CO_2 Interpretation from 4D Sleipner Seismic Images using Swin-Unet3D

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Abstract

The interpretation of CO_2 is important for monitoring the storage status of co_2 and the risk of leakage in Carbon Capture, Utilization, and Storage (CCUS). Traditional manual interpretation of imaging dataset, while informative, is labor-intensive and often suffers from inconsistency over the extended periods of monitoring. This inconsistency largely stems from the inevitable evolution of seismic acquisition and processing technologies, as well as the subjectivity inherent in manual interpretation methods. 3D convolutional neural networks (CNNs) have seen considerable applications in object detection within seismic imaging, achieving notable success. Yet, their design constraints, specifically the limited size of convolutional kernels, have resulted in an inherent limitation in capturing long-range dependencies within the data. While Vision Transformers (ViT) excel in learning such long-distance dependencies, they are burdened by a high parameter count and struggle with local dependency information in data-scarce scenarios. This study introduces the Swin-Unet3D model, innovatively adapted for CO_2 sequestration monitoring. This model reimagines voxel segmentation in geological imaging as a sequence-to-sequence prediction task. Its novel feature extraction sub-module is a hybrid architecture that combines the strengths of both Convolution and ViT. This parallel structure ensures comprehensive learning of both global and local dependency information within the image. The model, which is trained, validated, and tested using the Sleipner co_2 storage project's time-lapse dataset spanning from 1984 to 2010, marks an improvement in CO_2 interpretation.

Introduction

In our research, we introduce a novel neural network approach for delineating co_2 distribution from time-lapse seismic dataset using both baseline and monitor imaging processing results.Our method is anchored by a streamlined version of the Swin-Unet3D architecture, a model that has already demonstrated its effectiveness in 3D medical image segmentation. The model used in this study integrates the Swin Transformer Block3D for feature extraction in 3D medical images, paralleled with a traditional Convolution3D approach. This dual-structured model capitalizes on the strengths of both the Swin Transformer and CNN architectures. The dataset used in this study is from the Sleipner site. The 2019 Benchmark Model offered the first complete 3D model of the storage site encompassing all nine layers. At the core of this dataset are nine layers of sandstone, named Utsira L1 through Utsira L9 (FIG. 1). The detailed information in Sleipner site is show in FIG 1.

