Seismic Fault Detection on Raniganj Data using Deep Learning

Sreeja Kalyankar[1]*, Joseph Lalngaihawma[1,2], Ajay Malkoti[1,2], Pankaj Kumar[1,2], Nimisha Vedanti[1,2]

[1]CSIR-National Geophysical Research Institute, Hyderabad-500007, India
[2]Academy of Scientific and Innovative Research (AcSIR), Ghaziabad-201002, India

Presenting author: sreejak31@ngri.res.in

Subsurface characterization plays a vital role in CO_2 sequestration in geological reservoirs. In this, seismic method plays a major role in delineating the subsurface structures and detecting the faults present within them. Traditional fault interpretation methods, such as manual picking and edge-detection algorithms, are often time-consuming, subjective, and prone to inconsistencies, especially in complex geological settings. To address these issues, we attempt to develop a Machine learning-based approach for fault characterization.

In this study, we used synthetic seismic data to train the model in detecting fault structures (Wu et al., 2019). Seismic data contains amplitude variations, and to normalize such effects on data, we applied standardization techniques. This step ensures numerical stability, prevents extreme values from dominating the learning process, and helps the model learn more effectively. Given the limited size of the dataset, we incorporated data augmentation through vertical flipping, rotation, etc. to improve model performance. This technique helped the model generalize better by exposing it to different orientations of fault patterns, ultimately enhancing its ability to detect faults in real-world seismic data.

Our model follows a 3D UNet structure with a ResNet3D-based encoder for seismic fault detection. The model can be divided into three main parts- Encoder, Bottleneck, and Decoder. The encoder extracts hierarchical spatial features using four 3D convolutional blocks with various filters. Each block uses Leaky ReLU activation, batch normalization, and L2 regularization to improve stability and prevent overfitting. Stridden convolutions are used for downsampling that enhances feature extraction. The bottleneck layer serves as a compressed representation of seismic data, capturing essential fault-related features. It consists of a 3D convolutional layer (256 filters) with batch normalization and Leaky ReLU activation. The decoder reconstructs the seismic representation using transposed 3D convolutions for upsampling. Skip connections from the encoder layers help retain fine-grained spatial details. To bring in generalization, dropout is applied at each decoding stage. The final output layer uses a sigmoid activation to classify faults.

The model can be trained to identify the faults (a segmentation problem) using the synthetic data. However, the problem is that the seismic fault data is imbalanced (with non-fault regions dominating). This problem can be mitigated using a balanced cross-entropy loss function (Xie and Tu, 2015), provided below, ensuring the model was not biased toward non-fault regions.

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

Here, $\beta = \sum_{i=0}^{i=N} \frac{1-y_i}{N}$ 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.

Presented at: Beneath the Surface: Innovations in Geoscience, Organized by SEG, 18-20 June 2025, Hyderabad, India

Thereafter, the learned model was applied to Raniganj seismic data (Figure 1). The model effectively identified faults in the seismic section. The predicted faults aligned well with expected geological structures, demonstrating the model's ability to generalize beyond training data. Overall, our approach effectively captures and predicts fault structures in seismic data, showcasing its potential for real-world geophysical applications.

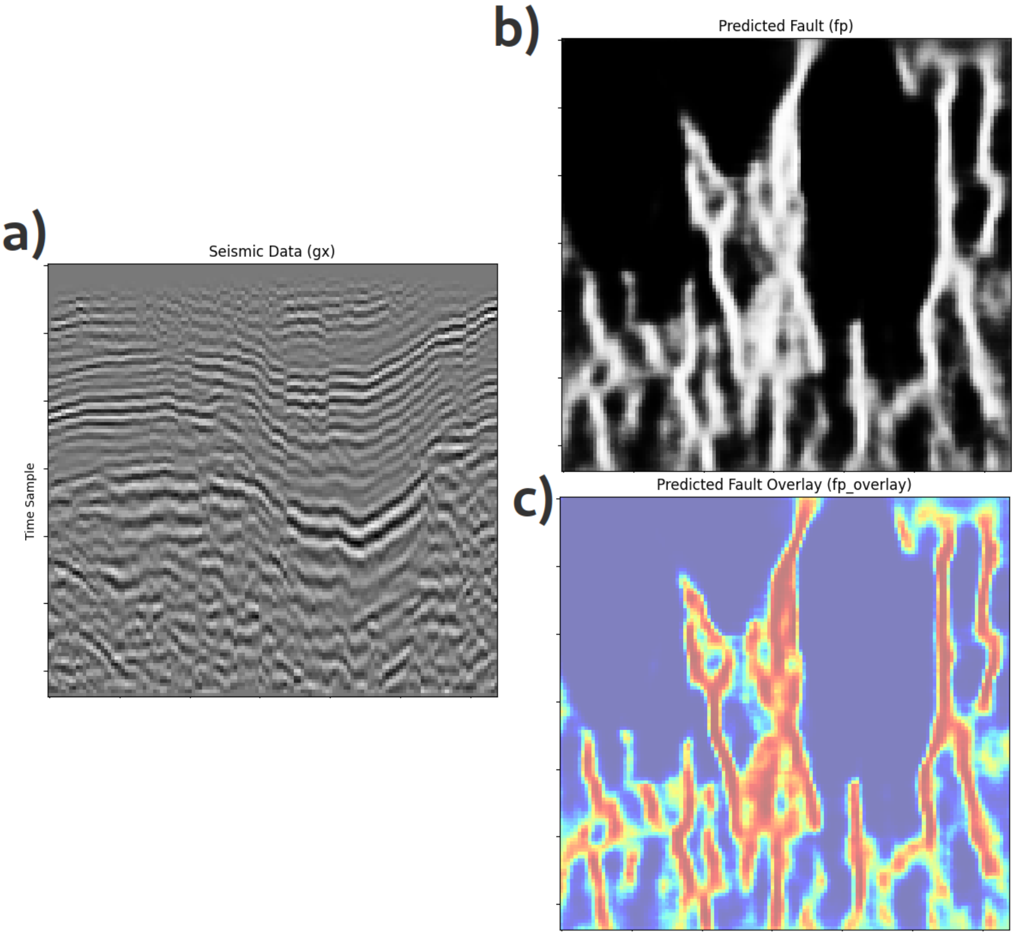

Figure 1: (a) The real seismic data from Raniganj, WB. (b, c) The predicted faults in different colormaps.

Acknowledgement

Authors thank Director, CSIR-NGRI for granting permission to publish this work. This study was conducted as a part of the CSIR, HCP-48 project.

References

Wu, X., Liang, L., Shi, Y., and Fomel, S. (2019). Faultseg3d: Using synthetic data sets to train an end-to-end convolutional neural network for 3d seismic fault segmentation. *Geophysics*, 84(3):IM35–IM45.

Xie, S. and Tu, Z. (2015). Holistically-nested edge detection. In *Proceedings of the IEEE international conference on computer vision*, pages 1395–1403.