Utilising Convolutional Neural Network to Perform Fast Automated Structural Analysis for Seismic Images

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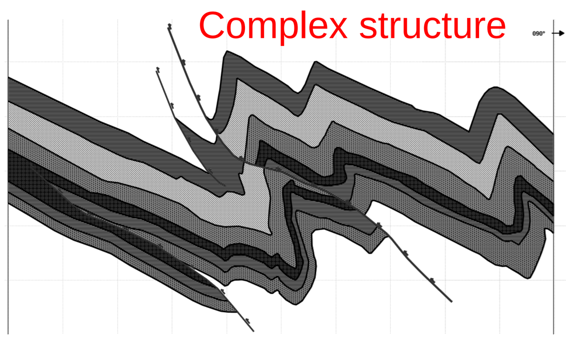
The Premise

Can we employ machine and deep learning techniques to interpret complex subsurface structures?

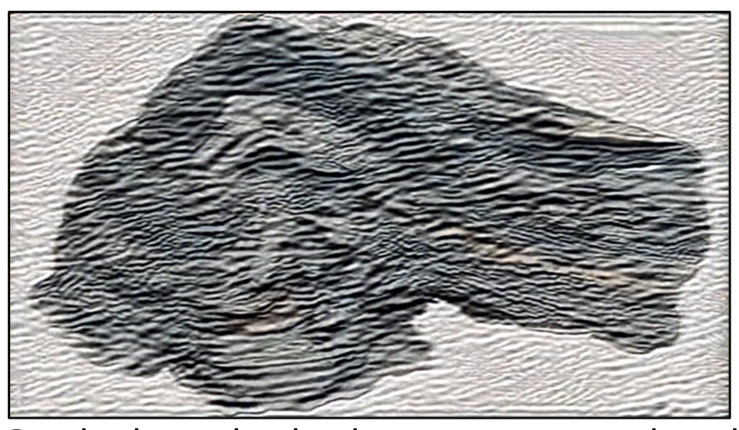


▪ Fold and fold-thrust structures have a complex structural history that is hard to unravel from limited data, and 'accurate' interpretations are compounded by uncertainties inherent in subsurface structural interpretation – **but can high-resolution synthetic data help?**

▪ Here, we show that high-resolution outcrop and coalmine data provide an excellent opportunity to illustrate deep learning automatic seismic interpretation using object detection.

Cawood and Bond (2020)