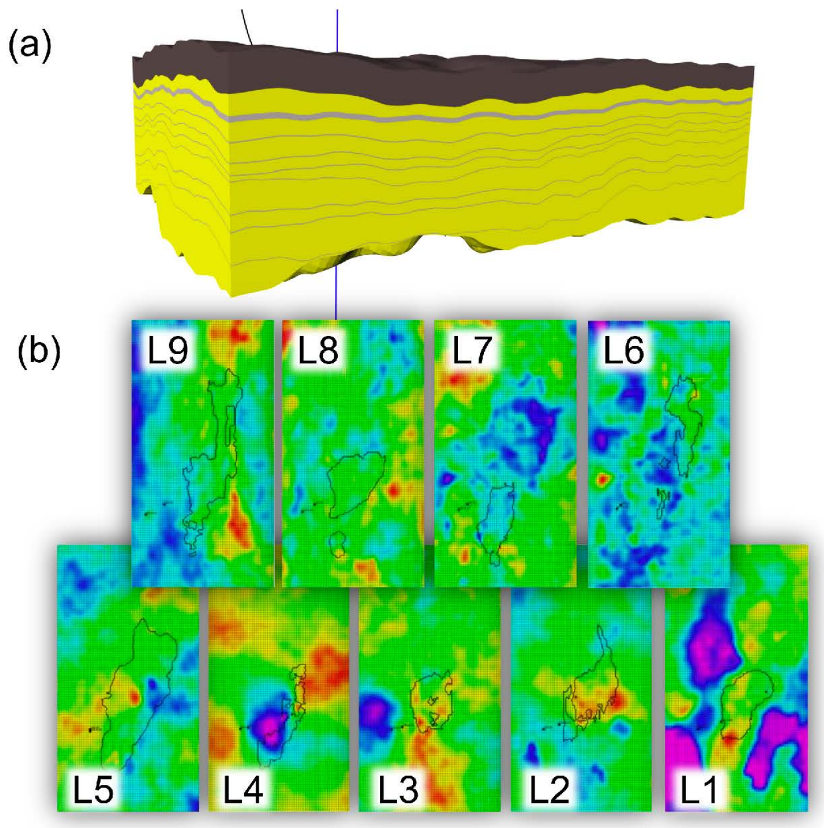

Figure 1: The geology information of sleipner site and co_2 boundary at each horizon.

Methods

Swin-Unet3D, which is tailored to capture the intricate spatial distribution of CO2, is a combination of an encoder, a jump connection, and a decoder, where the encoder harnesses the Swin Transformer Block3D to interpret long-range dependencies, essential for understanding broader image contexts, as shown in FIG 2 cai2023swin.

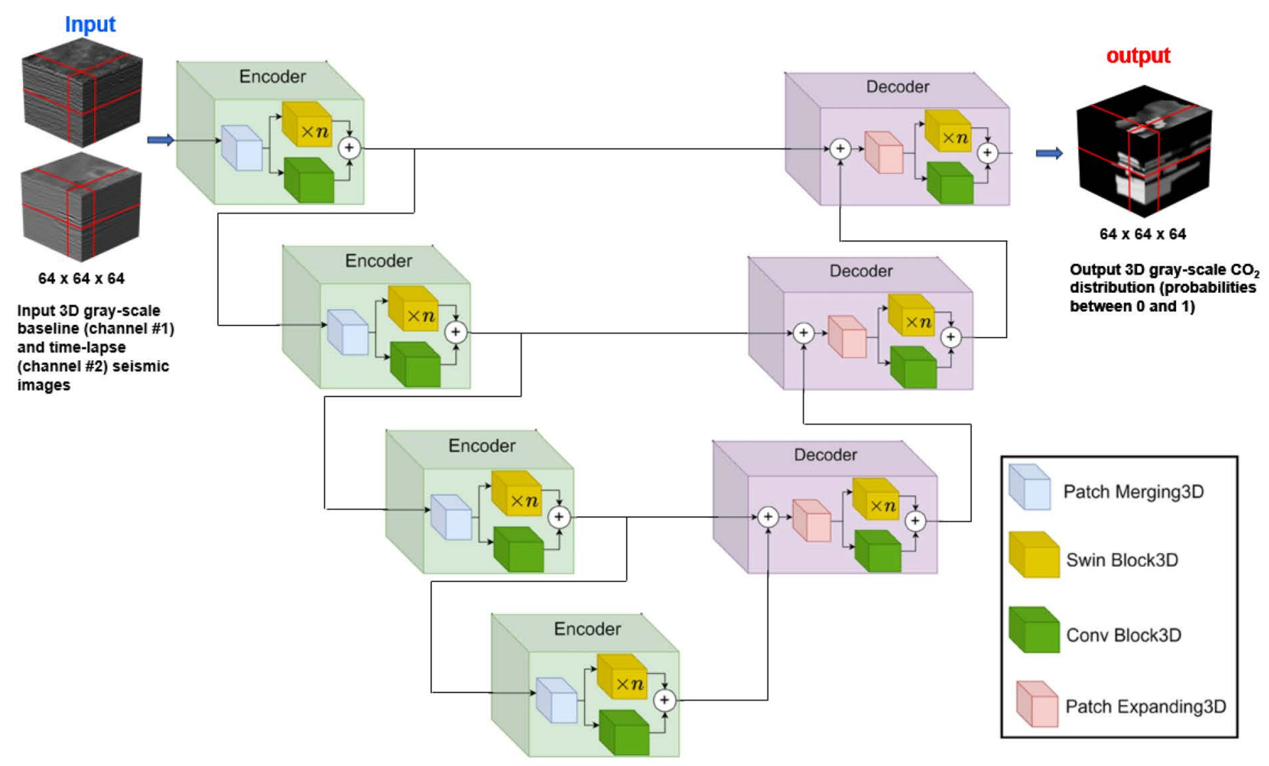

Figure 2: The architecture of the Swin-Unet3D.

