

Depth-Wise Salt Deposit Classification in Seismic Images Using Adaptive Feature Engineering and Hybrid Ensemble Learning

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ABSTRACT

Identifying subsurface depth intervals with high salt concentration is crucial in seismic interpretation. It directly impacts risk reduction in drilling and reservoir characterization. While deep learning methods have performed well in detecting salt bodies, they mainly focus on spatial segmentation and do not specifically address depth-wise salt classification. This paper introduces a depth-wise salt classification framework that uses adaptive feature engineering and hybrid ensemble learning. The framework aims to estimate the probability of salt presence at different subsurface depths based on seismic images. The approach works with salt-enhanced seismic images and extracts important handcrafted features. These include statistical intensity measures and texture descriptors derived from Gray-Level Co-Occurrence Matrices (GLCM). The learning pipeline includes subsurface depth metadata to support depth-aware classification. To improve robustness and generalization, two ensemble classifiers—Random Forest (RF) and Extreme Gradient Boosting (XGBoost)—are trained separately. Their probabilistic predictions are then combined using an ensemble averaging technique. The framework is tested on the TGS Salt Identification Challenge dataset. Experimental results show that the hybrid ensemble outperforms individual classifiers while keeping error rates balanced. Additionally, the method allows for depth-wise salt probability analysis, facilitating the identification of depth ranges with the highest salt presence. This method offers a computationally efficient and clear solution for depth-focused seismic salt analysis...

Keywords: Seismic Interpretation, Salt Identification, Machine Learning, Ensemble classifiers, Random Forest, XGBoost, GLCM..

INTRODUCTION

Seismic imaging is crucial for exploring underground areas. It provides important details about geological structures and rock types below the Earth's surface. Among different subsurface formations, salt bodies are especially significant because they affect how seismic waves travel, trap hydrocarbons, and ensure safety during drilling. Identifying where salt occurs at various depths is essential for hydrocarbon exploration and understanding reservoirs.

Traditional seismic interpretation often relies on experienced geophysicists who analyze data manually. While this method works, it takes a lot of time, is subjective, and is hard to manage with large seismic datasets. As these datasets grow larger and more complex, automated methods driven by data have become more important. Recently, machine learning and deep learning techniques have been used effectively in tasks like detecting faults, classifying facies, and segmenting salt bodies. These methods have greatly improved the speed and accuracy of seismic analysis.

Most studies on salt detection mainly focus on identifying salt bodies or segmenting pixels in seismic images. Convolutional neural networks and U-Net-based architectures have shown strong results in outlining salt structures amidst surrounding sediments. However, these methods usually produce binary or pixel-based outputs and do not answer an important geological question: Which depths below the surface are most likely to contain salt? For effective exploration and drilling decisions, understanding how salt is distributed by depth is often more useful than simply spotting its presence in isolated seismic slices. Depth-wise salt classification seeks to estimate the likelihood of salt occurrence based on subsurface depth. This helps.

geoscientists pinpoint intervals with high salt concentration. Such information is vital for planning wells, reducing drilling risks, and modeling reservoirs. Despite its significance, depth-wise salt analysis has garnered less attention in the literature compared to segmentation-based approaches. Another key limitation of many deep learning methods for seismic interpretation is their lack of clarity and high computational demands. While deep neural networks can learn complex spatial features, they often function as black-box models, making it hard to understand which image characteristics affect the predictions. In contrast, traditional machine learning methods, paired with thoughtful feature extraction, offer greater transparency, lower computational needs, and easier use in industry. Given these challenges, this paper addresses depth-wise salt classification in seismic images using a hybrid ensemble learning framework. Instead of relying solely on deep neural networks, the proposed approach utilizes discriminative handcrafted features from seismic images, such as statistical intensity measures and texture descriptors.