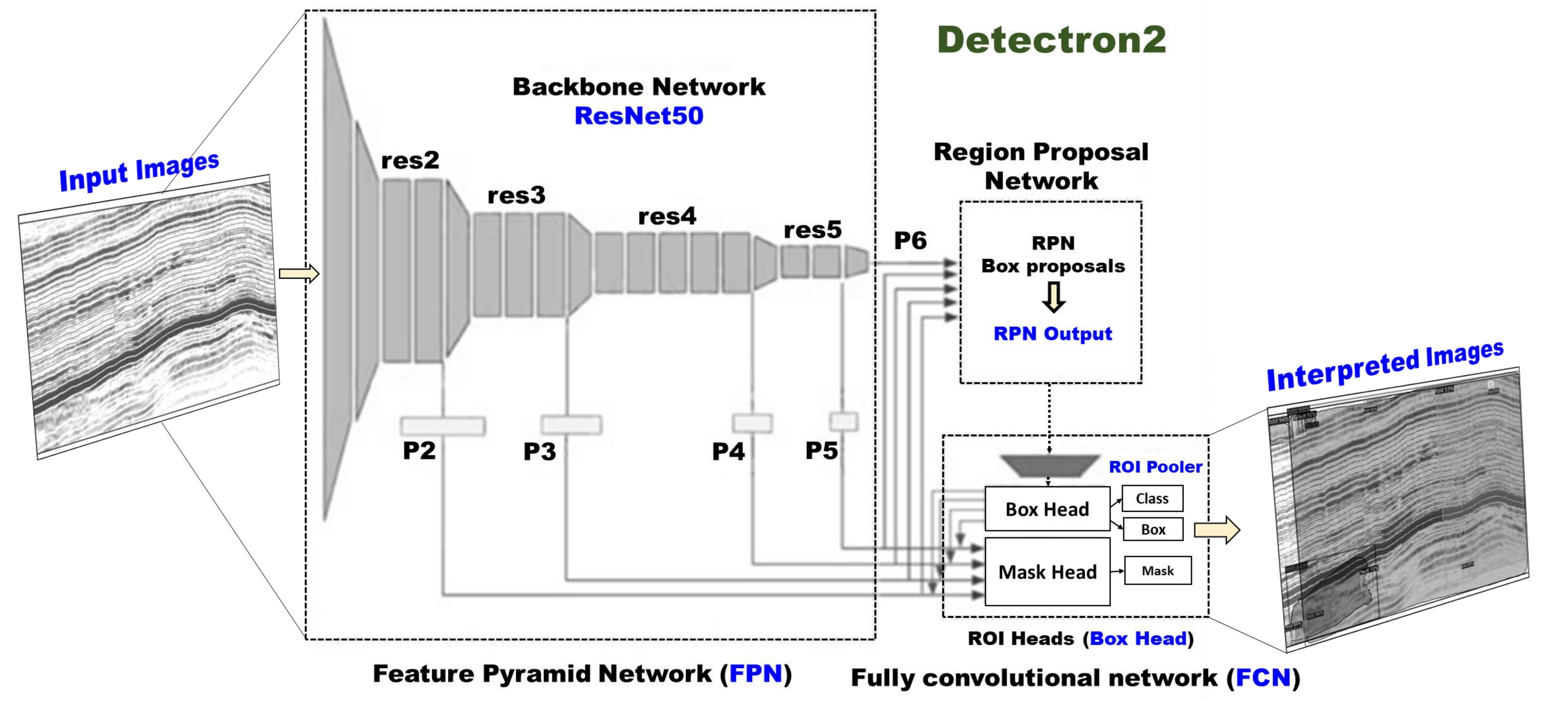
See eRock



▪ Asymmetric folds with multiple propagating thrusts derived from digital photogrammetric modelling.

▪ Synthetic seismic image generated using deep learning (Pytorch Neural Style Transfer)

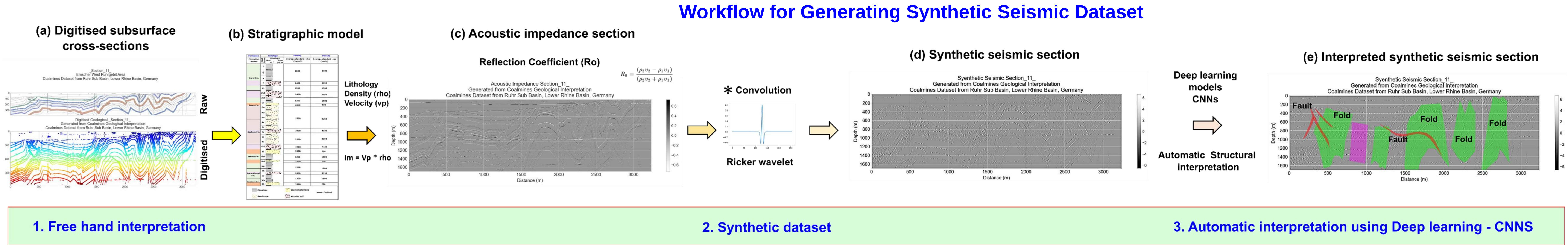
Architecture of the Detectron2 Model



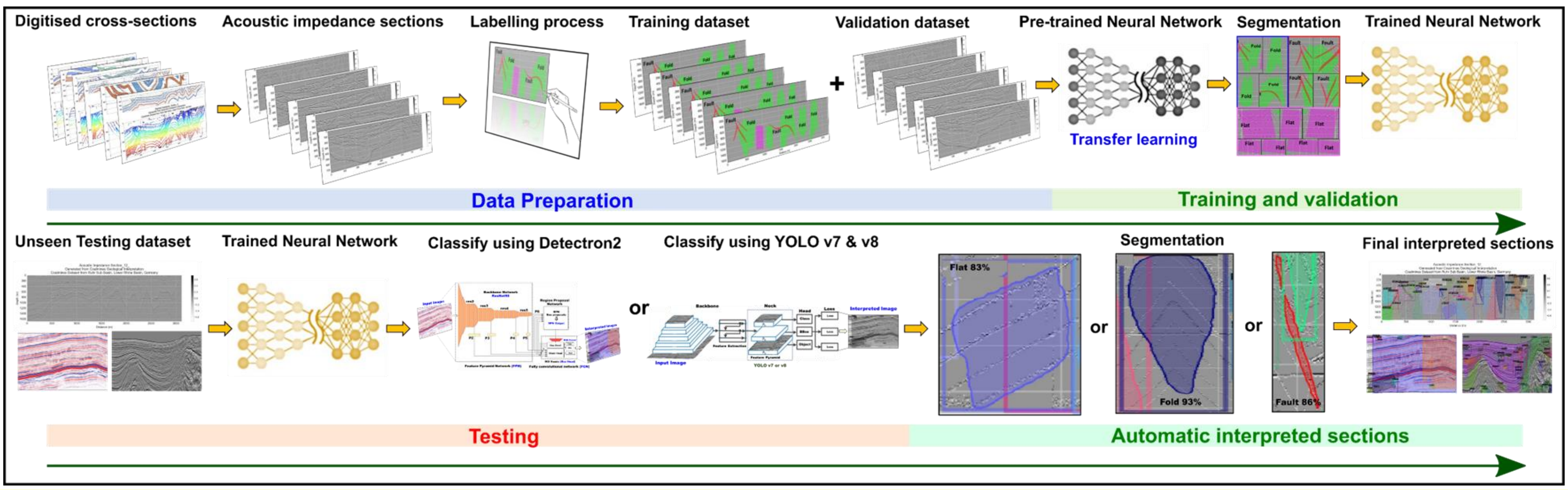
▪ Detectron2 Model with three main modules: backbone, region proposal network (RPN), and regions of interest (ROIs). The FPN uses a modified CNN framework called Mask R-CNN.