Training

In our study, we selected 3D cubes at random from one baseline, one time-lapse, and the corresponding label volumes. Initially, we extracted 1000 cubes with centers distributed randomly throughout the 3D volume, as shown in FIG 3. These samples were then randomly split into training and validation sets, containing 3500 and 500 samples, respectively.

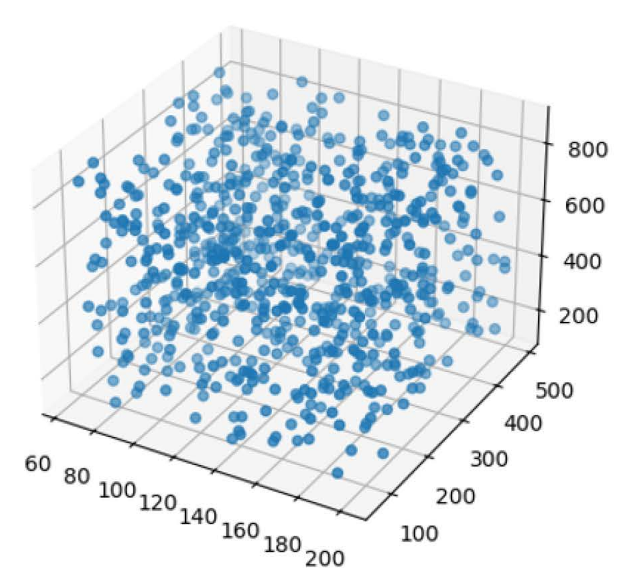

Figure 3: The center points of the sampled cubes generated randomly.

FIG 4 illustrates the progression of training and validation losses as the number of epochs increases. FIG 4a is the loss curve of a CNN training for reference, and FIG 4b is the loss curve of Swin-Unet3D training. Totally 200 epochs are chose through checking the validation loss. The total training takes approximately 1 hour using one node on GPU-A100.

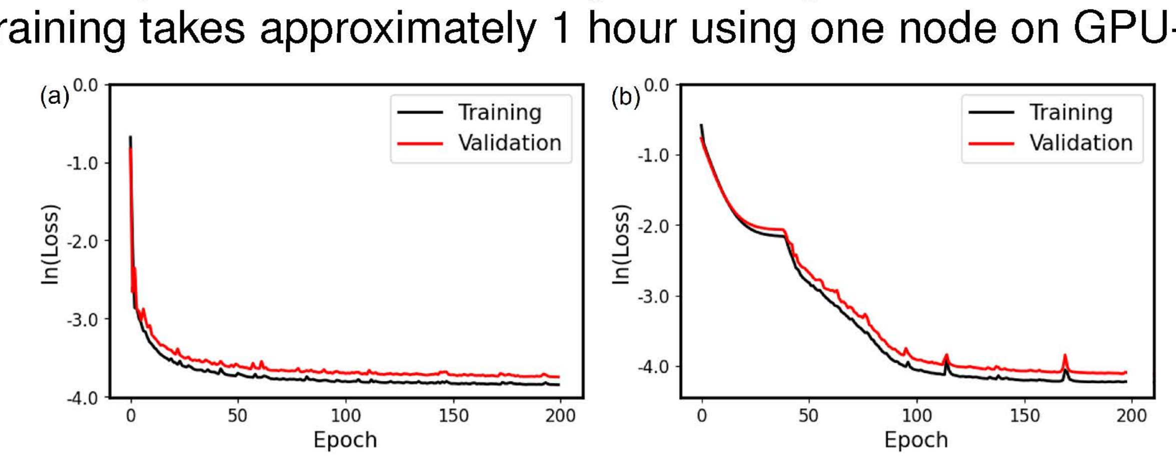

Figure 4: Trained NN predictions for two samples from the training data set. The first two rows are the baseline data and monitor data for these two cube samples. The third row are the label data. The fourth row are the NN predictions generated using CNN, and the last row are the NN predictions generated using Swin-Unet3D.

