Seismic fault identification using a hybrid ResNet-UNet architecture

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SUMMARY

Seismic fault detection is a critical task in subsurface interpretation, influencing hydrocarbon exploration, geothermal resource assessment, and geologic hazard analysis. Conventional fault detection methods, such as manual interpretation and attribute-based techniques (e.g., coherence, semblance and curvature), suffer from subjectivity, labor intensity and sensitive to noise. These approaches often fail to accurately delineate complex fault systems, especially in large-scale 3D seismic volumes, leading to inconsistent and biased results. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized seismic fault detection by enabling automated, high-fidelity interpretations. CNN-based methods, including UNet architectures and attention-enhanced architectures, outperform conventional approaches by leveraging large datasets and extracting hierarchical spatial features. In this study, we build a ResNet-encoder based UNet for detecting faults in 3D-seismic data. We use synthetic data for training and apply it to both synthetic and real data for testing. Results show that neural network trained only with synthetic data can predict faults from 3D-seismic images accurately.

INTRODUCTION

Seismic fault detection plays a crucial role in subsurface exploration, impacting hydrocarbon reservoir characterization, geothermal energy development and geohazard assessment. Faults act as fluid migration pathways or barriers, making their accurate identification essential for optimizing drilling strategies and mitigating risks. Traditional fault detection techniques rely on manual interpretation or attribute-based methods such as coherence, semblance, and curvature, which are computationally intensive, highly subjective, and prone to errors in complex geological settings.

Traditional fault detection techniques include coherence (Bahorich and Farmer, 1995), semblance (Marfurt et al., 1998), variance (Van Bemmel and Pepper, 2000), and curvature-based methods (Richard, 1994). While these techniques have been widely used, they struggle with noise sensitivity, require careful parameter tuning, and often fail to capture complex fault geometries. Additionally, manual interpretation remains a critical step in traditional workflows, making the process time-consuming and subjective (Chopra and Marfurt, 2005). Early machine learning techniques, such as artificial neural networks (ANNs) and support vector machine (SVMs), were introduced to seismic fault detection to improve automation and accuracy (Tingdahl and De Rooij, 2005; Di et al., 2017). These models relied heavily on manually selected seismic attributes, limiting their adaptability to different datasets and geological settings.

The introduction of deep learning revolutionized fault detection by allowing models to learn hierarchical features (Xiong et al., 2018). CNN-based methods significantly improved accuracy and fault continuity compared to coherence-based techniques (Huang et al., 2017; Pochet et al., 2018). However, training deep models required large labelled datasets, leading researchers to explore synthetic data augmentation strategies (Wu et al., 2019). End-to-end CNN architectures such as FaultSeg3D (Wu et al., 2019) demonstrated the effectiveness of training networks on synthetic seismic datasets, improving fault detection accuracy without extensive real-world labeling. Further advancements in CNN-based segmentation models, including UNet and attention-based architectures, have shown superior performance in fault detection tasks (Guo et al., 2018). Building upon these advancements, our work introduces a ResNet-based UNet architecture tailored for seismic fault detection. This model enhances feature extraction through deep residual learning while preserving spatial details via UNet's skip connections. Unlike traditional pre-trained CNNs, our model does not rely on a pre-trained ResNet encoder and is trained from scratch, ensuring adaptability to seismic datasets with varying noise levels and gelogical complexities. By leveraging spatial dropouts and kernel regularization, our approach improves generalization and robustness against over-fitting.

This study evaluates ResNet-based-UNet on synthetic and real seismic datasets, highlighting the advantages of deep learning for seismic fault detection, paving the way for more efficient and accurate subsurface interpretations.