Synthetic Seismic Creation and Deep Learning Structural Interpretation workflows

Workflow for Generating Synthetic Seismic Dataset

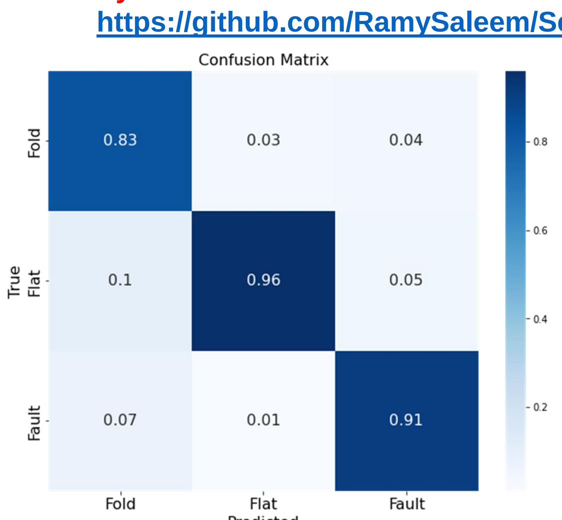


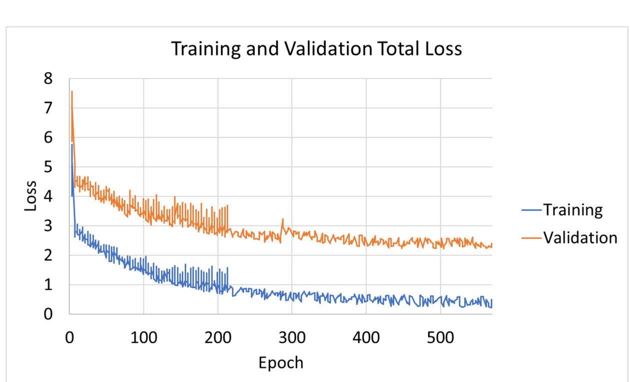
Automatic Structural Interpretation using Deep Learning Models – CNNs

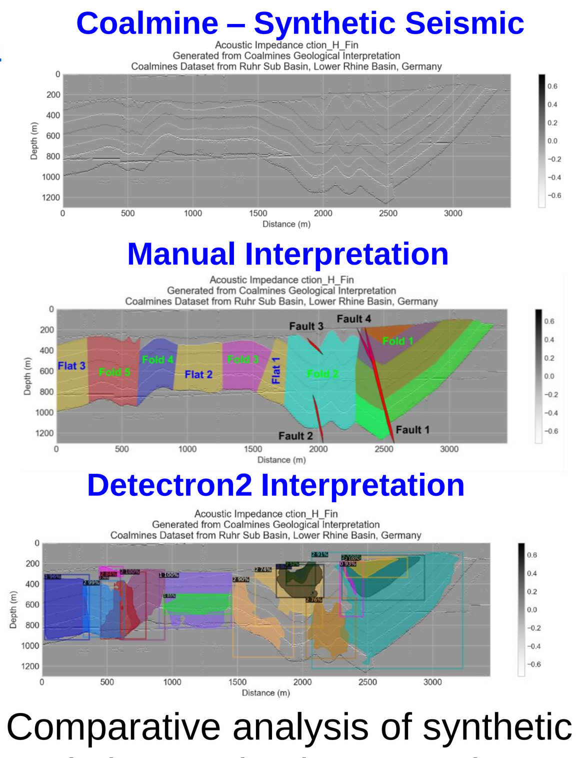


Detectron2 – Results of Training and Validation

Python code of the model is available at: https://github.com/RamySaleem/SeismicStructuralAnalysis-CNN-Object-Detection







▪ **Confusion matrix** of three classes. The model distinguishes well between Fault and Flat layers classes and needs improvement in identifying Folds.

▪ The **loss curve** is marked by a gradual decline followed by a plateau towards the end of the plot across all three models.

