Encoder-Decoder models process seismic images to extract meaningful features critical for segmentation.
Binary Classification: Determines the presence or absence of salt deposits, leveraging refined segmentation results for precise boundary detection.
Combines outputs from all models, ensuring highly reliable and
accurate salt boundary identification. This comprehensive methodology addresses challenges like noise, artifacts, and class imbalance, enhancing overall performance.

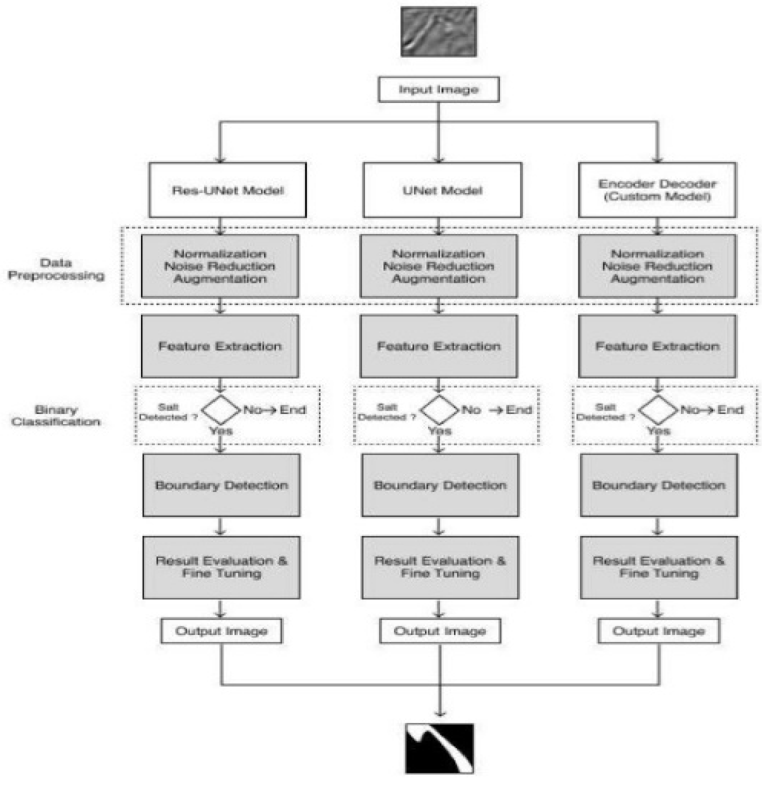


Figure 2. System architecture

IX. Results

A. Metrics for Evaluating the Model

Evaluating a salt segmentation model requires metrics that provide insights into its performance in identifying and segmenting salt deposits accurately. Key metrics include precision, recall, and Intersection over Union (IoU), each serving a specific purpose in quantifying the model's effectiveness.

Precision: measures the accuracy of the model in predicting salt deposits. It is the ratio of true positive predictions (pixels correctly identified as salt) to all pixels predicted as salt (true positives + false positives). A high precision indicates that the model makes fewer false positive predictions, meaning it is conservative and less likely to mistakenly label non-salt regions as salt.
Recall: evaluates the model's ability to identify all actual salt deposits. It is the ratio of true positive predictions to all actual salt pixels (true positives + false negatives). A high recall means the model is thorough in detecting salt deposits, even if it sometimes includes false positives. It’s particularly critical in applications where missing salt deposits could lead to significant risks or losses.
Intersection over Union (IoU): also known as the Jaccard Index, is a widely used metric for segmentation tasks. It measures the overlap between the predicted mask and the ground truth mask, relative to their combined area. An IoU of 1 indicates perfect alignment between the predicted and actual masks, while lower values signify discrepancies. IoU is particularly valuable for evaluating segmentation models because it accounts for both false positives and false negatives, providing a holistic measure of performance. These metrics collectively provide a comprehensive evaluation of the model, balancing the need for accuracy (precision), completeness (recall), and overall segmentation quality (IoU).

