Detailed Summary of Fracture Identification Using YOLO and Log Data

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1. Introduction

Detecting fractures in geological structures is crucial for subsurface analysis and decision-making in oil and gas operations. Traditional methods relying on manual annotation or simplistic algorithms are time-intensive and prone to errors. To address these challenges, this work investigates automated fracture detection using deep learning. Among the tested models—Faster R-CNN, Mask R-CNN, and YOLO—the YOLO segmentation model emerged as the optimal choice due to its balance between accuracy and inference speed. This paper elaborates on the workflow implemented for training, prediction, and post-processing using the YOLO model.

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2. Methodology

2.1 Model Selection and Overview

The YOLO segmentation model was selected for its real-time detection capabilities and adaptability to segmentation tasks. Variants such as YOLOv8n, YOLOv8s, YOLOv8m, and YOLO11m were utilized based on computational constraints. The model's architecture incorporates a single-stage detection pipeline optimized for speed and accuracy, making it suitable for the fracture detection task. I got best results with YOLOv8m model. Larger model may cause overfitting as they are more complicated.

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3. Workflow

3.1 Data Preparation

1. **Dataset Structure:**

   The dataset was organized into training and validation subsets, each containing geological images and their corresponding YOLO-format annotations. Annotations were provided as .txt files comprising class labels and normalized bounding box coordinates.

2. **Augmentation Techniques:**

   To enhance generalization, augmentations such as flipping, scaling, and rotations were applied to the training set.

3.2 Model Training

1. **Hyperparameter Tuning:**

- Batch size: 16, Learning rate: 0.00009, Number of epochs: 200

2. **Training Execution:**

   The YOLO model was trained on the prepared dataset, with metrics such as loss, precision, recall, mean Average Precision (mAP), and F1 score logged during each epoch. Validation performance guided the selection of the best model weights (best.pt).

3. **Validation:**
   Validation was performed on unseen data to ensure the model's ability to generalize. Visual outputs of bounding boxes on validation images were generated for qualitative review.

3.3 Prediction and Post-Processing

1. **Inference Setup:**
   The trained YOLO model (best.pt) was loaded for inference, with a confidence threshold of 0.35 determined from the training phase.

2. **Test Data Processing:**

   - **Images:** Test images were resized to 640 × 640 pixels for compatibility with the model.

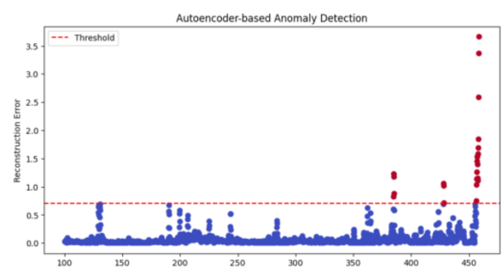
   - **Log Data:** Well log data (e.g., Sonic Travel Time [DT], Resistivity [ILD], Density [RHO], Neutron Porosity were preprocessed, and density porosity is calculated from density data. Also porosity difference between neutron and density calculated. These data were used for log anomaly detection. Anomalies were flagged using an autoencoder model based on reconstruction error thresholds.

Density Porosity Formula:

$$\phi_{\text{density}} = \frac{\rho_{\text{matrix}} - \rho_{\text{bulk}}}{\rho_{\text{matrix}} - \rho_{\text{fluid}}}$$

Where:

- ϕ_{density} = Density-derived porosity (fraction or %)
- ρ_{matrix} = Matrix (grain) density (Kg/m³)
- ρ_{bulk} = Bulk density (from RHO log) (Kg/m³)
- ρ_{fluid} = Fluid density (Kg/m³)



3. **Fracture Detection:**
   YOLO's outputs included bounding boxes, class probabilities, and confidence scores. Fracture depths were calculated using geometric relationships between bounding box coordinates and image scale.

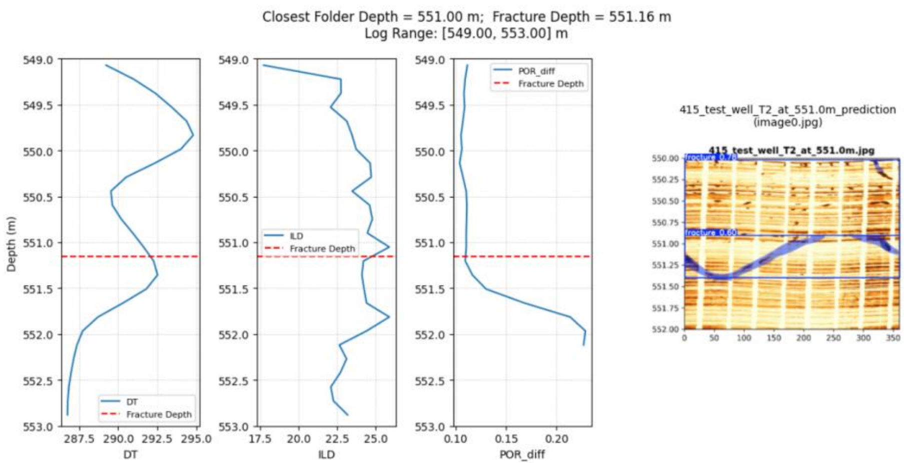
4. **Post-Processing:**
   Fractures were filtered based on a confidence score threshold (≥0.5) and minimum mask area specific to wells T1 and T2.

3.4 Integration with Log Data

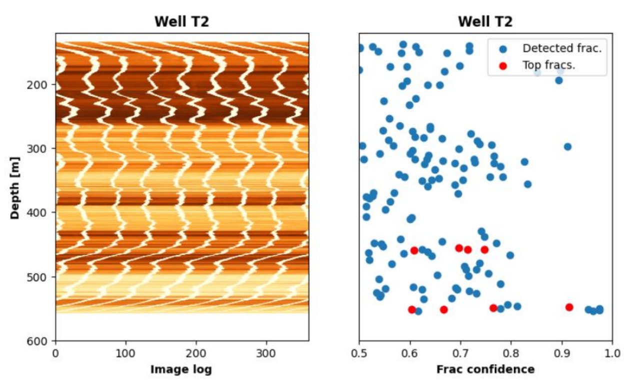
1. **Anomaly Confirmation:**

   Fractures detected by YOLO were cross-referenced with anomalies identified in the log data. Detected fractures without corresponding anomalies were discarded to enhance reliability.

Parameter	Oil-Filled Fracture	Water-Filled Fracture	Gas-Filled Fracture
DT (Sonic Transit Time)	Moderate increase	Moderate increase	Significant increase
ILD (Deep Resistivity)	Moderate to high increase	Low resistivity	Very high resistivity
Δ_{Porosity}	≈ 0 or slightly > 0	Large > 0	Negative (< 0)



2. **Filtering and Sorting:**
   Detected fractures were sorted by confidence scores in descending order. Only the top results, confirmed by anomalies, were retained.



3. **Final Checks:**

   Before submitting all fracture depths, we should double-check each of them using images and well logs to ensure they are good candidates for fractures. Additionally, we may adjust the depths slightly (mainly based on logs) to ensure they are accurate. For example, in well T2, we identified fractures at depths of 548m and 548.8m and decided to consolidate them into a single fracture at the average depth of both. Similarly, we had three fractures at different depths near 459m and decided to represent them with a single fracture at 459m. The results were compiled into a structured CSV for further analysis.