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# Development of a Multi-Sensor Data Science System for Monitoring a Solvent Extraction Process

November 2022

Changing the World's Energy Future

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Idaho National Laboratory

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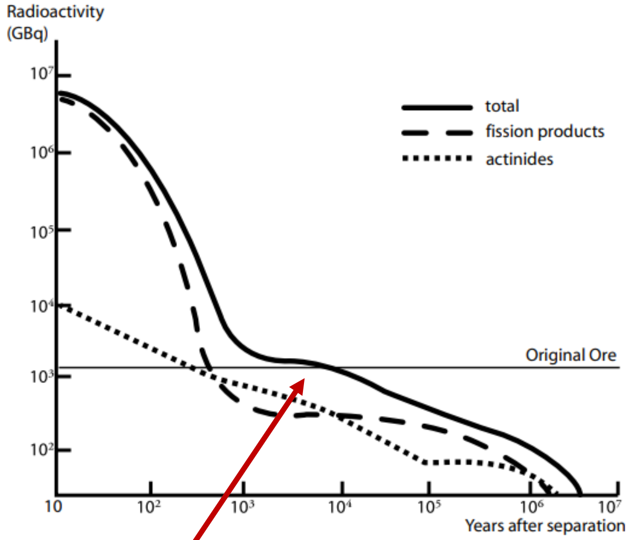
# Introduction – Solvent Extraction & Beartooth

- Solvent extraction
  - Nuclear industry
    - PUREX - recover uranium and plutonium
    - Reduce nuclear waste
- INL initiative to promote nuclear fuel cycle stewardship
  - **Beartooth**
    - Infrastructure: glove box lines, dissolution equipment, solvent extraction equipment
    - Test novel separations methods
    - Train early-career researchers

**Decay of high-level waste from reprocessing 1 metric ton of spent fuel from a pressurized water reactor.**




Quirk, T., "The Safe Disposal of Nuclear Waste", Institute of Public Affairs, (2005) vol. 57, no. 2.

Takes ~5,000 years before radioactivity from (PWR) spent fuel equals that from uranium orebody.

# LDRD Overview - Multi-Sensor Monitoring

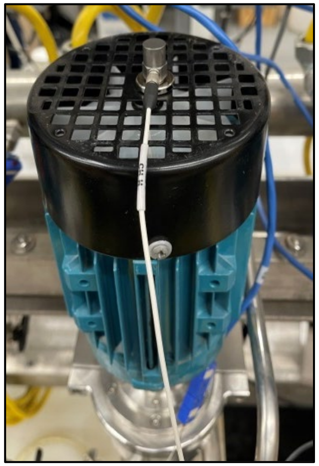
| | |
|---|---|
| **Goal 1** | Integrate a variety of atypical sensors into a system of centrifugal contactors for signal discovery. |
| **Goal 2** | Use machine learning, data analytics, and signal analysis techniques to extract features that identify process stages and equipment usage in various stages of operation. |