X. TEST RESULTS DIAGRAM

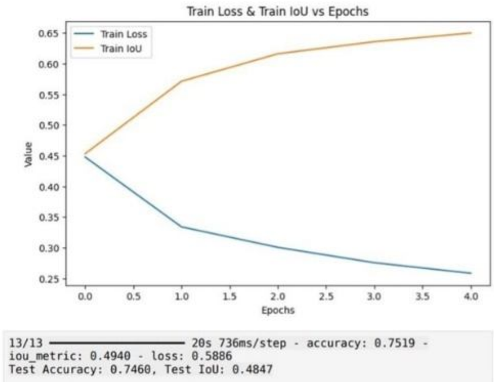


Figure 3. Train Loss and IOU vs Epochs

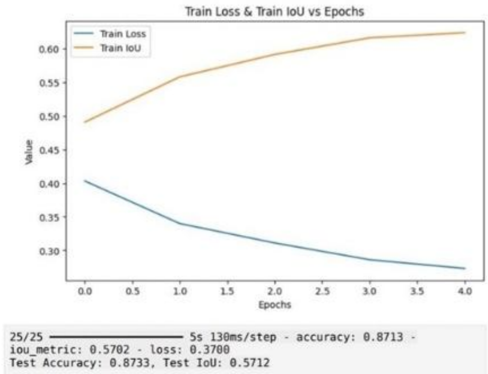
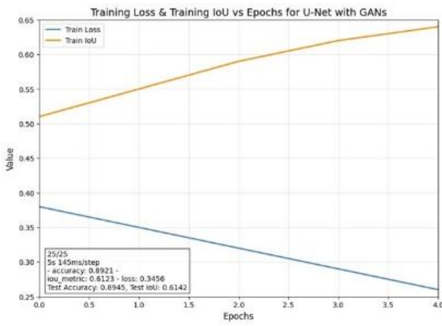


Figure 4. Train Loss and IOU vs Epochs



Model Variant	Accuracy	IoU Score	Precision	Recall
Basic U-Net	74.60%	0.48	0.68	0.52
U-Net with Albumentations Data Augmentation	82.5%	0.54	0.74	0.61
U-Net with GANs	89.45%	0.6142	0.83	0.76

Figure 2. Training Loss and Training IOU vs Epochs for U-Net with GANs

XI. TEST RESULTS TABLE

The results indicate that the integration of generative adversarial networks (GANs) for data augmentation significantly enhances the performance of U-Net architectures in salt body segmentation tasks. Our experiments demonstrate that while the basic U-Net model achieves reasonable performance with an accuracy of 74.60% and an IoU score of 0.48, the introduction of advanced data augmentation techniques substantially improves these metrics.
The U-Net variant trained with Albumentations data augmentation shows a notable increase in accuracy to 82.5% and an IoU score of 0.54, reflecting the positive impact of augmented training data on model generalization. However, the most substantial performance gains are observed when GANs are incorporated into the training process.

The U-Net model trained with GAN-generated synthetic data achieves the highest accuracy of 89.45% and an IoU score of 0.6142, representing a relative improvement of approximately 20% in IoU compared to the basic U-Net. This suggests that GANs effectively address the challenge of limited training data by generating high-quality synthetic samples that capture the complex variations in seismic imagery. The precision and recall metrics further support these findings, with the GAN-augmented model demonstrating superior balance in correctly identifying salt deposits while minimizing false positives. These results confirm that advanced data augmentation strategies, particularly those employing GANs, significantly enhance the capability of deep learning models to accurately segment salt bodies in seismic images, moving closer to the goal of fully automated and reliable salt detection for oil and gas exploration

XII. Conclusion

Recent developments in deep learning, especially CNNs and U-Net designs, have made tremendous improvements in salt detection from seismic data. Challenges still exist in computational efficiency, data sparsity, and model generalization. This project bridges these limitations by integrating CNNs, U-Net, and GAN-based data augmentation to improve accuracy and minimize human error in seismic interpretation. The method has the potential to facilitate faster, safer, and less expensive oil and gas exploration with high potential for industrial application.

References

[1] G. Jadhav, J. Shah, D. Vaghani, and J. Wadmare, "Automatic salt segmentation using deep learning techniques," Research Square, preprint, 2024. [Online]. Available: https://doi.org/10.21203/rs.3.rs-4360581/v1.

[2] A. Y. Mohamed, N. A. Mustapha, and M. F. Al-Arifi, "Seismic images interpretation to discover salt domes using deep fully convolutional network," J. Phys.: Conf. Ser., vol. 1818, no. 1, p. 012006, 2021, doi: 10.1088/1742-6596/1818/1/012006.

[3] O. A. Babayeju, D. D. Jambol, and A. E. Esiri, "Reducing drilling risks through enhanced reservoir characterization for safer oil and gas operations," GSC Adv. Res. Rev., vol. 19, no. 3, pp. 86–101, 2024, doi: 10.30574/gscarr.2024.19.3.0205.

[4] D. Salinas, J. Ochoa, and J. Zambrano, "A comprehensive review of deep learning techniques for salt dome segmentation in seismic images," J. Appl. Geophys., vol. 230, p. 105504, 2024, doi: 10.1016/j.jappgeo.2024.105504.