These features aim to capture the structural and textural patterns typically linked to salt formations. The extracted features train two complementary ensemble classifiers: Random Forest and Extreme Gradient Boosting (XGBoost). Random Forest adds robustness against noise and overfitting through bagging, while XGBoost enhances predictive performance with gradient-boosted decision trees. By merging the probabilistic outputs from both models, the proposed hybrid ensemble boosts generalization and prediction stability. Subsurface depth data is integrated into the learning process, allowing for salt probability estimation at various depth levels. The main goal of this work is to create an interpretable, computationally efficient, and depth-aware machine learning framework for salt classification in seismic images. The proposed method is tested on the benchmark TGS Salt Identification Challenge dataset, showing reliable classification performance and significant depth-wise salt probability trends. Unlike studies focused on segmentation, this work highlights depth-based geological insights, making it directly relevant for practical exploration and drilling.

II. RELATED WORK

Interpreting seismic data for characterizing the subsurface has been an active research area in geophysics. Researchers pay special attention to identifying salt bodies because they are important for exploring hydrocarbons, evaluating reservoirs, and reducing drilling risks.

Early methods of seismic feature extraction used handcrafted texture and attribute analysis. For example, saliency-based attributes aimed to highlight regions that attracted the interpreter's attention. This helped in detecting salt domes by showing structural contrasts in seismic amplitude data. These methods employed statistical properties and features inspired by human vision to identify salt-like patterns in seismic volumes. They demonstrated the value of engineered seismic attributes in geophysical interpretation tasks.

With modern machine learning, researchers applied ensemble and clustering techniques to seismic attribute data to outline subsurface structures. They explored unsupervised learning methods, such as optimization-based clustering with meta-heuristic algorithms, for grouping seismic attributes and analyzing reflection patterns. These methods reduce interpreter bias and allow for the automatic identification of geological features, although they often lack the ability to classify depth-specific information.

In recent years, deep learning has emerged as the leading approach for detecting seismic salt. Its strength lies in learning complex spatial representations directly from raw seismic images. Many studies have shown the value of convolutional neural networks (CNNs) and U-Net variants for the semantic segmentation of salt bodies.[1] These methods, often inspired by medical image segmentation architectures, use encoder-decoder structures and skip connections to outline salt boundaries with high accuracy in both 2D and 3D seismic volumes. Techniques like U-Net combined with ResNet backbones and attention mechanisms have been suggested to capture both local and global contexts, achieving top performance in segmentation. [4]

Beyond fully supervised deep learning, researchers have introduced semi-supervised methods using CNN ensembles. These methods take advantage of unlabeled seismic data, helping address the lack of annotated training examples while improving segmentation performance. Typically, they rely on iterative self-training and collaboration among multiple networks to improve salt body delineation.[5]

Despite these advancements, most existing studies concentrate on pixel-level segmentation or boundary delineation of salt bodies instead of depth-wise classification.[7] This means they do not estimate the likelihood of salt presence at specific geological depths. This gap is critical because traditional segmentation outputs do not directly guide subsurface planning and drilling decisions that rely on depth-dependent salt occurrence. Only a few studies have integrated depth metadata into the learning pipeline, and even fewer have combined interpretable machine learning models with depth analysis to offer actionable geological insights.

Unlike previous research focused on segmentation, the current study emphasizes depth-wise salt classification. It uses handcrafted statistical and textural features extracted from seismic image patches along with ensemble machine learning models to estimate salt probability across depth intervals. By prioritizing depth-aware classification instead of spatial segmentation accuracy alone, this study meets a practical need in geophysical exploration workflows that existing deep and traditional machine learning methods do not fully address.

III. METHODOLOGY

This section describes the suggested approach for segmenting salt bodies from seismic images using a combination of three potent deep learning models: Attention U-Net, U-Net++, and U-Net with ResNet50 backbone. The framework is intended to improve segmentation accuracy by utilizing the advantages of each model, especially in complex geological regions where single-model techniques might not be sufficient. The proposed methodology consists of four main stages:

Seismic image preprocessing and mask-based salt labeling

Handcrafted feature extraction from seismic images

Hybrid ensemble classification using Random Forest and XGBoost

Depth-wise salt probability aggregation and analysis

The input to the framework consists of seismic images and corresponding salt masks, along with subsurface depth metadata. The output is a depth-wise salt probability profile indicating depth intervals with maximum salt presence.