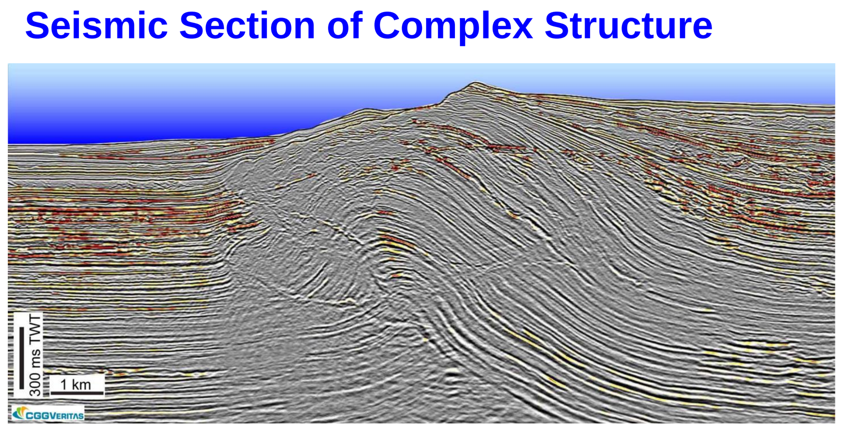
▪ Comparative analysis of synthetic coalmine section interpretations.

AI Seismic Interpretation

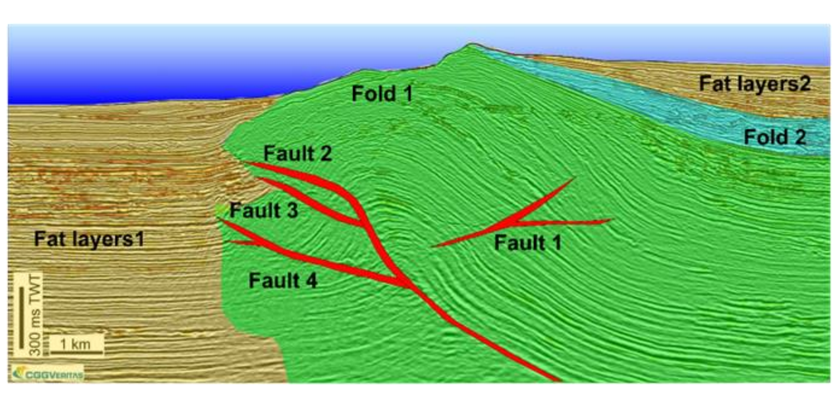
Take-home Message

▪ AI offers a potential technique to efficiently and objectively interpret subsurface structures, free from human bias or the limitations of conceptual models.

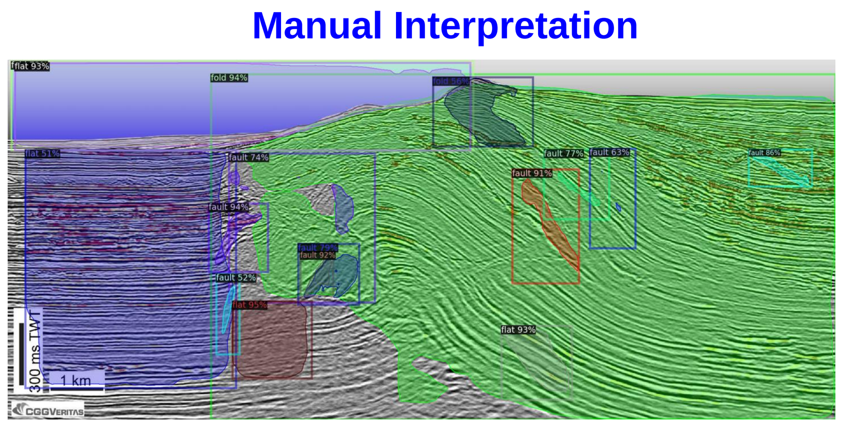
Seismic Section of Complex Structure



▪ Fold-thrust structure within the deepwater Niger fan – Adapted after Butler and Bond (2020).



Manual Interpretation



Detectron2 Interpretation

Conclusions

▪ Detectron2 – deep learning-based instance segmentation algorithms can interpret seismic sections successfully through training on thousands of instances per class using transfer learning.

▪ The Detectron2 algorithm is better than the YOLO v8 and v7 (Average Precision of IUO – mA50-mAP95 of the Detectron2 = 0.82%, YOLO v8 = 0.66% and YOLO v7 = 0.52%).

▪ Synthetic acoustic impedance and seismic sections derived from free-hand interpretation with end-members conceptual models for training detection algorithms can help to interpret seismic images.

▪ Limitations: These automatic interpretation models heavily rely on training with synthetic seismic data.

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