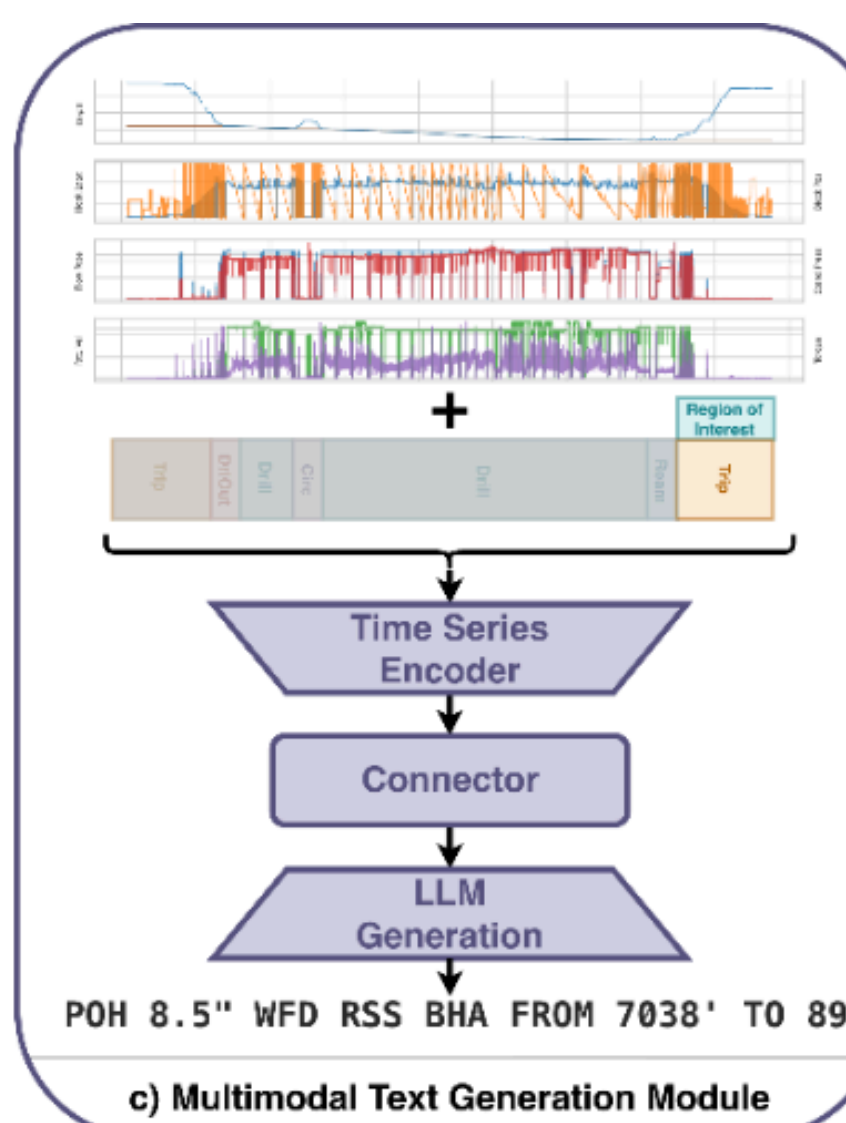
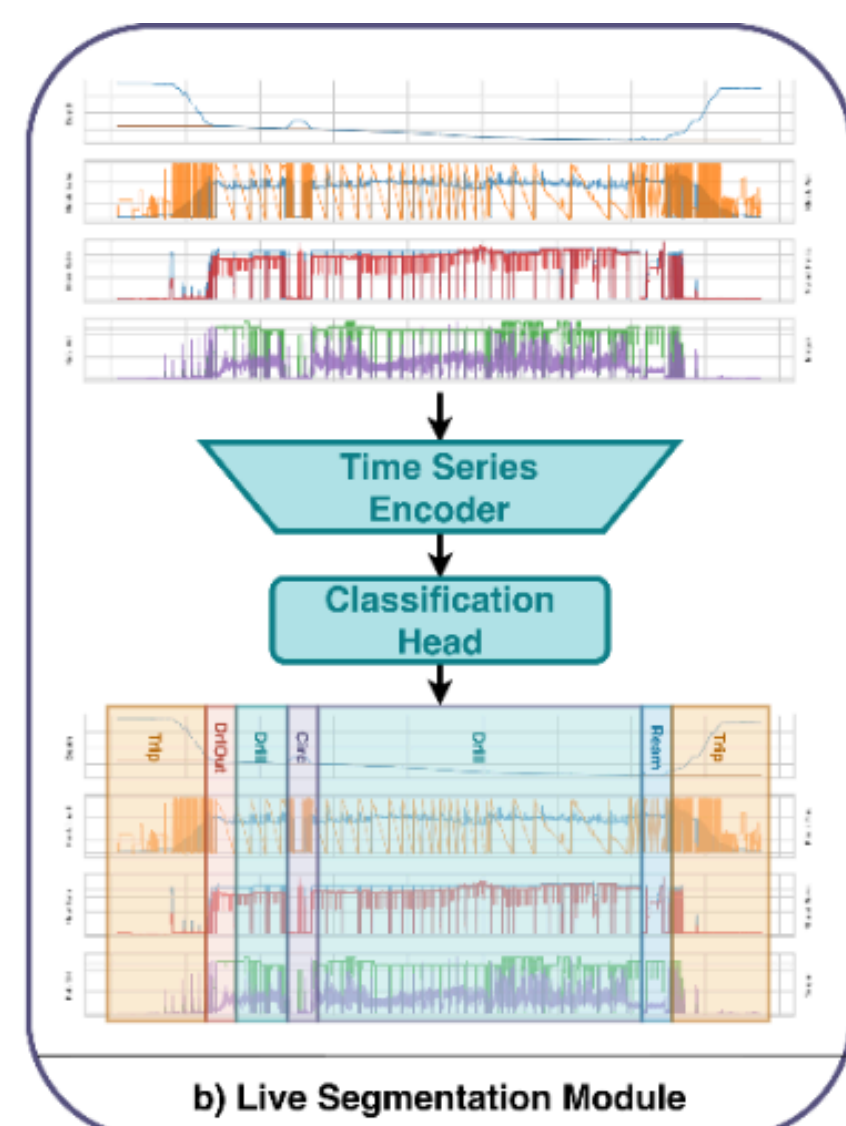
