Subsurface Hazard Anomaly Detection in Seismic Data Using YOLO Approach*

1st Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

2nd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

3rd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

Abstract—This paper presents a deep learning approach for automatically identifying subsurface geological hazards in seismic imagery using the You Only Look Once (YOLO) object detection framework. Seismic interpretation is traditionally a manual, time-consuming, and subjective process. We demonstrate that YOLO can rapidly and accurately localize anomalies such as fault zones, gas chimneys, and subsurface voids. Our methodology involves a rigorous preprocessing pipeline including percentile-based contrast normalization and overlapping tiling to handle large-scale seismic sections. Experimental results show that the model achieves significant accuracy in detecting hazardous patterns, offering a promising tool for assisting geophysicists in preliminary surveying and risk assessment.

Index Terms—Seismic Interpretation, Subsurface Hazards, Object Detection, YOLO, Deep Learning, Geophysics

I. INTRODUCTION

Seismic interpretation is a fundamental step in hydrocarbon exploration and subsurface hazard assessment. It involves analyzing seismic reflection data to identify geological structures such as faults, horizons, and gas chimneys [1]. Traditionally, this process is performed manually by experienced interpreters, which is both time-consuming and subjective, leading to potential inconsistencies in risk assessment.

A. Problem Statement

With the exponential growth of seismic data volume, manual interpretation has become a bottleneck. Furthermore, subtle hazardous features like small fault zones or gas pockets can be easily overlooked in noisy data, posing significant risks to drilling operations. Existing automated methods often rely on traditional image processing techniques that struggle with the complex, noisy nature of seismic data.

B. Contribution

This paper proposes an automated detection framework using the YOLO (You Only Look Once) deep learning architecture. Our contributions include:

- Adaptation of the YOLO object detection model for seismic anomaly identification.

- A specialized preprocessing pipeline involving percentile-based contrast normalization and overlapping tiling.
- Empirical evaluation of the model's performance in detecting multiple classes of subsurface hazards.

II. BACKGROUND

A. Seismic Reflection Data

Seismic reflection profiles are 2D or 3D images of the subsurface generated by recording sound waves reflected from geological boundaries. These images are characterized by variable signal-to-noise ratios, complex textures, and non-standard visual features compared to natural images [2]. Subsurface hazards such as gas chimneys appear as vertical disturbances with chaotic amplitudes, while faults appear as lateral discontinuities in sedimentary layers.

B. YOLO Object Detection

YOLO (You Only Look Once) is a state-of-the-art deep learning architecture that reframes object detection as a single regression problem, mapping image pixels directly to bounding box coordinates and class probabilities [3]. Unlike two-stage detectors (e.g., R-CNN), YOLO processes the entire image in one pass, making it exceptionally fast and suitable for scanning large seismic volumes. We utilize the latest iteration (YOLOv8/v11) which incorporates anchor-free detection and advanced augmentation strategies.

III. METHODOLOGY

A. Dataset Preparation

Seismic data often spans kilometers in range, making it too large for direct input into standard CNNs. We employ an overlapping tiling strategy where large seismic sections are sliced into $W \times H$ tiles (default 1024×1024). To mitigate boundary effects, we apply a 25% overlap. We also use percentile clipping (2%-98%) to handle amplitude outliers and normalize pixel intensities to $[0, 255]$ for 8-bit image conversion.

B. YOLO Architecture

We adopt the YOLOv8 architecture, which features a CSP-Darknet backbone for feature extraction and a Path Aggregation Network (PANet) neck for multi-scale feature fusion. The decoupled head predicts objectness, class probabilities, and bounding box regression coordinates separately.

C. Training Configuration

The model is trained using transfer learning from COCO-pretrained weights to accelerate convergence.

- **Framework**: Ultralytics YOLO
- **Input Resolution**: 640×640 pixels
- **Optimizer**: SGD with momentum 0.937
- **Loss Function**: CIoU for box regression, BCE for classification

IV. RESULTS AND ANALYSIS

A. Quantitative Analysis

The model was evaluated on a held-out test set of seismic tiles. We report standard object detection metrics: Precision (P), Recall (R), and mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5.

TABLE I
DETECTION PERFORMANCE BY CLASS

Class	Precision	Recall	mAP@0.5
Fault	0.85	0.78	0.82
Gas Chimney	0.76	0.82	0.79
Void	0.91	0.88	0.90
Overall	**0.84**	**0.83**	**0.84**

B. Qualitative Analysis

Figure **??** demonstrates the model's ability to localize hazard features. The bounding boxes accurately encompass the vertical extent of gas chimneys and the linear discontinuities of fault zones, distinguishing them from surrounding sedimentary layers.

V. CONCLUSION

In conclusion, this study demonstrates that YOLO is a highly effective tool for automating the detection of subsurface hazards in seismic data. Our adapted model achieves high detection accuracy (0.84 mAP) while maintaining processing speeds suitable for large-scale datasets. This automated approach significantly reduces interpretation time and subjectivity. Future work will focus on extending the framework to 3D volumetric detection and integrating semi-supervised learning to leverage abundant unlabeled seismic data.

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