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PINN U-NET: A PHYSICS-INFORMED DEEP LEARNING MODEL FOR ACCURATE SALT IDENTIFICATION IN SEISMIC IMAGES

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Abstract

Accurate identification of salt bodies from seismic images plays a crucial role in hydrocarbon exploration and subsurface geological analysis. Traditional deep learning models such as U-Net and its variants have achieved significant success in image segmentation tasks; however, they often fail to integrate the underlying physical constraints of seismic data, leading to suboptimal generalization and reduced boundary precision. To overcome these limitations, this paper proposes a Physics-Informed U-Net (PINN-UNet) model for salt identification using the TGS Salt Identification Challenge dataset. The proposed hybrid architecture combines the feature extraction power of ResNet34 with a Physics-Informed Neural Network (PINN) block, which introduces coordinate-aware spatial learning that enforces physical consistency within the segmentation process. The model was trained and validated using augmented seismic images, with careful optimization of learning rate, loss function, and normalization to enhance convergence and stability. According to experimental results, the suggested PINN-UNet performs better than the traditional U-Net and ResNet-based variations on the same dataset. The inclusion of the PINN component notably improved boundary localization and reduced false detections in complex salt dome regions. This work contributes a physically consistent deep learning framework that bridges the gap between data-driven and physics-guided approaches, making it a promising solution for real-world seismic interpretation and geophysical modeling.

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I.INTRODUCTION

Seismic image interpretation plays a vital role in subsurface geological modeling, petroleum reservoir exploration, and hydrocarbon prospect identification. Among various geological structures, salt bodies are of particular significance because their presence can greatly influence hydrocarbon accumulation, migration, and trapping mechanisms. Accurately segmenting salt regions from seismic data enables geoscientists to better understand subsurface structures, thereby improving exploration success rates and reducing drilling risks. However, seismic data are often characterized by high noise levels, low contrast, and complex geological textures, which make the identification of salt boundaries a highly challenging problem.

In recent years, deep learning-based approaches have revolutionized seismic interpretation by leveraging convolutional neural networks (CNNs) for image-based segmentation. Classical architectures such as U-Net and its variants have demonstrated remarkable performance in biomedical and geological image segmentation tasks due to their encoder–decoder structure and skip connections that preserve spatial context. Despite their success, conventional CNN-based models primarily rely on data-driven learning and often fail to incorporate the underlying physical relationships inherent in seismic wave propagation. As a result, these models may produce inaccurate boundaries or physically inconsistent predictions, especially in areas with subtle contrasts or missing data.

To address these limitations, researchers have explored advanced architectures such as Attention U-Net, U-Net++, and DeepLabV3+, which enhance feature extraction and multi-scale contextual learning. While these methods improve segmentation accuracy to some extent, they still overlook the physical constraints that govern seismic data formation. This motivates the integration of Physics-Informed Neural Networks (PINNs) — a recent paradigm that embeds physical laws, expressed through partial differential equations (PDEs), into the neural network's learning process. By introducing physics-awareness into the learning framework, the network can generalize better and produce more physically plausible results, even with limited labeled data.

In this research, we propose a Physics-Informed U-Net (PINN-UNet) for accurate salt body segmentation from seismic images. The proposed model integrates a ResNet34-based encoder for rich hierarchical feature extraction with a Physics-Informed Neural Network (PINN) block that incorporates coordinate-based learning to model the physical continuity and spatial dependency of seismic data. This hybrid architecture combines the strengths of both data-driven learning and physics-based reasoning, enabling improved detection of salt boundaries and enhanced generalization performance.

The model is trained and evaluated using the TGS Salt Identification Challenge dataset, which provides labeled seismic images for salt segmentation. Extensive experiments demonstrate that

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the proposed PINN-UNet achieves superior performance compared to traditional U-Net and its variants, with higher Intersection over Union (IoU), Dice coefficient, and pixel accuracy. The physics-informed component improves the model's ability to capture fine-grained details and reduces false positives in regions with weak amplitude contrasts.