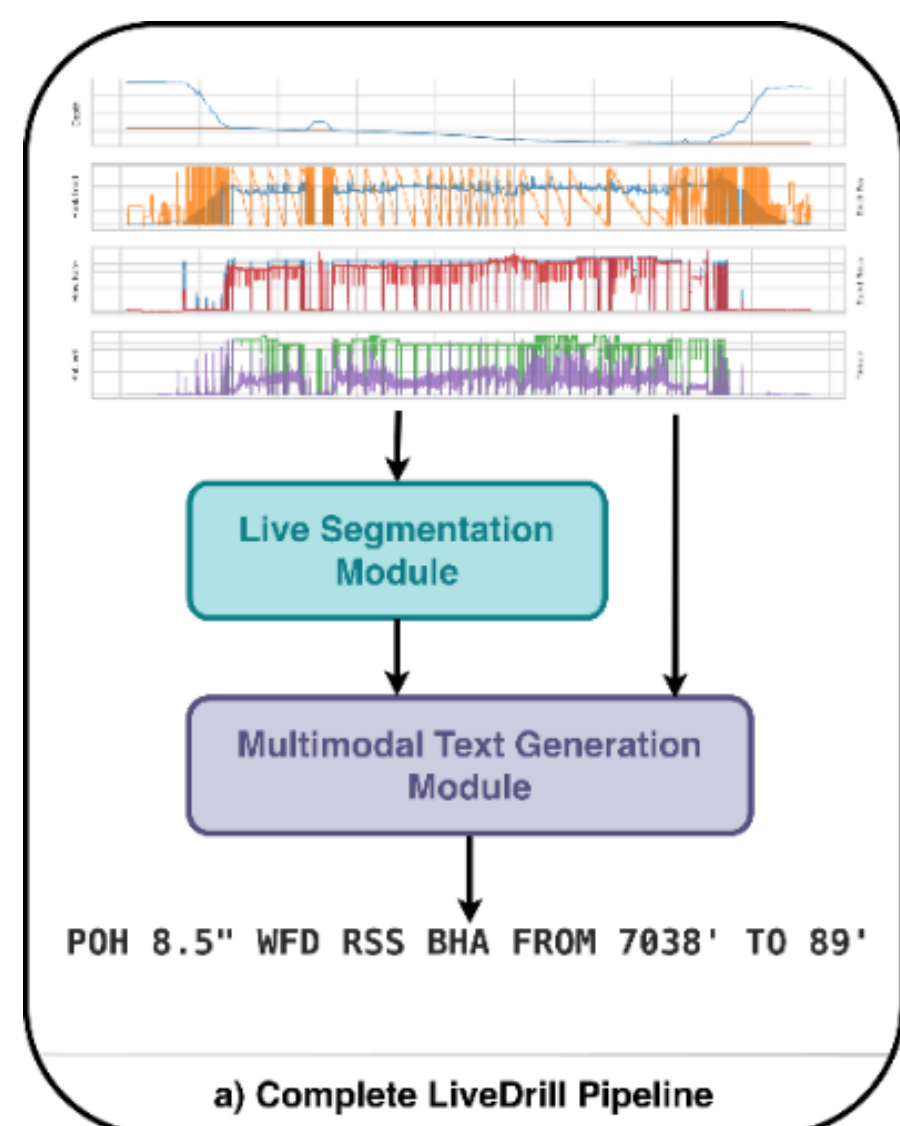