TRAINING DATA

In this study, we utilized a dataset (Wu et al., 2019) that consists of synthetic seismic images and corresponding fault labels for training and validating our CNN model. The training dataset consists of 200 seismic data-cubes, each with a size of $128 \times 128 \times 128$. A sample of the seismic data and corresponding fault data is shown in Figure 1. Each cube contained more than five faults to enhance the effectiveness of CNN-based fault segmentation. The final training images were obtained by removing the near edge part of the data cube, so that the artifacts can be minimized. Th fault data consists of binary values (0 and 1) where a fault was identified with the value 1 (Figure 1). In image, the fault had a width of atleast two pixels where one pixel corresponds to the hanging wall side and other to footwall side. For training purpose, a total of 200 pairs of seismic images and corresponding fault labels were used. For validation, a 20 pairs of seismic images and fault labeled images were used.

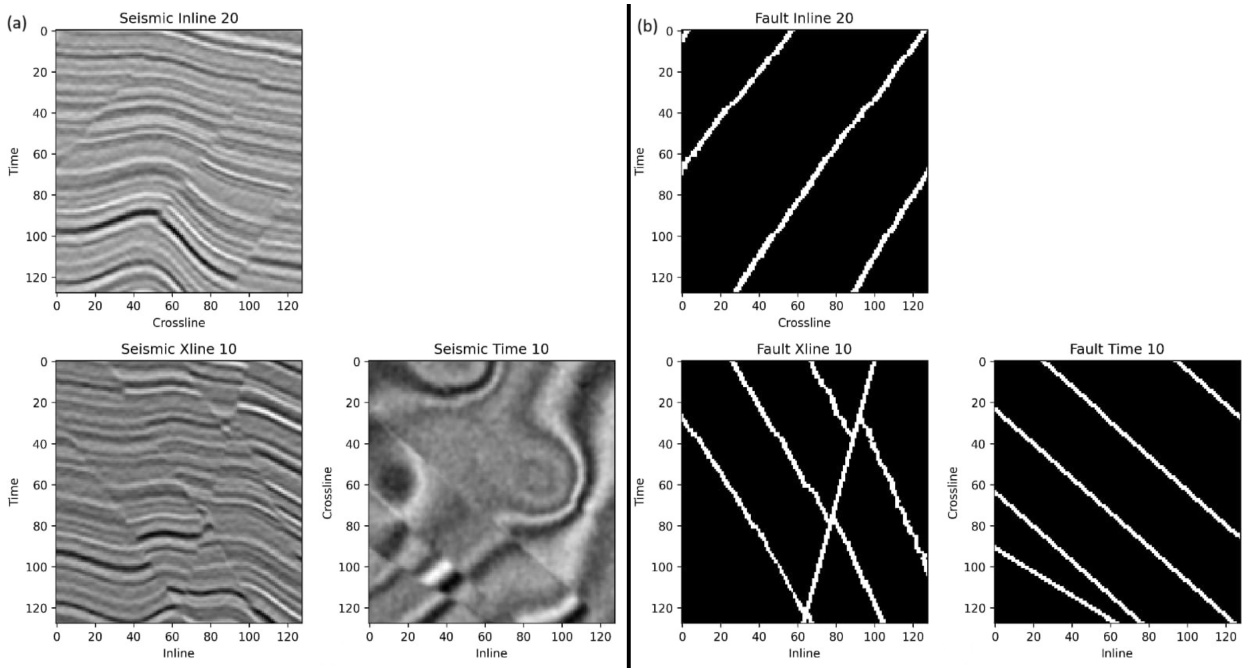

Figure 1: Synthetic used for training. (a) seismic data, and (b) corresponding fault-labeled data where fault are shown in white color (= 1) and non-faulted area with black (= 0). For each kind of data, we have shown the inline, crossline and time section.

METHODOLOGY

The first step is to homogenize the data dimension in 3D-seismic volume. If for the real data is used for the training, validation or test purpose, it might be required to take care of noise filled regions. In this case however we are using the synthetic for test and validation. For testing we have be used the real data. Since seismic data contains amplitude variations, standardization techniques are applied to normalize values, improving model stability and ensuring no feature dominates the learning process.