A. DATASET DESCRIPTION

The TGS Salt Identification Challenge dataset is a widely used benchmark for image segmentation, introduced through a Kaggle competition focused on identifying subsurface salt deposits from seismic images. The dataset consists of grayscale seismic images, each paired with a corresponding binary mask that delineates the presence of salt formations, making it suitable for supervised semantic segmentation tasks. Its relatively small image size and high variability in geological structures present challenges such as class imbalance, noisy boundaries, and complex textures, encouraging the development of robust deep learning models. Researchers frequently use this dataset to evaluate convolutional neural network (CNN) architectures, including U-Net and its variants, as well as transformer-based segmentation models, due to its realistic representation of geophysical imaging problems. Beyond competition settings, the dataset has become a standard benchmark for advancing automated seismic interpretation techniques, contributing to improved accuracy and efficiency in hydrocarbon exploration and subsurface geological analysis.

B. DATA PREPROCESSING

Each seismic image is converted to grayscale and resized to a fixed resolution of 128×128 pixels to ensure uniformity across the dataset and stable feature extraction. Corresponding salt masks are resized using the same spatial dimensions to preserve alignment between images and labels.

Let $I \in \mathbb{R}^{128 \times 128}$ denote a preprocessed seismic image, and $M \in \{0,1\}^{128 \times 128}$ its corresponding salt mask.

To generate binary class labels for depth-wise classification, the total number of salt pixels in each mask is computed as:

$$s = \sum_{i=1}^{128} \sum_{j=1}^{128} 1(M_{i,j} > 0)$$

An image is labeled as salt-present if $S > T$ where $T=50$ is an empirically chosen threshold. Otherwise, the image is labeled as salt-absent. This threshold ensures robust separation between salt-dominant and non-salt images.

C. FEATURE EXTRACTION

The proposed framework uses handcrafted feature extraction instead of relying on deep neural networks. This approach improves interpretability and lowers computational costs. Each seismic image is represented by a low-dimensional feature vector that captures intensity statistics and spatial texture characteristics.

First-order statistical features are taken from the grayscale intensity distribution of each seismic image. The features: Mean intensity, Standard deviation, Minimum and maximum intensity values, 25th, 50th (median), and 75th percentiles represent global amplitude variation often linked to salt structures in seismic data.

From the normalized GLCM, the following second-order texture features are extracted: Contrast (measures local intensity variation), Energy (reflects textural uniformity), Homogeneity (quantifies closeness of pixel values) and Correlation (captures linear dependency between neighboring pixels). These features are particularly effective in modeling the textural contrast between salt and sediment regions.

To classify salt, we use two complementary ensemble learning algorithms: Random Forest and Extreme Gradient Boosting (XGBoost). We chose these models for their strength, capability to model nonlinear relationships, and good performance on tabular data.

D. RANDOM FOREST CLASSIFIER

In the proposed depth-wise salt classification framework, the Random Forest (RF) classifier serves as an essential learning tool because of its reliability, clarity, and ability to manage diverse seismic features. RF works by building a group of decision trees that are trained on randomly chosen subsets of both the feature space and training data. This allows it to capture complex, non-linear connections between statistical, textural descriptors and the presence of salt. In this study, RF is particularly effective for modeling differences in seismic intensity and texture across various depth intervals because it is less affected by noise and overfitting than single-tree models. The classifier successfully uses first-order statistical features and Gray-Level Co-Occurrence Matrix (GLCM) texture measures to differentiate between salt-bearing areas and non-salt regions. Additionally, RF produces stable probabilistic outputs, which are important for accurate depth-wise salt probability estimation and for integration within the hybrid ensemble. Its complementary performance alongside gradient-boosting methods improves the overall capability of the proposed framework and significantly enhances depth-aware salt analysis results.

