Machine Learning Advances within NDSF

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Motivation

- Fall 2024 expedition on E/V Nautilus (NA165 - Soule)
  - Remote operations component with AUV Sentry
  - Areas of focus: watchstanding, data processing, troubleshooting, and training new personnel

- Highlighted the value of developing tools in support of in situ data processing
  - Reduce required ship to shore data transfer for post-dive analysis
  - Reduce human error and need for onboard experts
  - Provide improved consistency in analysis and QA/QC both onboard and on shore

Credit: Chris German

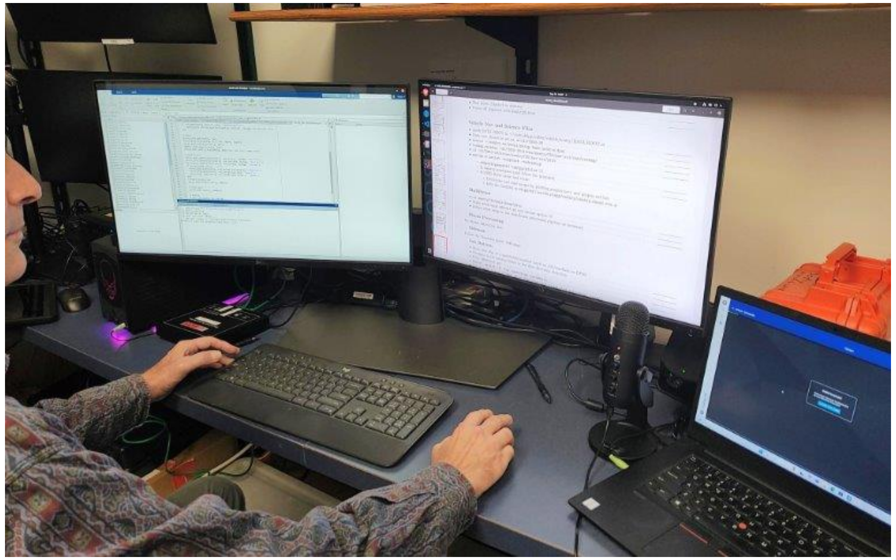
Objectives

- Develop a pipeline/tool for detecting anomalies and faults of various sensor data in post-dive processing using ML/AI techniques

- Initial tool is intended to run as an automated post-dive script
  - Flag any abnormalities in the collected data
  - Allows a remote operator to only transfer a subset of the dive's data for closer inspection

- Offline approach allows for extensive testing and exploration of approaches, de-risking future real-time onboard applications
  - "Crawl, walk, run" approach
  - Benchmark specifications for onboard hardware selection

- Increase vehicle reliability through predictive maintenance informed by these ML/AI techniques



