





# **Explainable Al solutions for Industry and Water**

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## **Presentation Overview**



- Personal Background
- Brief Al Overview From Specialists Perspective
  - Al Onion
  - LLM Comments
  - ML High Level Workflow and Flowchart

#### Industry Examples

- Amalgamated Sugar AI Project Example via High Level ML Workflow
- Aquifer Pumped Hydro
- UI CDA

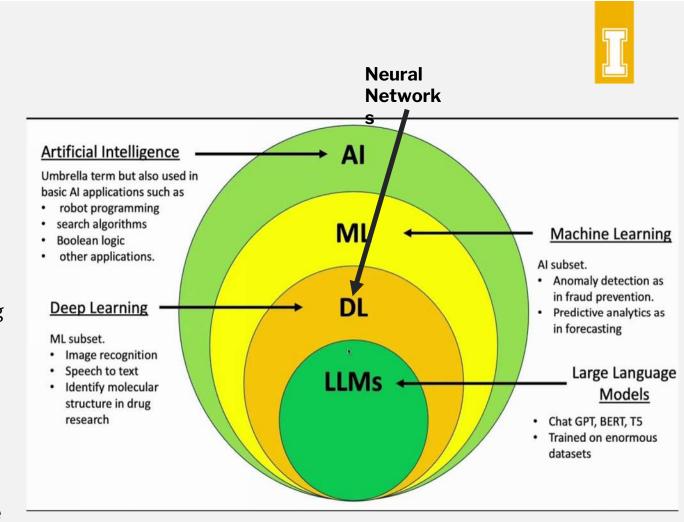
## Personal Background



- Education
  - A.S from North Idaho College in Computer Science
  - B.S from University of Idaho (Moscow) Computer Science and Mathematics
  - M.S from University of Idaho (CDA) Computer Science
    - Worked with National Institute for Advanced Transportation Technologies/ PacTrans
  - PhD Candidate as of July 2025
    - Working on Amalgamated Sugar AI research project
- Work
  - NASA Artemis Mission
  - Graduate Researcher
  - Wapiti Consulting
- Career Goal: Solve complex problems in infrastructure and manufacturing using explainable AI models

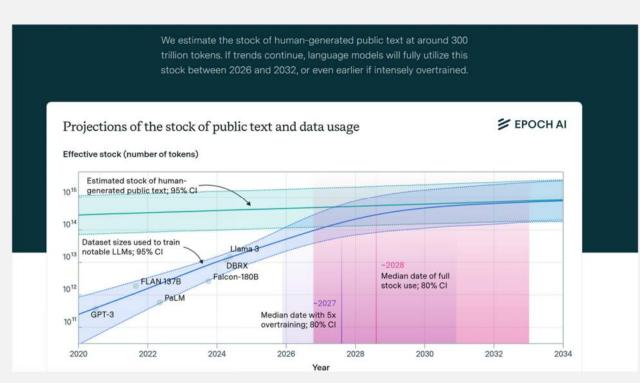
#### **AI Onion**

- AI = Very broad Field
  - Started in 1956 at Dartmouth
- Too many acronyms
  - Multiple websites dedicated to defining these acronyms
- Combines science with engineering
  - Writing code = engineering
  - Why is my model inaccurate? =Science
- Would not be surprised if Al eventually becomes its own degree
- Many people think it's just ChatGPT



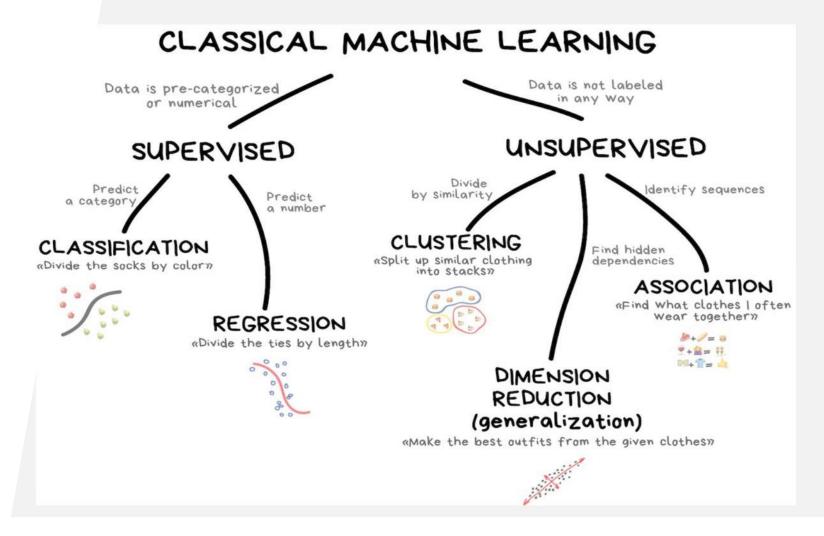
# Why I Think You Should Minimally Rely on LLMS