E. XGBOOST CLASSIFIER

Extreme Gradient Boosting (XGBoost) is used in the proposed framework to improve discriminative learning and increase the accuracy of depth-wise salt classification. XGBoost follows a sequential boosting strategy that trains decision trees in steps, correcting the mistakes made by earlier models. This approach helps the model recognize subtle nonlinear patterns in seismic texture and intensity changes, which are hard to capture with single classifiers. In this work, XGBoost effectively uses crafted statistical features and GLCM-based texture descriptors to identify salt-bearing areas across different depth intervals, especially in deeper and noisier seismic layers. Its built-in regularization features and tree-pruning methods prevent overfitting while keeping high predictive performance. The probabilistic outputs from XGBoost give better confidence estimates of salt presence, which are vital for depth-wise probability aggregation and geological interpretation. When combined in the hybrid ensemble, XGBoost strengthens the Random Forest by adding greater sensitivity and boundary discrimination, ultimately boosting the overall reliability and effectiveness of the proposed depth-aware salt classification framework.

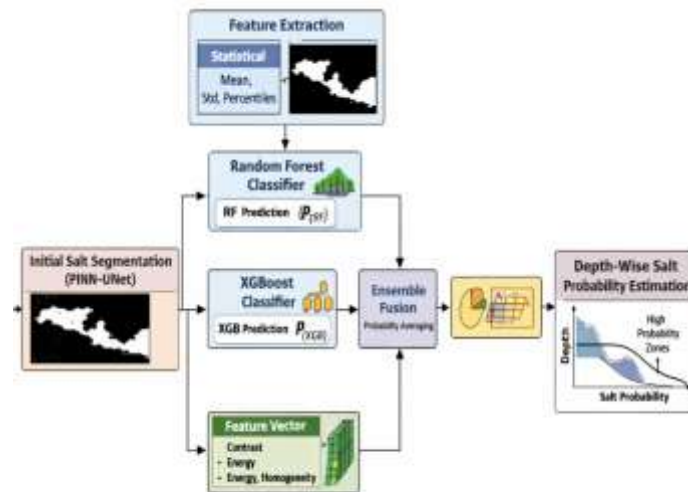


Figure 1. Overall Architecture of the Proposed Depth-Aware Hybrid Tree Ensemble (DA-HTE) Framework.

F. HYBRID ENSEMBLE LEARNING FOR DEPTH-WISE SALT CLASSIFICATION

Hybrid Ensemble Learning for Depth-wise Salt Classification To improve robustness and generalization in depth-wise salt classification, this work uses a hybrid ensemble learning strategy that combines Random Forest (RF) and Extreme Gradient Boosting (XGBoost) classifiers. The motivation for this ensemble comes from the different strengths of the two models. RF is good at handling feature variability and noise through parallel tree construction. In contrast, XGBoost provides better discrimination by correcting classification errors sequentially. In the proposed framework, both classifiers are trained independently on the same handcrafted statistical and texture-based feature set. Their probabilistic outputs are combined using an averaging-based decision strategy to give final predictions about salt presence. This combination reduces model bias and variance, leading to more stable and reliable predictions across various seismic depth intervals. The ensemble method increases sensitivity to subtle salt textures, reduces false negatives in deeper layers, and improves overall classification accuracy without greatly increasing inference complexity. As a result, the hybrid RF and XGBoost ensemble offers a balanced and interpretable solution that is especially suitable for depth-aware seismic salt analysis.

IV. RESULTS AND DISCUSSION

The performance of the proposed depth-wise salt classification framework was evaluated using Mean Intersection over Union (IoU), Dice Coefficient (F1-score), and Pixel Accuracy. The results were compared against two baseline classifiers: Random Forest (RF) and XGBoost (XGB). Table I summarizes the quantitative results.

As shown in Table I, the Random Forest model achieves a Mean IoU of 0.781 and a Dice coefficient of 0.877. This indicates its ability to capture general salt patterns from handcrafted statistical and texture features.