Remote operator at WHOI

High-Level Architecture & Design

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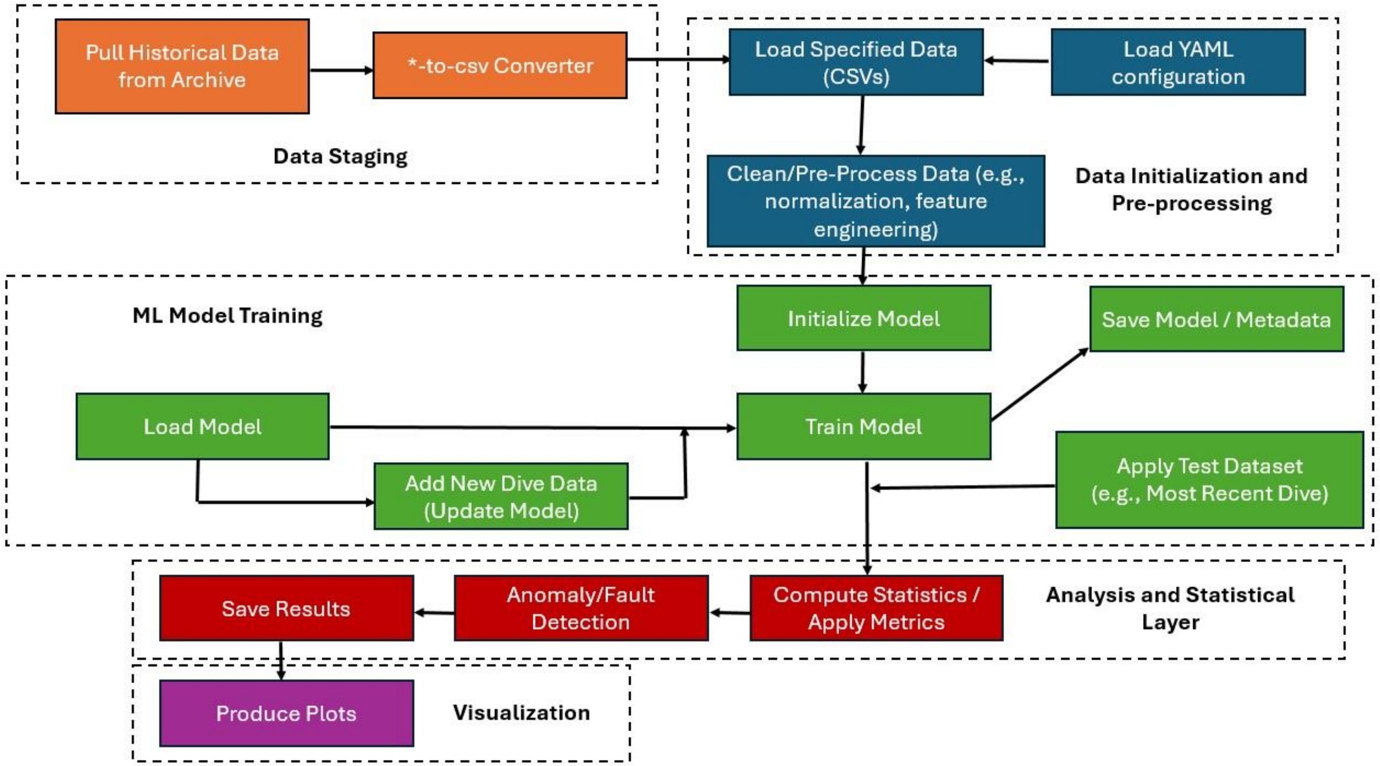
- Infrastructure built using Python
- Common libraries used such as Sci-kit Learn and Tensorflow

```
sensors:
  - sensor_id: ''orp''
    ml_algorithm:
      k-clustering:
          n_clusters: 2
          random_state: 42
    time_var: ''hdr_t''
    vars:
      - ''v''
      - ''dorpdt''
  - sensor_id: ''battery''
    ml_algorithm:
      LSTM:
          batch_size: 16
          epochs: 80
          learning_rate: 0.0001
          laten_dim: 16
    time_var: ''hdr_t''
    vars:
      - ''total_voltage''
      - ''charge_ah''
```

YAML config file for setting parameters



High-Level Architecture of Designed Pipeline

A. J. Dalpe, S. Kelley and A. Bowen, "Data-Driven Machine Learning Approaches to Anomaly and Fault Detection in the Context of Remote Operations," OCEANS 2025 - Great Lakes, Chicago, IL, USA, 2025, pp. 1-8, doi: 10.23919/OCEANS59106.2025.11245099.