LiveDrill: Multimodal Segment-Triggered Data-to-Text for Time Series Foundation Models

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AIQ

Introduction & Methodology



Research Question:

Can Time-Series Foundation Models (TSFMs) be used to automate live industrial reporting by coupling real-time activity segmentation with segment-grounded multimodal data-to-text generation?

Methodology:

LiveDrill: A Streaming Pipeline for Real-Time Reporting

LiveDrill transforms continuous **multivariate sensor** streams into automated **Daily Drilling Reports (DDRs)** in **real-time**. It introduces a segment-triggered architecture that decouples activity detection from text generation.

This design shifts reporting from delayed, manual summaries to continuous, segment-grounded narratives, ensuring updates are timely and explicitly tied to operational events.

LSM	TSE: Moment-large			TSE: Moirai-large		
	Seg $F1_{IoU}$	Avg LLM	Combined	Seg $F1_{IoU}$	Avg LLM	Combined
Moment-large	0.467	0.359	0.405	0.467	0.340	0.394
Moirai-large	0.484	0.359	0.412	0.484	0.340	0.399

Live Segmentation Module (LSM):

This module comprises a **pretrained time-series foundation model encoder (Moment or Moirai)** followed by a **dense classification head** to assign per-step **activity** labels in **real-time**.

Segmentation Model	Overall	
	$F1_{IoU}$	$F1_{pw}$
Moment-large	0.467	0.827
Moirai-large	0.484	0.809

Fast and Efficient: It is highly optimized for speed (~192ms latency), easily handling messy, high-frequency data streams without lagging behind live operations.

Strong Generalization: It generalizes well across different drilling phases, achieving high point-wise accuracy and qualitatively strong alignment with ground truth despite signal noise.

Small Segment Sensitivity: It struggles with very short or fragmented segments, where minor signal noise can cause the model to split a single activity into multiple pieces.

Rare Class Detection: Performance drops for infrequent or complex anomaly classes (like Stuck Pipe), which are harder to capture than stable operations.

Multimodal Text Generation Module (MTGM):

An **event-triggered generator** that fuses sensor data with a Region-of-Interest (ROI) mask via a **pretrained time-series foundation model encoder** and **connector** to **soft-prompt** a **frozen LLM** for text creation.

Qualitatively Grounded: It produces coherent, segment-grounded descriptions that accurately reflect the sensor dynamics, proving effective even when applied to messy field data.