Results

In our approach, we finely segmented the entire 3D volume into small, regularly overlapping cubes as input for our neural network. We then synthesized the comprehensive 3D CO2 distribution through weighted summation.FIG 5 shows the whole target volumn predictions for both CNN and Swin-Unet3D trained network. When analyzing the prediction results, the similarities between the label data and the NN's predictions are strikingly close, with minimal discernible differences.

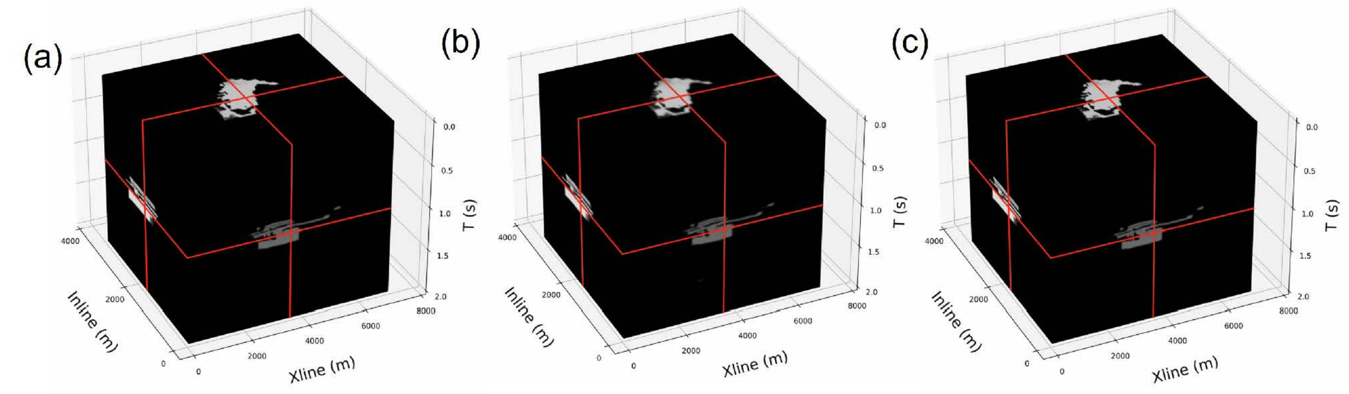

Figure 5: Trained NN predictions for the whole volumn, (a) is the ground-truth label data, (b) is the predicted result of the model train by CNN, (c) is the predicted result of the model trained by Swin-Unet3D.

Conclusions

In this study, we have harnessed the capabilities of the Swin-Unet3D model to interpret the 3D distribution of CO_2 from a series of time-lapse seismic datasets. Our findings demonstrate that the Swin-Unet3D model, with its innovative architecture that synergizes the strengths of CNNs and Vision Transformers, offers a more intricate and detailed characterization of CO_2 plumes compared to CNN approaches. The Swin-Unet3D's ability to capture long-range dependencies and intricate details significantly enhances the accuracy of CO_2 boundary delineation within the seismic images. The application of this model to the Sleipner project's dataset has not only expedited the interpretation process but has also provided a level of consistency and detail that surpasses conventional manual interpretation methods. The improved resolution and sharpness of the boundaries in the model's predictions underscore its potential to transform CO_2 monitoring practices in Carbon Capture, Utilization, and Storage projects. Our results indicate that incorporating advanced machine learning models like Swin-Unet3D into the workflow can lead to more reliable and efficient monitoring of CO_2 storage sites. The potential for these technologies to contribute to safer, more effective CCUS practices is substantial and holds promise for broader application in the geosciences field.

References

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