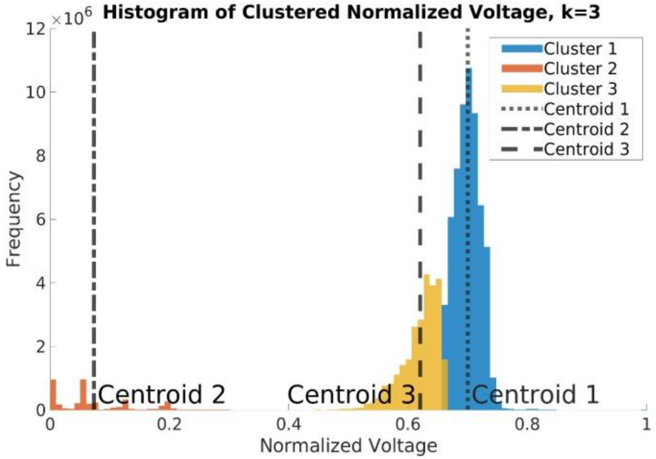
Case Study 1: ORP Sensor

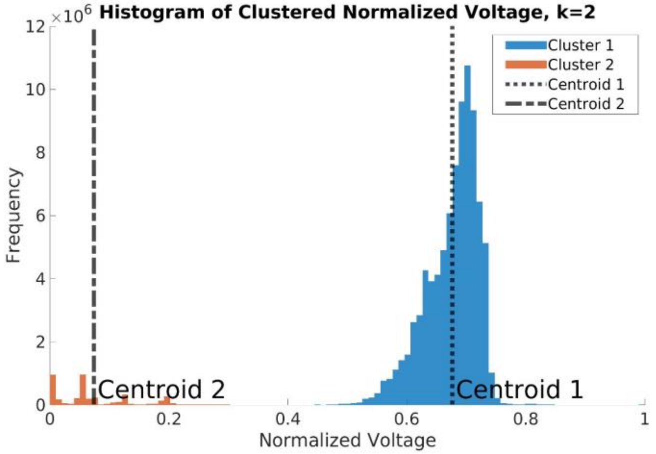
- **Oxidation-Reduction Potential (ORP) sensor**
  - Detects hydrothermal vents and cold seeps
  - Uses the time derivative (dORP/dt) as the primary indicator
  - Measures chemical shifts signaling hydrothermal activity

- **Challenge: Identifying True Anomalies**
  - Sensor designed to detect anomalies
  - Must distinguish true ORP hits from sensor failures

- **K-means clustering chosen as approach**
  - Unsupervised algorithm
  - Partitions data into clusters based on proximity to cluster centroids

- **Improved Two-Stage Strategy:**
  - Rare ORP hits required a refined workflow:
    - Apply K-means to the voltage data
    - Classify dORP/dt detections
      - Transform dORP/dt into a binary detection vector
      - Use a threshold of 5× the dataset standard deviation (consistent with scientific practice)





Voltage Level	ORP Hit	Category
Low	True	Sensor Fault
Normal	True	"Good" Anomaly
Normal	False	Background Environment
Low	False	Sensor Fault