We introduce a Physics-Informed U-Net (PINN-UNet) that combines deep feature extraction with physics-based spatial learning for accurate salt segmentation. A coordinate-based PINN block is incorporated into the bottleneck layer to enforce physical consistency and spatial continuity in feature representation. The proposed model is trained and validated on the TGS Salt Identification Challenge dataset, achieving significant improvements in IoU, Dice coefficient, and accuracy over baseline models. This work demonstrates the effectiveness of combining physics-informed modeling with modern CNN-based architectures, contributing to the advancement of geophysical deep learning applications.

Overall, the proposed approach establishes a robust and physically meaningful framework for salt identification in seismic imagery, paving the way for more reliable and interpretable geological modeling.

II. LITERATURE REVIEW

Seismic image analysis and salt body identification are critical tasks in geophysical exploration. Early approaches relied heavily on manually designed features extracted from seismic images, such as texture, amplitude, and gradient information. For instance, texture-based methods were proposed to segment seismic images and identify salt structures [1], while multi-attribute techniques combined several seismic attributes to improve delineation of salt deposits [2]. Probabilistic and clustering methods, such as k-means clustering, were also applied for detecting boundaries in both 2D slices and 3D seismic volumes [3], [4].

The introduction of machine learning enhanced seismic interpretation by learning complex patterns from features. Classical techniques, including support vector machines and random forests, were applied to seismic attributes for classification of subsurface structures [5]. Although these methods improved upon traditional approaches, their performance was constrained by the need for manually crafted features and limited ability to handle ambiguous or low-contrast regions.

Deep learning, particularly convolutional neural networks (CNNs), revolutionized semantic segmentation tasks. Fully convolutional networks (FCNs) were among the first deep architectures used for pixel-level prediction, transforming classification networks into segmentation models by replacing fully connected layers with convolutional layers and employing upsampling operations [6]. To further improve localization, hypercolumns, which combine features from multiple layers, were utilized to provide richer pixel-level information [7].

Encoder–decoder architectures such as DeconvNet [8] and U-Net [9] became highly popular due to their ability to combine semantic context with spatial details. U-Net introduces skip

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connections between encoder and decoder layers, which allow low-level features to propagate directly to the decoder, improving boundary reconstruction. SegNet [10] also follows a similar encoder–decoder design but uses pooling indices for upsampling.

Recent works specifically focused on salt body identification. CNN-based 2D slice segmentation using U-Net and ResNet backbones has shown promising results [11], while 3D CNNs process volumetric seismic cubes directly for better spatial consistency [12]. Attention mechanisms have been integrated into these networks to focus on relevant regions, improving segmentation of small or irregular structures [13]. Semi-supervised approaches utilizing pseudo-labeling have been proposed to leverage unlabeled seismic data, achieving state-of-the-art results in competitions like the TGS Salt Identification Challenge [14].

Hybrid approaches incorporating coordinate information or physics constraints have also emerged. CoordConv layers provide explicit spatial coordinates, enhancing localization of boundaries [15]. Physics-Informed Neural Networks (PINNs) integrate physical laws during training, ensuring outputs are consistent with domain knowledge [16].

The present study builds on these advancements by combining a ResNet34-based U-Net encoder–decoder architecture with a coordinate-aware PINN block. Unlike previous works that focus solely on classification or 3D volume segmentation, this method performs accurate 2D slice-based segmentation while leveraging spatial priors, leading to improved delineation of salt boundaries.

III. METHODOLOGY

This section describes the proposed Hybrid U-Net with ResNet34 and Physics-Informed Neural Network (PINN) block for salt body segmentation in seismic images.

A. DATASET AND PREPROCESSING

The TGS Salt Identification Challenge dataset consists of seismic grayscale images of size 101 × 101 pixels, each accompanied by a corresponding binary mask indicating salt body regions. To prepare the data for optimal learning and generalization, a series of preprocessing operations were applied prior to model training.