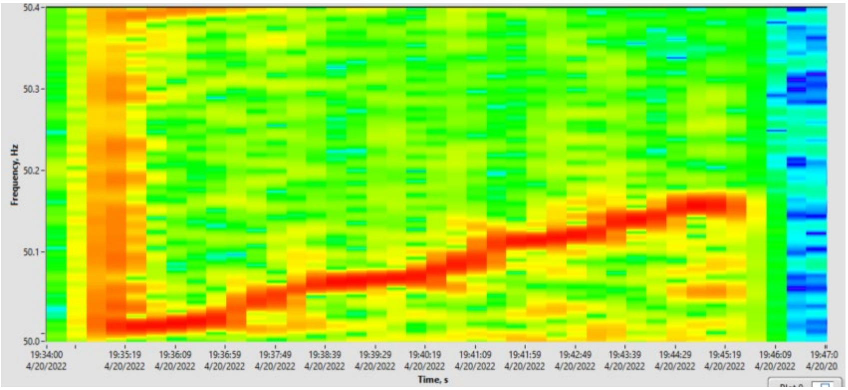
# Project Impact

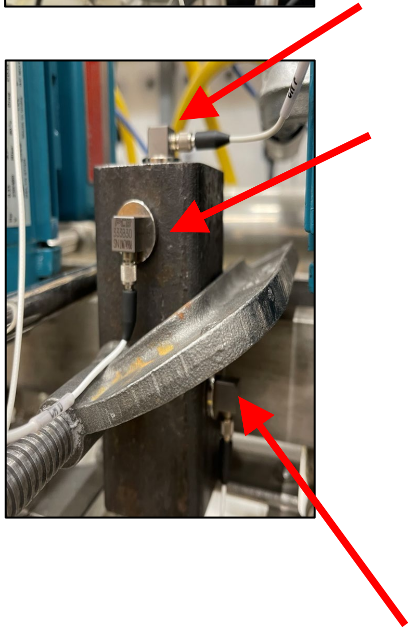
| | |
|---|---|
| **Local Impact** | Provide system operators with process awareness that can inform them of:<br>• Normal/abnormal process conditions<br>• Predict equipment failures<br>• Increase scientific understanding of separations processes. |

| | |
|---|---|
| **Broad Impact** | If features provide evidence of diversion, this research has the potential to enhance nuclear safeguarding of special nuclear materials. |

# Overview of Vibration Sensors

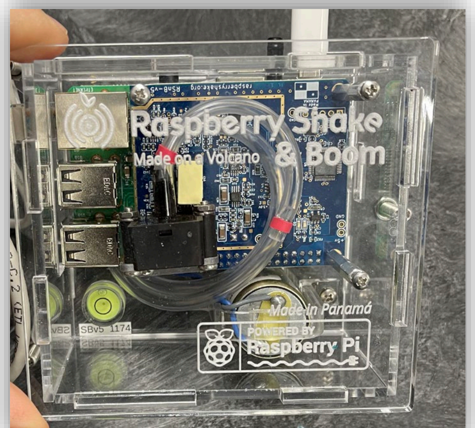


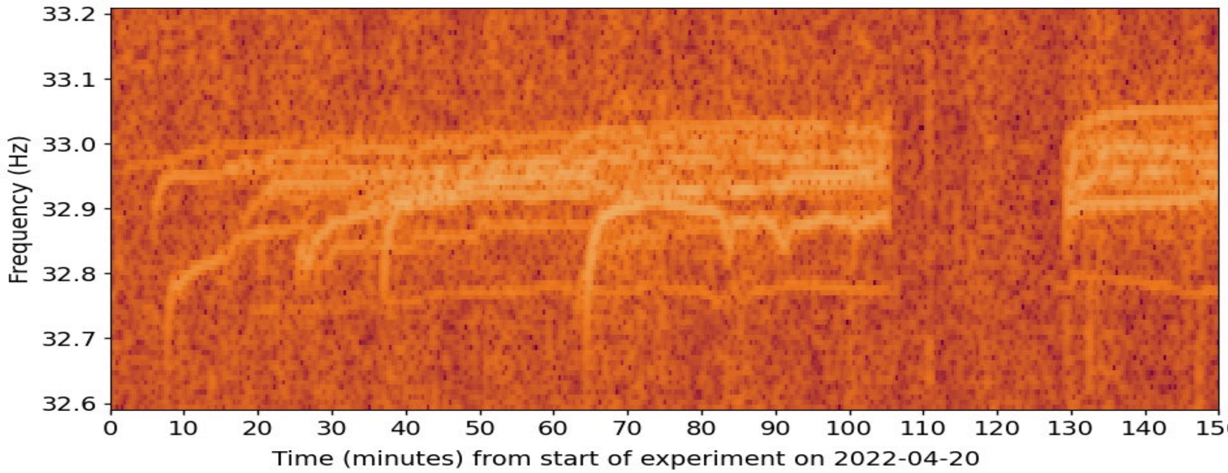


- Sensing range: 0.5 Hz – 10 kHz.
- Experiment: Increased the number of revolutions per minute of the contactor motor from 3000 to 3010 in 1 RPM increments.
- Results: Able to detect 1 RPM increases using vibration sensors.