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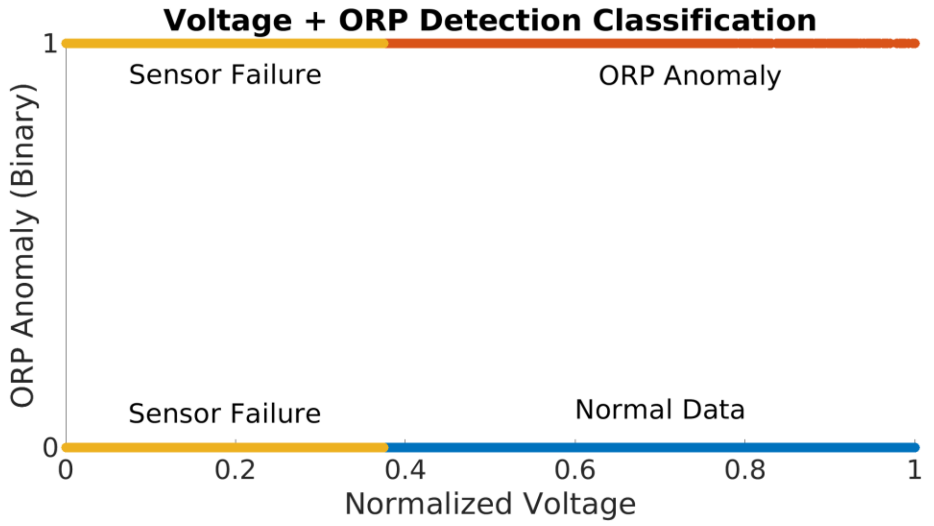
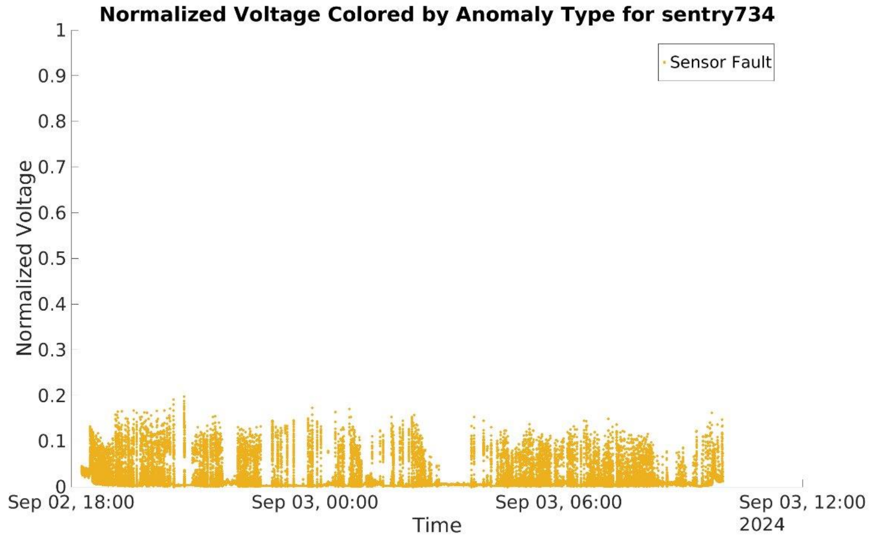
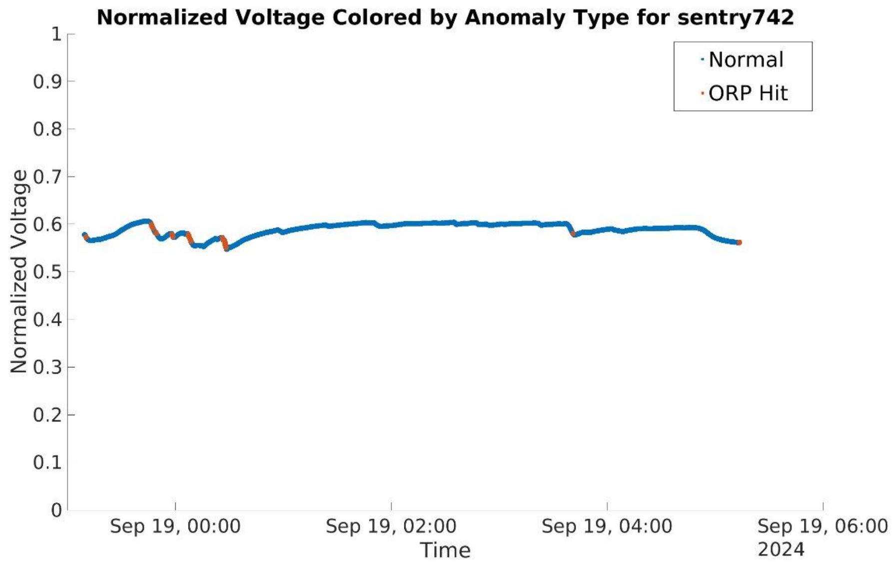
Case Study 1: Results



- Illustrates the ability of the pipeline to provide an efficient pass-and-fail sensor check after a dive.
- Calculating a percent anomaly score from the results would provide a fast, low-bandwidth, and singular value, giving insight on performance to a remote operator.