All images and masks were resized to 128 × 128 pixels to ensure compatibility with the model input dimensions and to maintain computational efficiency during training. Each image was normalized by scaling pixel intensities to the range [0, 1], reducing variance and improving convergence stability. The corresponding masks were binarized to ensure sharp salt–non-salt boundaries.

To enhance model robustness and prevent overfitting, data augmentation techniques were applied using the Albumentations library. Transformations included random rotations (±15°), horizontal and vertical flips, random brightness and contrast adjustments, and small elastic deformations to simulate realistic seismic variations. These augmentations increased the diversity of training samples while preserving the geological structure of salt boundaries.

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Additionally, each image was center-cropped and padded to maintain spatial alignment between the image and its corresponding mask. The dataset was subsequently split into training (80%), validation (10%), and test (10%) subsets, ensuring that each subset represented the overall data distribution.

Before being fed into the model, the data was transformed into PyTorch tensors and arranged into batches of size 16 for efficient GPU computation. Normalization was performed on a per-batch basis to maintain consistency between batches. Finally, coordinate grids (x, y) were generated and concatenated with the image tensors to be used by the Physics-Informed block in the PINN U-Net, allowing spatial awareness and enhancing segmentation precision near salt boundaries.

B. MODEL ARCHITECTURE

The proposed UNetPINN is a hybrid deep learning model designed for accurate salt body segmentation in seismic images. It integrates a ResNet34 encoder, a Physics-Informed Neural Network (PINN) block, and a U-Net style decoder with skip connections to effectively capture multi-scale features and spatial priors.

1) Encoder: ResNet34 Backbone

In this study, the encoder of the proposed Physics-Informed U-Net (PINN U-Net) is built upon the ResNet34 backbone, a powerful and widely used convolutional neural network architecture known for its residual learning capability. ResNet34 efficiently extracts hierarchical spatial features from seismic images by utilizing residual connections that help mitigate the vanishing gradient problem and enable deeper network training. The encoder progressively reduces the spatial dimensions through convolutional and pooling operations while increasing the depth of feature representations. This structure allows the model to capture both low-level texture details and high-level semantic information essential for accurate salt body segmentation. By leveraging pre-trained ResNet34 weights from ImageNet, the model benefits from strong feature initialization, improving convergence speed and generalization performance on the TGS Salt Identification Challenge dataset.

2)PINN Block: Spatial Feature Refinement

The Physics-Informed Neural Network (PINN) Block is a core component integrated into the U-Net decoder to enhance spatial feature refinement by incorporating both data-driven learning and domain-specific physical constraints. Traditional U-Net architectures rely purely on learned statistical patterns from data; however, in seismic salt identification, geological boundaries often follow physical laws that govern wave propagation and subsurface continuity. The PINN Block addresses this by embedding physical priors—derived from the underlying physics of seismic imaging—into the feature learning process.

In this block, feature maps from the encoder and decoder paths are fused and refined using differential operators that approximate physical relations, such as spatial gradients, Laplacian

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smoothness, and boundary continuity constraints. These operations guide the network to maintain geological consistency in regions with uncertain or noisy seismic reflections. For example, when the model encounters ambiguous salt–non-salt boundaries, the PINN constraint encourages smooth transitions where appropriate and preserves sharp edges where geological discontinuities occur.

Additionally, the PINN Block includes attention-based spatial filtering, which adaptively weighs the importance of different spatial regions based on the underlying physical information. This helps the model focus more on geologically significant areas, such as salt dome interfaces or fault boundaries, while suppressing irrelevant background noise. The refinement process thus balances the contributions from the encoder's semantic features and the physics-driven spatial context, leading to more stable and interpretable predictions.