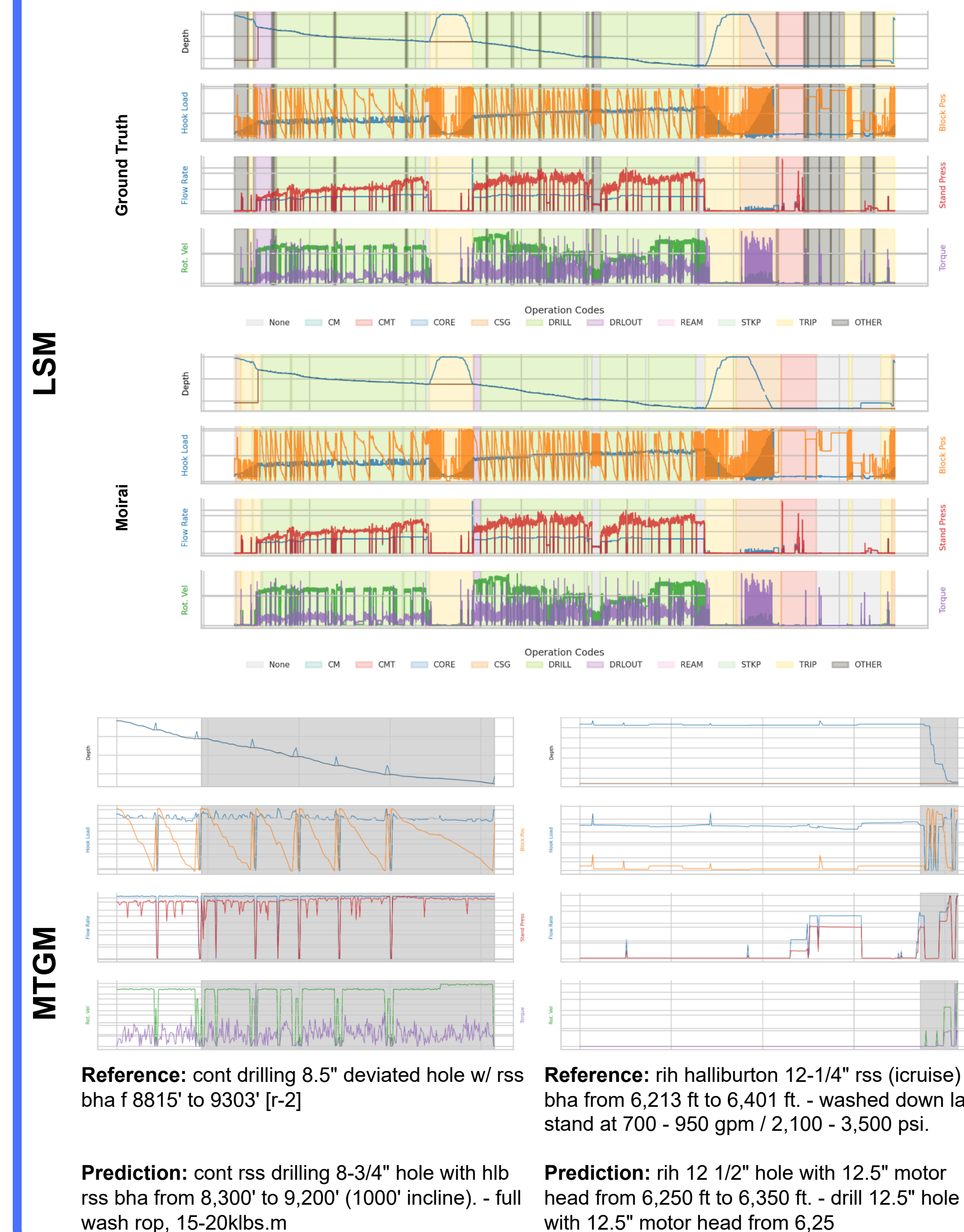
Model Agnostic: The system is robust regardless of the backbone used; swapping between Foundation Models (Moment vs. Moirai) results in negligible performance differences.

Dependency on Segmentation: It is sensitive to input quality; if the LSM detects a "very small" or fragmented segment, the MTGM lacks the context to generate a meaningful report.

Transition Complexity: While good at stable phases, it struggles to generate accurate narratives for complex, infrequent transition events where data patterns are less distinct.

TSE Model	Avg LLM [0-1]	CM	CMT	CORE	CSG	DRILL	DRLOUT	REAM	STKP	TRIP
Moment-large	0.359	0.137	0.333	0.291	0.353	0.590	0.456	0.499	0.114	0.200
Moirai-large	0.340	0.212	0.344	0.309	0.354	0.563	0.368	0.454	0.210	0.157

Qualitative Results:



Future Work:

- Pretrain **sensor-text foundation models** directly on aligned pairs (not just forecasting) to improve zero-shot transition detection.
- Investigate **differentiable connectors** that **allow text generation loss** to backpropagate and **refine segmentation boundaries**, minimizing error propagation.

Scan QR code for the full paper.