# Acoustic Sensors

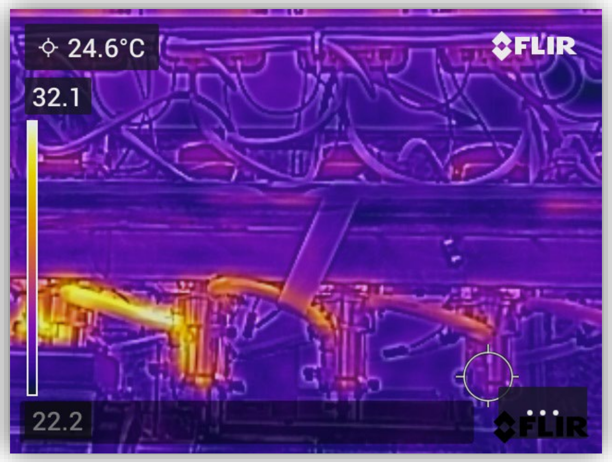




- Sensing range: 0.05 Hz – 20 kHz.
- Distance from contactor 1: Varies from 120 cm (directly below contactor) to 790 cm (far side of room).
- Experiment: Turn on each contactor one-by-one starting with contactor 30.
- Results: Able to detect contactor operation with acoustic sensors.

**Acoustic sensors are not attached to equipment providing an opportunity for stand-off detection.**

# Infrared Camera


Contactor 30 to 29




Solution enters contactor 27


Flow is constant

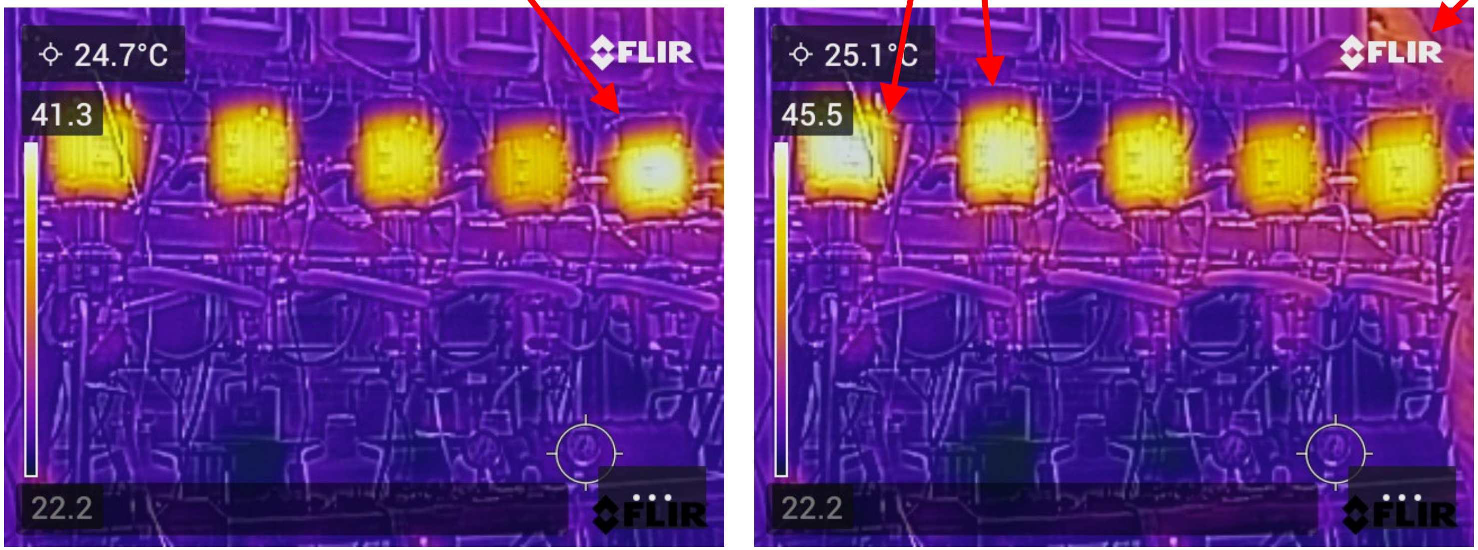
- Sensing range: 0 – 100 deg C.
- Location: Behind contactors.
- Experiment: Turn on each contactor one-by-one starting with contactor 30. Start with aqueous solution with temperature set at 55 deg C.
- Results: Able to detect solution flowing from contactor to contactor.