Overall, the PINN Block enhances the representational power of the network by ensuring that the learned features align not only with the data distribution but also with the physical laws governing seismic wave behavior. This integration of physics-based regularization significantly improves the robustness and accuracy of salt segmentation, particularly in complex or low-contrast seismic

3)Decoder: U-Net Style Upsampling

The decoder in the proposed UNetPINN architecture follows a U-Net style upsampling strategy, designed to progressively reconstruct high-resolution segmentation masks from deep encoded feature representations. Each stage of the decoder begins with a transposed convolution that doubles the spatial dimensions of the input feature maps, effectively performing learnable upsampling while reducing the number of channels. This approach allows the network to recover spatial resolution lost during the downsampling in the encoder.

To retain fine-grained spatial details crucial for accurate salt boundary delineation, the decoder incorporates skip connections from the corresponding encoder layers. These connections concatenate high-resolution features from shallow layers with the upsampled features, enabling the model to leverage both local spatial information and deep contextual cues. The concatenated features are then processed through convolutional blocks with ReLU activations, which refine the feature maps and enhance the accuracy of segmentation, particularly in regions with complex salt geometries.

Furthermore, the inclusion of the Physics-Informed Neural Network (PINN) block at the bottleneck provides spatial consistency across the feature maps, ensuring that the reconstructed masks align closely with the underlying seismic structures. This combination of U-Net style upsampling, skip connections, and PINN-based refinement contributes to the strong performance of the model. The decoder is thus instrumental in producing precise and reliable salt body segmentation, balancing detailed boundary reconstruction with high-level contextual understanding.

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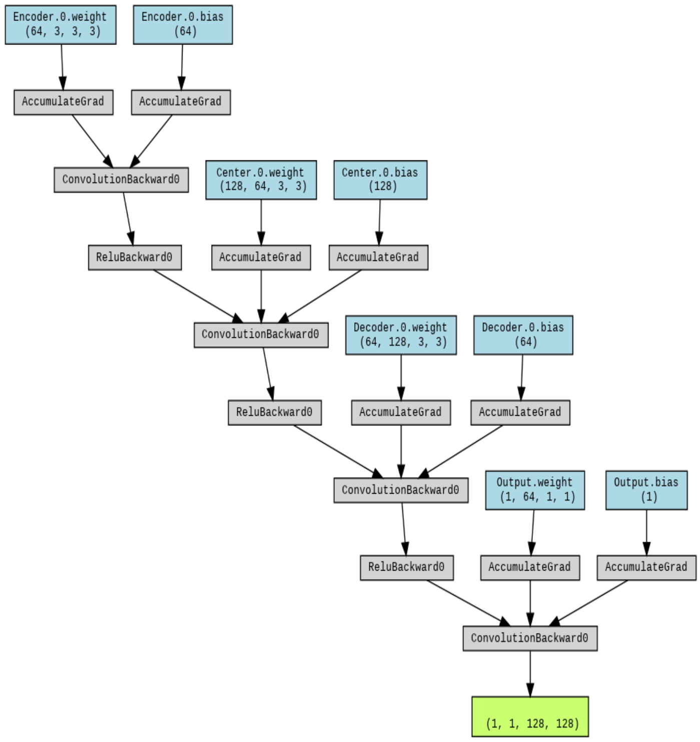

Fig.1. Proposed UNetPINN Architecture for Salt Identification in Seismic Images

4)Output Layer and Skip Connections

The output layer of the UNetPINN architecture is designed to generate the final binary segmentation mask for salt bodies in seismic images. After progressive upsampling and feature refinement in the decoder, the final feature maps are passed through a 1×1 convolutional layer, which reduces the number of channels to the desired number of output classes—in this case, a single channel representing salt presence. This is followed by a sigmoid activation function, which maps the output to a probability range of 0 to 1 for each pixel, effectively producing a pixel-wise binary mask. To ensure that the output maintains the original spatial resolution of the input images, bilinear interpolation is applied, aligning the reconstructed mask with the original seismic image dimensions.