As it might be observed the dataset is quite limited therefore we have also performed the data augmentation to improve the learning. This technique artificially increases the dataset size by generating transformed versions of the original data. In this study, horizontal/vertical flipping is specifically used to create mirrored copies of seismic data. Augmentation is crucial in deep learning, as it helps the model learn to recognize faults from different perspectives, improving its ability to generalize to unseen data. Additionally, augmentation reduces model overfitting by preventing the model from memorizing specific samples instead of learning meaningful geological patterns.

Our proposed model is a ResNet-based UNet designed (Figure 2) to enhance the seismic fault detection by combining deep feature extraction with precise localization. The model follows an encoder-bottleneck-decoder structure, optimized for high-resolution 3D-seismic data segmentation.

Encoder block: It takes the input data (seismic data) and tries to compress it to lower dimensional data. It consists of four 3D-convolution blocks, each incorporating following elements

- A 3D convolution layer with kernel size (3,3,3) and stride (2,2,2) to progressively down-sample the input.
- Batch Normalization and ReLU activation to stabilize training.
- Residual connections ensuring efficient gradient propagation and mitigating vanishing gradient issues.
- Increasing feature maps per block (16, 32, 64, 256).
- Each encoder block consists of a single 3D-convolutional layer followed by batch normalization and ReLU activation.
- Residual connections are applied across the layers to improve gradient flow and training stability. Strided convolutions replace max pooling for better feature extraction.

Bottleneck: It is the low dimensional or compressed representation of the data. The relation between the seismic data and labeled fault data is best represented in it. In this study we used the bottleneck block with following specifications.

- A 3D-convolutional bottleneck layer (256 filters, kernel size $3 \times 3 \times 3$) to encode high-level fault representations.
- Spatial dropout (0.5) to prevent overfitting.
- L2 kernel regularization to ensure stable learning and avoid overfitting.

Decoder block: It takes the low dimensional, compressed data and using that it tries to reconstructs the original representation. In the process it loses the data due to reduction in dimensionality, however, it tries to retain the important feature (e.g.

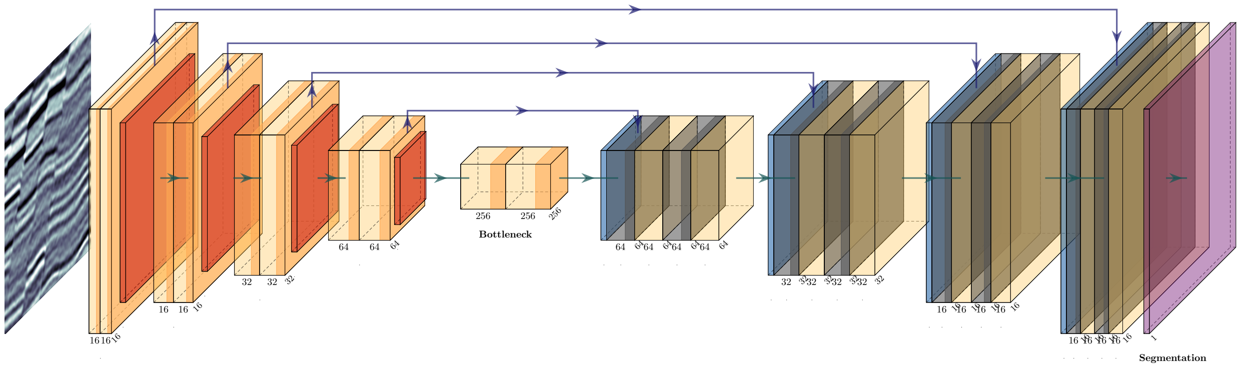

Figure 2: The 3D-UNet with ResNet encoder architecture used for fault detection in seismic data.