Case Study 2: Battery Health

- **Explore ways to capture and predict long-term battery degradation**
  - Expected mission length
  - Predictive maintenance
  - Reduce mission-critical breakdowns before they escalate

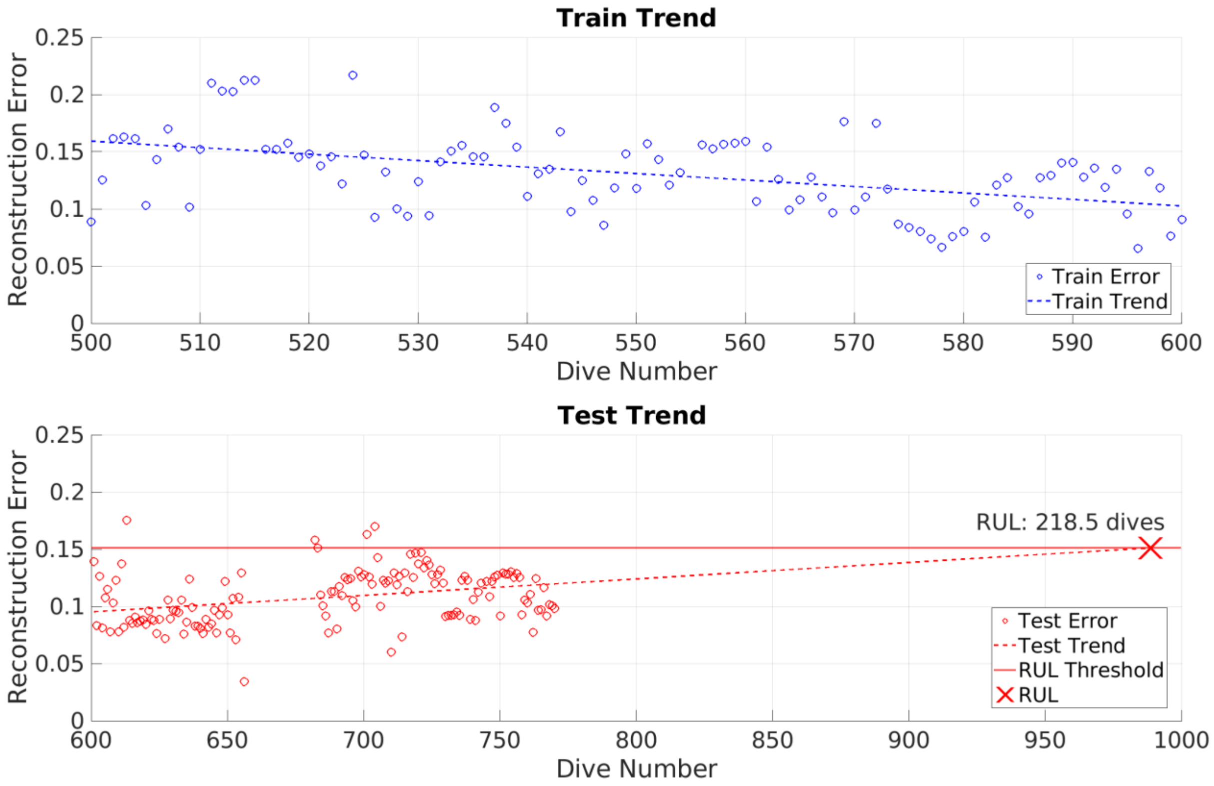
- **Utilized the Long Short-Term Memory (LSTM) algorithm**
  - Capable of capturing long-term patterns from time-series data
  - Can reconstruct and forecast depending on use case

- **This application used reconstruction error to detect anomalies**
  - Features: total voltage and charge
  - Each dive defined as a distinct sequence
  - Model learns to reconstruct "normal" time-series data
  - Expect that as dive number increases, reconstruction error should increase from the reconstructed sequences computed during earlier dives used for training

Panasonic NCR18650A model—vehicle contains 7,140 of these cells distributed across 5 battery buckets