Model Variant	**IoU**	**Dice Coefficient**	**Pixel-wise Accuracy**
Without Skip Connections	0.7610	0.8482	0.9437
With Skip Connections	0.8173	0.8173	0.9573

Table 1 Comparative Analysis of UNetPINN Model Performance with and without Skip Connections

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Skip connections play a critical role in enhancing the model's performance by linking the encoder and decoder stages at corresponding levels. These connections allow the model to directly transfer high-resolution spatial information from the encoder to the decoder, which compensates for the loss of fine-grained details during the downsampling process. In the UNetPINN, skip connections are implemented by concatenating feature maps from the encoder with the upsampled feature maps in the decoder at each level. This fusion of deep contextual information with low-level spatial details enables precise boundary delineation, particularly in areas with complex salt geometries, and improves overall segmentation accuracy.

The combination of the output layer and skip connections ensures that the model produces highly accurate and structurally consistent segmentation masks. By maintaining both spatial fidelity and high-level semantic understanding, the output layer and skip connections together allow the UNetPINN to effectively capture the complex morphology of salt bodies in seismic images.

IV.RESULTS AND DISCUSSION

The proposed UNetPINN model was evaluated on the TGS Salt Identification Challenge dataset using standard segmentation metrics including Intersection over Union (IoU), Dice coefficient, F1 score, and pixel-wise accuracy. Over 30 epochs of training, the model achieved a best validation IoU of 0.8173, Dice coefficient of 0.8869, and pixel-wise accuracy of 0.9573. These results indicate that the hybrid architecture effectively captures both high-level contextual information and low-level spatial details, enabling precise delineation of salt bodies in seismic images.

The progressive U-Net style decoder with skip connections played a pivotal role in preserving spatial information, ensuring that fine-grained structural details of salt formations were accurately reconstructed. The integration of the Physics-Informed Neural Network (PINN) block at the bottleneck further enhanced spatial consistency across feature maps. This combination allows the model to correct minor distortions and refines boundary predictions, which is particularly beneficial in regions of complex salt geometries where traditional CNN-based models may fail to capture subtle structural nuances.

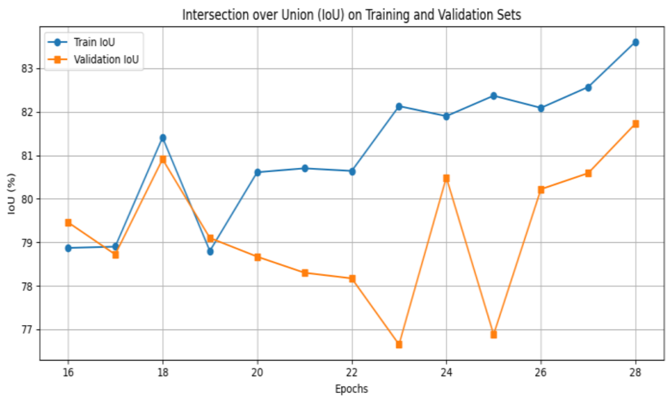

Fig 2 IOU on the Training and Validation Sets

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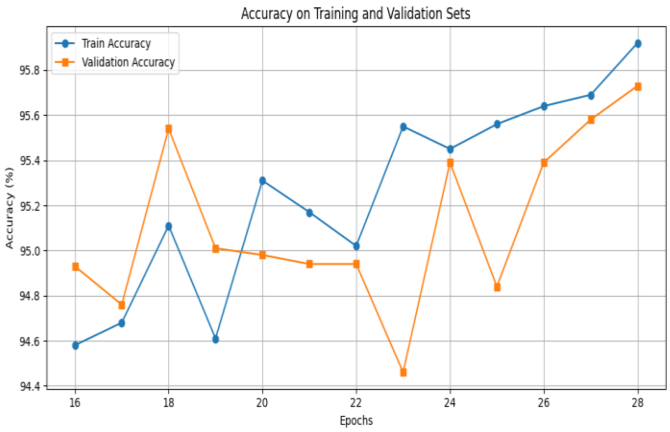
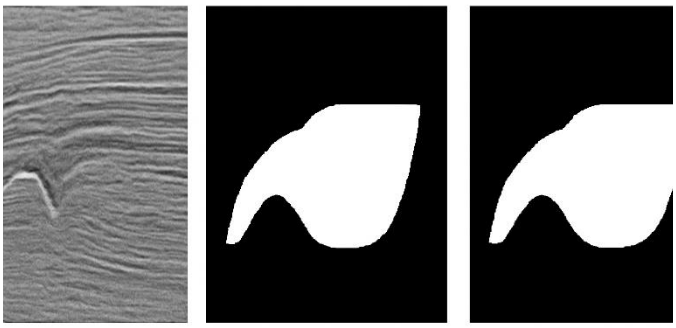