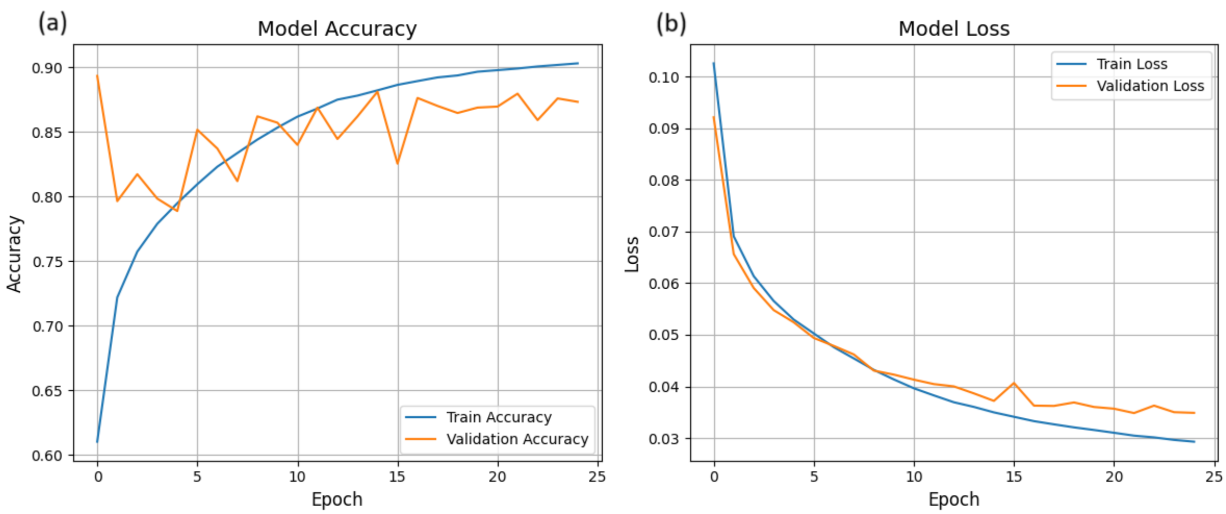

Figure 3: The model accuracy and loss function observed with given architecture for fault detection in seismic data.

faults here) as guided by the training. The important components of decoder are following.

- Transposed 3D convolution layers for upsampling.
- Skip connections from encoder layers to retain fine-grained spatial information.
- Progressive reduction of feature maps (256, 64, 32,16).

It is important to carefully select the loss function or obtaining right convergence. Generally, the binary cross-entropy loss function is used in binary segmentation problems. It is effective for images where zero and nonzero samples are relatively balanced. However, in case of fault data zeros may constitute more than 90% of the data. Training the neural network with this loss function can lead to incorrect convergence, causing the network to predict zeros everywhere. This happens because, in the fault segmentation problem, predicting only zeros minimizes the loss, making it an appealing but incorrect solution. To address the issue, we employ a Balanced Cross-Entropy Loss Function Xie and Tu (2015).

$$L = -\beta \sum_{i=0}^{i=N} y_i log(p_i) - (1-\beta) \sum_{i=0}^{i=N} (1-y_i) log(1-p_i)$$

where $\beta = \sum_{i=0}^{i=N}(1-y_i)/N$ represents the ratio between non-fault pixels and the total image pixels, whereas $1-\beta$ denotes the ratio of fault pixels in the 3D seismic image.

The model is trained using the Adam optimizer with an initial learning rate of 10^{-4}. Kernel regularization (L_2) is applied to prevent overfitting and spatial dropout is used in deeper layers to improve generalization.

RESULTS

We have carried out training of the the data for the 25 epoch and received a relatively good model loss and moderate model accuracy (Figure 3). After training the ResNet-based UNet model on synthetic seismic datasets, the model was applied to