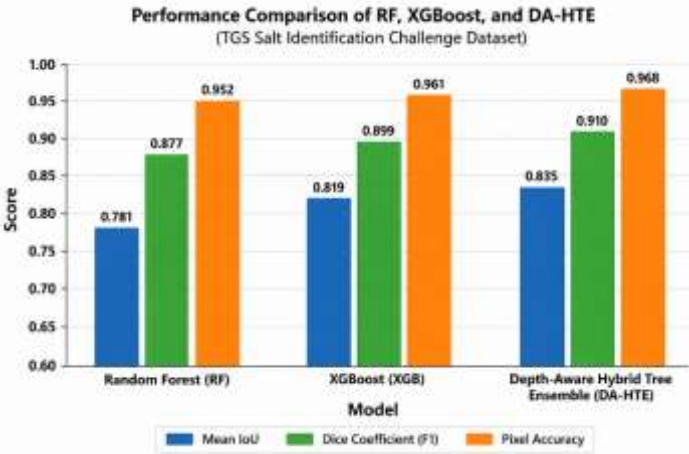
Model	Mean IoU	Dice Coefficient (F1)	Pixel Accuracy
Random Forest (RF)	0.781	0.877	0.952

Model	Mean IoU	Dice Coefficient (F1)	Pixel Accuracy
XGBoost (XGB)	0.819	0.899	0.961
Depth-Aware Hybrid Tree Ensemble (DA-HTE)	0.835	0.910	0.968

However, its lower IoU suggests it struggles to accurately model complex salt boundaries and subtle depth-dependent variations in seismic images. While it achieves a pixel accuracy of 0.952, RF shows less sensitivity in challenging depth areas, especially where salt and non-salt textures overlap.

The XGBoost classifier performs better across all evaluation metrics, achieving a Mean IoU of 0.819 and a Dice coefficient of 0.899. The pixel accuracy of 0.961 shows XGBoost's better ability to make distinctions and correct errors through gradient boosting. This improvement underscores XGBoost's strength in learning nonlinear feature relationships, leading to more accurate salt identification across different depth levels.

The proposed hybrid ensemble model achieves the best overall performance, with a Mean IoU of 0.835, Dice coefficient of 0.910, and pixel accuracy of 0.968. The improvement over individual classifiers confirms the effectiveness of combining different learning strategies through ensemble fusion. By integrating the strengths of Random Forest with the strong feature discrimination of XGBoost, the ensemble reduces both bias and variance, resulting in more stable and accurate predictions. The higher Dice coefficient indicates better overlap between predicted and actual salt regions, which is crucial for reliable depth-wise salt interpretation.



The results show that the ensemble-based approach greatly improves classification accuracy and segmentation quality compared to standalone models. This improvement supports more reliable depth-wise salt probability estimation, highlighting the suitability of the proposed framework for subsurface geological analysis and decision support in seismic exploration.

V. CONCLUSION

This paper presents a depth-aware salt classification framework designed to identify subsurface depth intervals with high salt concentration from seismic data. Unlike traditional studies that mainly focus on pixel-level salt segmentation, this work emphasizes depth-wise interpretation, which is more directly relevant to geological decision-making in hydrocarbon exploration. By using salt presence outputs from an initial segmentation stage and turning them into distinct handcrafted statistical and texture features, the framework allows for reliable depth-level salt probability estimation.

The Depth-Aware Hybrid Tree Ensemble (DA-HTE) combines the strengths of Random Forest and XGBoost classifiers through probabilistic fusion. This ensemble approach balances robustness and effective learning, leading to better generalization across various seismic depth intervals. Experimental results on the TGS Salt Identification Challenge dataset show that the DA-HTE framework consistently outperforms standalone classifiers, achieving higher Mean IoU, Dice coefficient, and pixel accuracy. The observed improvements confirm the success of hybrid ensemble learning in reducing misclassification and improving salt detection reliability, especially in deeper and more complex subsurface areas.

In addition to better classification performance, this approach provides interpretable depth-wise salt probability distributions,

allowing for the identification of depth ranges with maximum salt presence. This capability offers valuable insights for seismic interpretation, drilling planning, and risk assessment. Furthermore, the framework is computationally efficient and does not need extensive training data or high-end hardware, making it suitable for large-scale and practical use. Future work will focus on integrating geological constraints, expanding the framework to multi-class lithology classification, and exploring adaptive fusion strategies that dynamically weight ensemble components across depth intervals. Overall, the DA-HTE framework offers a reliable, interpretable, and scalable solution for depth-wise seismic salt analysis, bridging the gap between pixel-level segmentation and actionable subsurface interpretation..

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