**Solution location desired by process operator.**

# Infrared Camera - Unexpected Event

Contactor temperature high

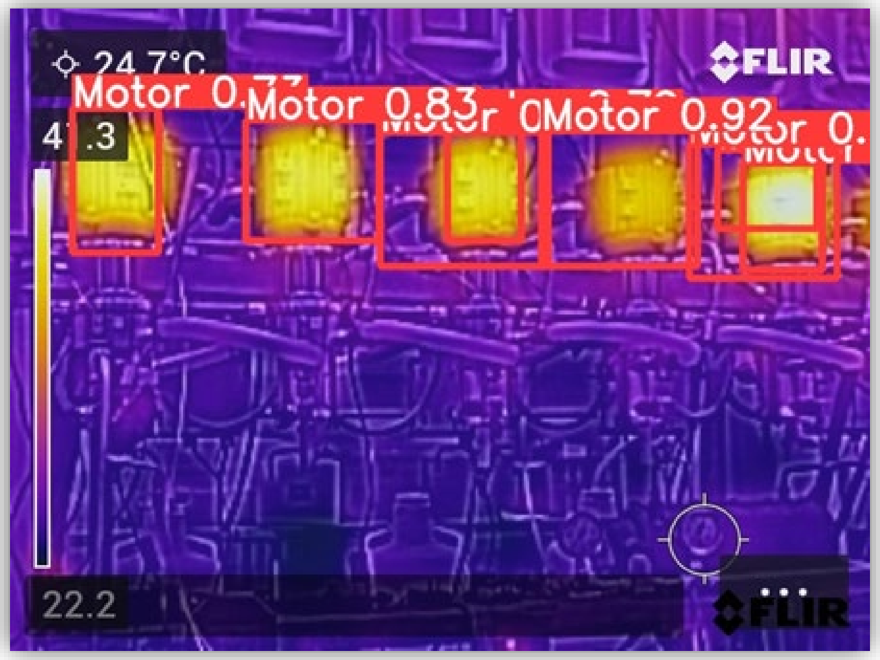
VFD Error, Reset




- Location: In front of contactors.
- The organic solution was not heated.
- Contactor 5 motor temperature increased, overheated, failed.
- Flooding occurred.

**Temperature changes were measured in the sensors before staff realized a failure.**

# Infrared Camera and Machine Learning




**YOLO = You Only Look Once**

- Used for object detection.
- Trained to pick out the motors in this image.
- ML method used to place the red boxes around the motors.
- Number are the confidence that the objects are contactors.

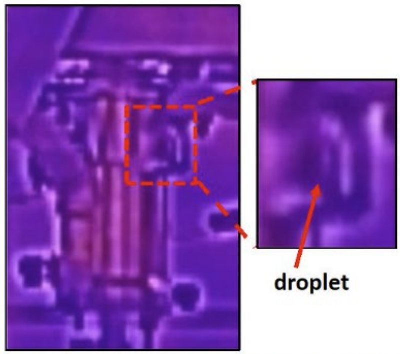
**YOLO can identify where the motors are in the image, so we can determine temperatures and help to predict motor failures.**

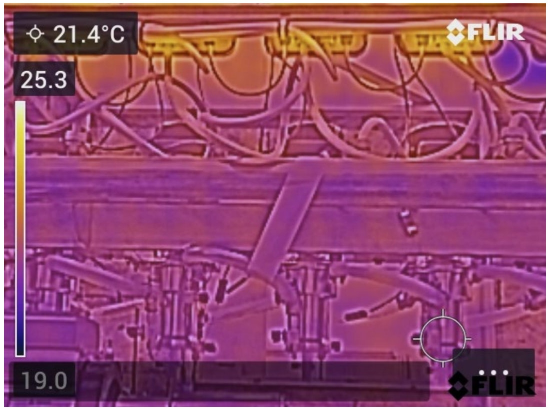
# Leaks are common, so we're making a ML algorithm to detect them.

- A leak occurred during the startup of our experiment that was detectable by the thermal imaging camera.