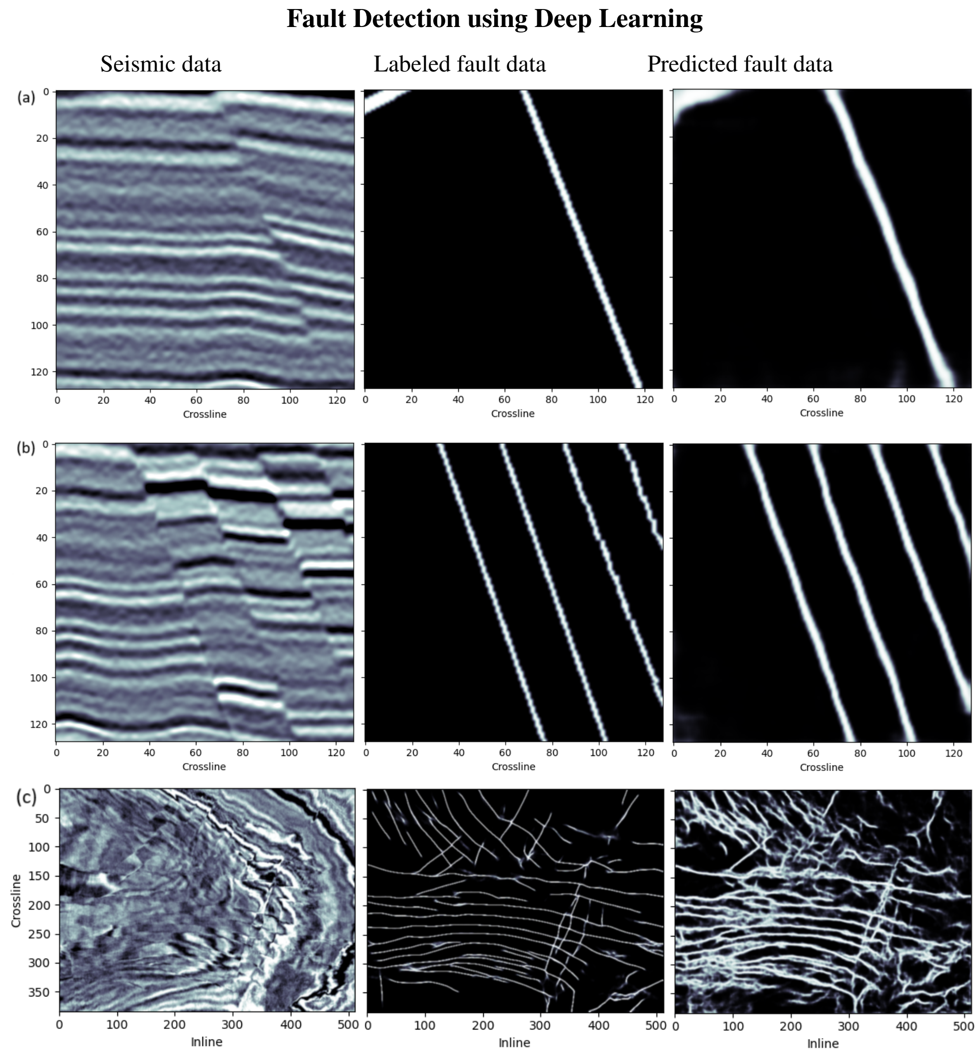

Figure 4: Results obtained for validation dataset (top and middle row) and for the real dataset (bottom row). First column shows the input, second column shows the labeled data (expected output) and third column shows the this method output.

real seismic data from the Netherlands off-shore F3 block seismic data to assess its generalization ability. The results demonstrated that the model was capable of detecting fault structures in real datasets (Figure 4). The predicted fault maps show continuous fault features that closely matched geological expectations, indicating that the model successfully transferred knowledge from synthetic training to real-world seismic interpretation. Our model can predict majority of the fault in the real data, but also has some unresolved faults in some regions.

CONCLUSIONS

Detecting faults in seismic data is challenging because of imbalance dataset, where faults are rare (very few pixels) in comparison to non-fault regions. This imbalance favors non-fault regions, leading to poor fault detection. In this study, we demonstrated how ResNet encoder with a UNet decoder can be used for detecting fault. We used Balanced Cross-Entropy loss that gives appropriate weights to all type faults and thus mitigate the problem. Additionally, we applied data augmentation techniques such as vertical flipping to create diverse training samples. This helped the model generalize better to different geological conditions and unseen data. The main advantage of using ResNet encoder over UNet encoder is that significantly improved feature extraction due to its residual connections, which enable the model to learn deep representations while retaining the important details. We have demonstrated its application on both, field data and real-datsets, where the model was able to detect faults reasonably well.

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