Case Study 2: Results

- Reconstruction error for each dive from the **training** dataset
  - **Negative slope** --> expected behavior as the reconstruction error should decrease or plateau as the model learns each sequence and improves
  - 100 dives used for training
    - Too many dives in training set can lead to the model learning degradation behavior
    - This value is sensitive and requires tuning
- Reconstruction error for each dive in the **test** dataset
  - **Positive slope** --> Increasingly deviating from "normal" behavior indicating degradation
  - Example Remaining Useful Life (RUL) line added
    - 110% of mean reconstruction error over first few training set dives
    - Difference between predicted failure dive and current dive gives RUL



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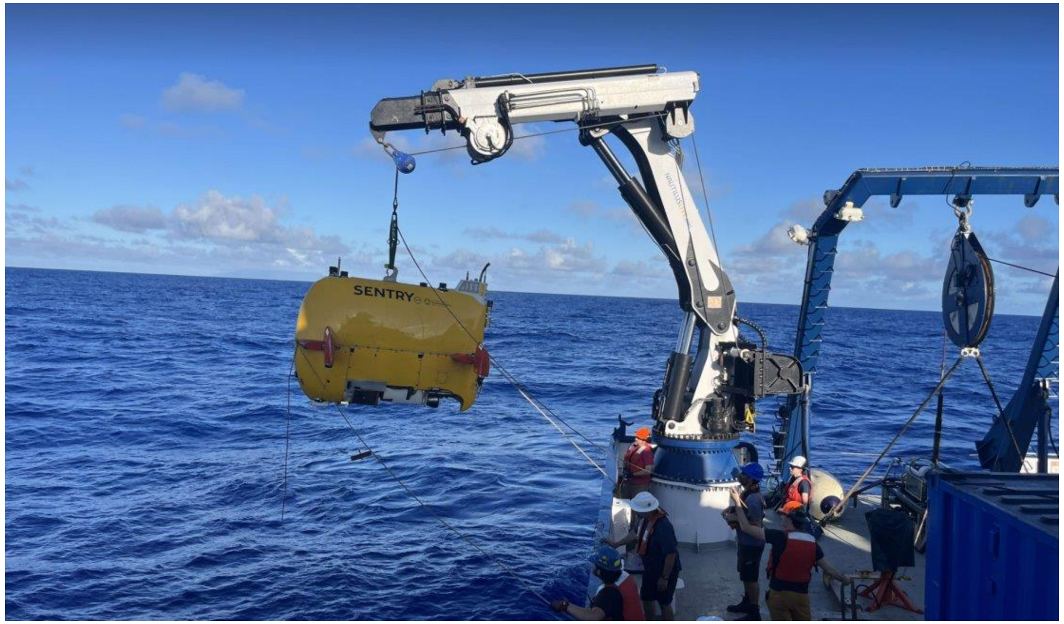
Discussion

- **Balancing Two Priorities**
  - Developing a scalable, generalized framework
  - Creating customized models tailored to the unique characteristics and failure modes of each sensor or system

- **Model Design Considerations**
  - Input parameter choices can significantly affect outputs
  - Overfitting is a common challenge
  - Requires a careful, deliberate design process



- **Building Trust in ML-Based Systems**
  - ML models can feel like a black box
  - Improve confidence through:
    - Transparent model architectures
    - Clear documentation of training assumptions
    - Human-in-the-loop oversight

Conclusions / Future Work

- Presented a ML-based framework for anomaly and fault detection in post-dive processing to facilitate participation from remote operators

- Maintained flexibility and scalability by utilizing YAML configuration files and by-device algorithm selection that can generalize to other vehicles and platforms

- Two case studies introduced using historical Sentry data to demonstrate utility of the approach
    - Science sensor payload performance (ORP sensor)
    - Battery health

- Future work:
    - Expand suite of supported models
    - Continue testing on additional sensors / data streams
    - Refine metrics and anomaly thresholds
    - Integrate the workflow into AUV Sentry post-dive procedures
    - Extend methods to real-time onboard fault and anomaly detection

Acknowledgements

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Questions?

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