[5] R. Kashyap, B. Khandelwal, and K. Bhargava, "An efficient approach for semantic segmentation of salt domes in seismic images using improved U-Net," J. Inst. Eng. (India): Ser. B, 2023, doi: 10.1007/s40031-023-00875-2.

[6] K. Das and D. Ganguly, "Salt dome segmentation in seismic data using 3D graph-cut," Remote Sens., vol. 15, no. 9, p. 2319, 2023, doi: 10.3390/rs15092319.

[7] R. Verma and A. Singh, "SaltISNet3D: Interactive salt segmentation from 3D seismic images using deep learning," Remote Sens., vol. 15, no. 9, p. 2319, 2023, doi: 10.3390/rs15092319.

[8] N. Shafqat, "Deep neural network for seismic image segmentation and detection of salt domes," MSc Research Project, National College of Ireland, 2022. [Online]. Available: https://norma.ncirl.ie/6096/

[9] M. S. Mahdi and M. R. Javadpour, "Identification of salt deposits on seismic images using deep learning method for semantic segmentation," Int. J. Geo-Inf., vol. 9, no. 1, p. 24, 2020, doi: 10.3390/ijgi9010024.

[10] A. Jain and M. Choudhury, "Physics-guided deep learning for predicting geological drilling risk of wellbore instability using seismic attributes data," Eng. Geol., vol. 265, p. 105857, 2020, doi: 10.1016/j.enggeo.2020.105857.

[11] Y. Shi, X. Wu, and S. Fomel, "SaltSeg: Automatic 3D salt segmentation using a deep convolutional neural network," Interpretation, vol. 7, no. 3, pp. SE113–SE122, 2019, doi: 10.1190/int-2018-0235.1.

[12] Y. Babakhin, A. Sanakoyeu, and H. Kitamura, "Semi-supervised segmentation of salt bodies in seismic images using an ensemble of convolutional neural networks," in Pattern Recognition. DAGM GCPR 2019, Lecture Notes in Computer Science, vol. 11824, Cham: Springer, 2019, pp. 218–231, doi: 10.1007/978-3-030-33676-9_15.

[13] H. G. Gholami and A. M. S. Arefi, "Salt-dome detection using a codebook-based learning model," IEEE Geosci. Remote Sens. Lett., vol. 13, no. 7, pp. 962–966, Jul. 2016, doi: 10.1109/LGRS.2016.2547701.

[14] H. Gholami and H. Moradzadeh, "Robust salt-dome detection using the ranking of texture-based attributes," Appl. Geophys., vol. 13, pp. 373–384, 2016, doi: 10.1007/s11770-016-0569-6.

[15] M. Khoshrou, A. Barzegaran, and M. Babaei, "Robust concurrent detection of salt domes and faults in seismic surveys using an improved U-Net architecture," IEEE Access, vol. 8, pp. 229501–229514, 2020, doi: 10.1109/ACCESS.2020.3045563.

[16] B. L. Biondi, 3D Seismic Imaging, 1st ed. Tulsa, OK: Society of Exploration Geophysicists, 2006, doi: 10.1190/1.9781560801689.

[17] A. Di, A. Veganzones, and M. Dalla Mura, "Using deep learning-based methods to classify salt bodies in seismic images," J. Appl. Geophys., vol. 179, p. 104084, 2020, doi: 10.1016/j.jappgeo.2020.104084.

[18] A. Afshari and M. Alqahtani, "Machine learning for seismic exploration: Where are we and how far are we from the holy grail?," Geophysics, vol. 89, no. 2, pp. V183–V198, 2024, doi: 10.1190/geo2023-0129.1.
[19] S. AlFaraj, "Detection of salt-dome boundary surfaces in migrated seismic volumes using gradient of textures," presented at SEG Int. Exposition and Annual Meeting, 2015. [Online]. Available: https://www.onepetro.org/conference-paper/SEG-2015-65673
[20] W. Wu, X. Xie, and M. Zhang, "Seismic fault detection using an encoder–decoder convolutional neural network with a small training set," J. Geophys. Eng., vol. 16, no. 1, pp. 175–189, 2019, doi: 10.1093/jge/gxy032.
[21] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A deep convolutional encoder-decoder architecture for image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 12, pp. 2481–2495, Dec. 2017, doi: 10.1109/TPAMI.2016.2644615.
[22] M. R. Javadpour, "Forecasting the metal ores industry index on the Tehran stock exchange: A gated recurrent unit (GRU) approach," J. Artif. Intell. Capsule Netw., vol. 6, no. 4, pp. 436–451, 2024. [Online]. Available: https://irojournals.com/aicn/article/view/6/4/4.