Challenges:

- The overall change in color due to the rescaling of temperature may play a major role in the algorithms output.
- That there is enough training data available for this analysis. We have a time series with only one time period with a fault.

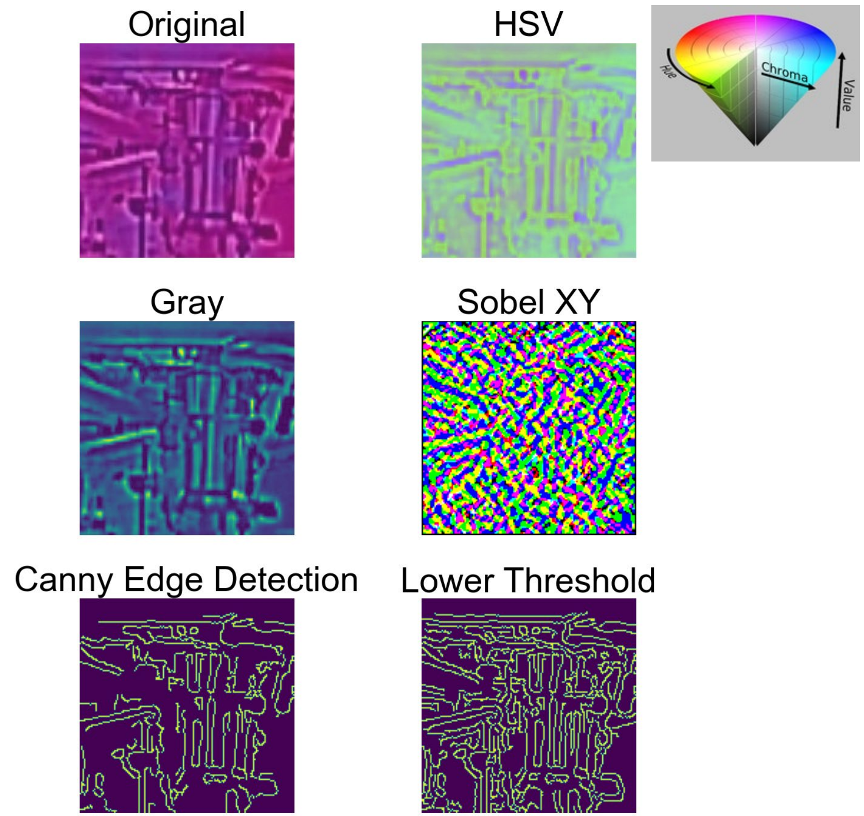




# Training data for the leak was improved with data augmentation and image modification.

- Data augmentation was used to generate new images and improve model robustness:
  - Shear, Zoom, and Flip
- Image modification techniques were used as an attempt to extract new information from the images.
- 257 original images in the training data were extrapolated into 2,000 images.
- The leak identification model used the pre-trained, Xception, that wrapped with additional layers and fine-tuned for our dataset.



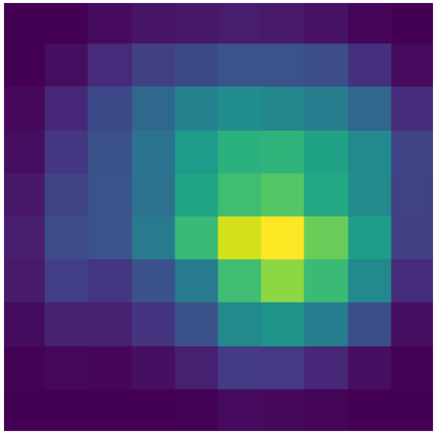
# Model accuracies using image augmentation + Xception model + fine tuning.