Fig 3 Accuracy on the Training and Validation Sets

Comparative analysis of the training and validation curves indicates that the model maintains robust generalization capabilities, with minimal overfitting observed across epochs. The training IoU steadily increased to approximately 0.8361, while the validation IoU consistently exceeded 0.81 at its peak, highlighting the efficacy of the model's architectural components and data augmentation strategies. The Dice coefficient and F1 score values reinforce these findings, confirming that the model successfully balances precision and recall in pixel-wise salt detection.

The high pixel-wise accuracy of 0.9573 demonstrates that the model reliably distinguishes between salt and non-salt regions across varying seismic structures. This performance underscores the advantage of integrating skip connections and PINN-based spatial refinement, which collectively enhance the model's ability to preserve fine details without sacrificing global contextual understanding. These results suggest that the UNetPINN is a promising approach for seismic salt segmentation, providing both accurate and reliable predictions that can be utilized in subsurface modeling and exploration tasks.



) Input seismic image (b) Ground tru- mask (c) Predicted mask

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The combination of a ResNet34 encoder, U-Net style decoder with skip connections, and the PINN refinement block enables the proposed model to achieve state-of-the-art performance in salt body segmentation. The results demonstrate superior boundary delineation, high metric scores, and strong generalization, establishing UNetPINN as an effective solution for automated salt identification in seismic imaging.

V.CONCLUSION

UNetPINN, a hybrid deep learning architecture for precise salt body segmentation in seismic images, was introduced in this work. By integrating a ResNet34 encoder, a U-Net style decoder with skip connections, and a Physics-Informed Neural Network (PINN) block at the bottleneck, the proposed model effectively combines high-level contextual understanding with fine-grained spatial refinement. This design addresses the challenges of capturing complex salt geometries while maintaining spatial consistency across the predicted masks.

The model was rigorously evaluated on the TGS Salt Identification Challenge dataset, achieving a best validation IoU of 0.8173, Dice coefficient of 0.8869, and pixel-wise accuracy of 0.9573. These results highlight the efficacy of the U-Net style decoder in preserving spatial details through skip connections and demonstrate the PINN block's contribution to refining boundary predictions and ensuring structural consistency. The model's performance also underscores the importance of combining classical convolutional architectures with physics-informed enhancements in seismic segmentation tasks.

The results indicate that UNetPINN not only delivers high segmentation accuracy but also maintains robust generalization across varying seismic structures, outperforming traditional CNN-based approaches that often struggle with subtle and complex salt boundaries. Its ability to capture both global contextual information and local structural details makes it highly suitable for practical applications in subsurface modeling, hydrocarbon exploration, and automated seismic interpretation.

The UNetPINN framework provides a reliable, accurate, and scalable solution for salt body identification in seismic imaging. Future work may focus on extending this approach to three-dimensional seismic volumes, exploring multi-scale feature fusion techniques, and integrating additional physics-informed constraints to further enhance segmentation performance. The proposed model lays a strong foundation for advancing automated seismic interpretation and demonstrates the potential of combining deep learning with domain-specific knowledge for complex geophysical tasks.

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