- # of original training images = 2,000, validation images = 45
- Positive class represented images from normal operation (pre-flow, establishing flow, and full flow.)
- Negative class contained images with the leak.
- High accuracy stemmed from over-training on a single leak.
- A supplemental leak experiment is planned this December.
- 1.00 on recall and 0.77 on precision means there is a class imbalance, and the AI guessed the dominant class for each prediction.

| Image Type | Accuracy | Precision | Recall | F1 score |
|---|---|---|---|---|
| Original | 1.00 (0.961) | 1.00 | 1.00 | 1.00 |
| Gray | 1.00 (0.859) | 1.00 | 1.00 | 1.00 |
| HSV | 0.977 (0.988) | 1.00 | 0.97 | 0.985 |
| Sobel XY | 0.77 (0.75) | 0.77 | 1.00 | 0.87 |
| Edge | 0.75 (0.56) | 0.75 | 1.00 | 0.86 |
| Threshold | 0.77 (0.56) | 0.77 | 1.00 | 0.87 |

# GradCAM++ was used to identify where the model was looking to make its classification.

- GradCAM++ utilizes the last convolutional neural network layer to generation a class activation map.
- Used a pretrained Xception model in combination with fine tuning. (20,000,000+ trainable parameters).
- It's mainly looking at the dead center of the contactor, which is encouraging as it is not looking at the background image colors (that can change as the scale changes)

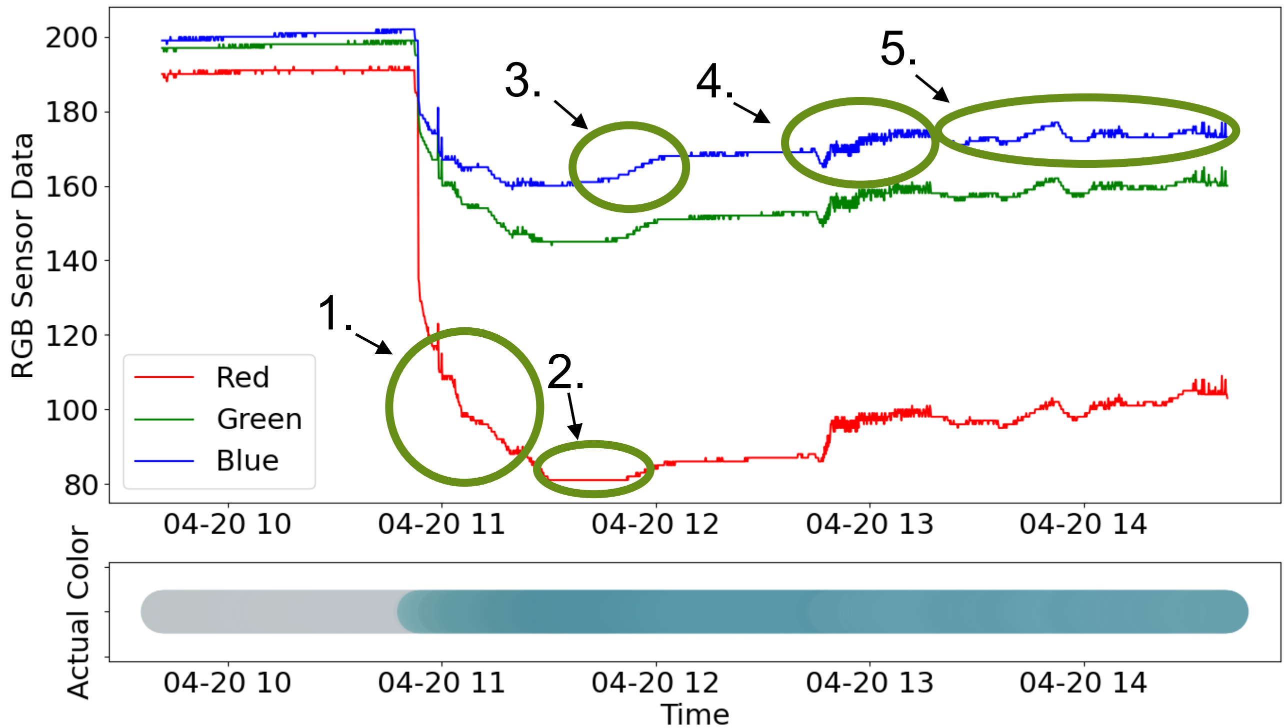


Class activation map

Heat map superimposed over image

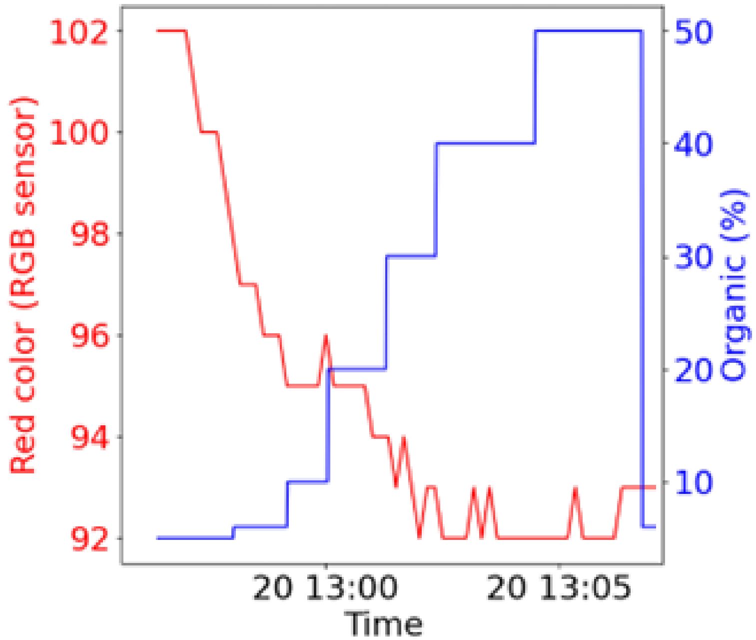
# Color Sensor

Port hole allows solution to flow into holder.




1. The aqueous solution is filling the beaker
2. System stopped due to leak.
3. Restarting system and aqueous flow was reestablished.
4. RPM increases from 2000 to 4000 in 250 increments for all contactors at once.
5. Changed the RPM of a group of contactors.

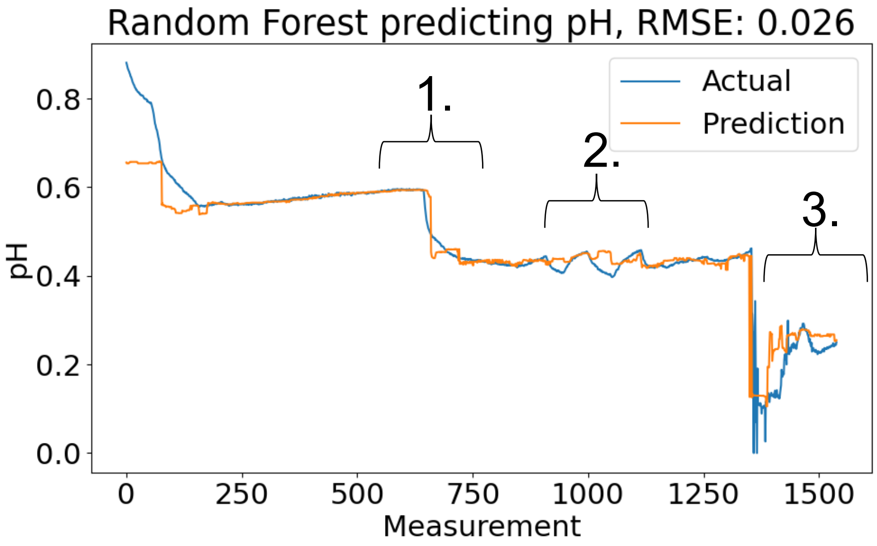
# Color Sensor




- Process operators want to know the concentration of the solution.
- Can color sensor help determine the concentration?
- The aqueous flow rate remained constant while the organic flow rate increased.
- Increased the organic concentration in the beaker.
- Color value appears to be inversely correlated to the flow rate up to about a 30%.

# Predicting pH using Machine Learning

- The pH sensor was in the flow through beaker.
- Used Random Forest to predict the pH.
- Kfold 20 used for cross validation.
- RMSE = 0.026; model was good at predicting the pH.




Activities:

1. Establishing organic flow.
2. Changing VFD speeds.
3. Changing organic concentration.

Local feature contributions to the model's output were determined by **Local Interpretable Model-Agnostic Explanations (LIME).**

- For measurement 1000, Conductivity is the most influential variable.
- RGB colors and solution temperatures were also used in the prediction.

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