- The amount of new data being produced on the internet is significantly slower than the models consumption
  - 2026-2032 peak
- Companies understanding the value of the data
  - New York Times Sueing OpenAl (ChatGPT) for copyright infringement
- Maybe models themselves will improve on learning from the data but it seems far out
- Synthetic data has a questionable impact



# **Machine Learning Flowchart**





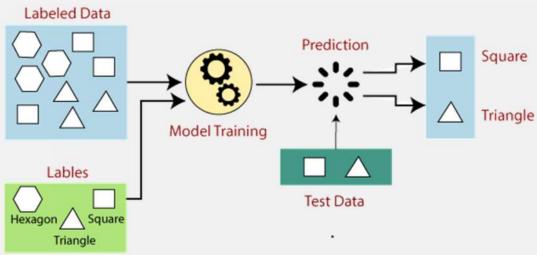
# High Level ML Model Development Workflow



#### DATA GATHERING

- o Garbage in = garbage out
- More data is better
  - Can always remove later
  - Hard to know what's relevant.
  - Storage has gotten cheap
- Data formatting/ preprocessing
- Model Selection
- Training the model(s)
- Evaluating and testing the model(s)
  - Need a subject matter expert to help verify models
- Model Integration

#### **EX: Supervised Classification ML Model**



# **AS Research Background**

- Amalgamated Sugar
  - Complex real time multimodal process environment
  - Second largest sugar manufacturer in US
  - 1.7% of Idaho's GDP and employs over
    1700 individuals
  - Have multiple complex process problems
- Wanted research conducted on their Steam Dryer
  - Biggest issue being a plugging event
  - No engineering solution so far (just guesses)
    - Attempt a "hot standby"
  - 2020 steam dryer malfunction led to 5 individuals going to the emergency room



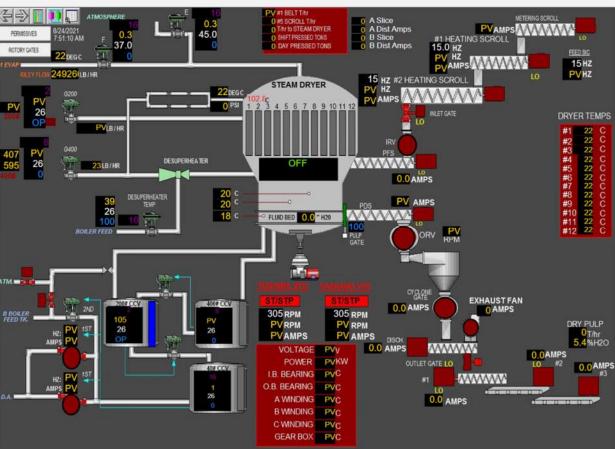
# **Steam Dryer Details**

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- 4 stories tall
- Uses a 200lb and 400lb boiler to dry beet cossettes in roughly 90 seconds.
  - Roughly 75% humidity to around 11%
  - Used for animal feed

 Carries significant financial and safety risks if not properly managed

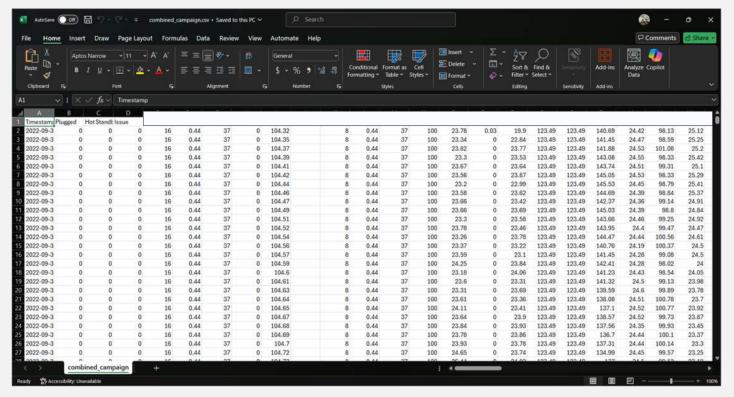




# **Amalgamated Sugar (AS) Data Gathering**



- This portion of the process was already done for me
- They used the dataPARC historian to log there data at about 1 minute intervals
  - Educated guess is about 10 years worth of data
- Took the data and exported it into excel so we could start formatting the data for our ML models



### AS Data Formatting/ Processing

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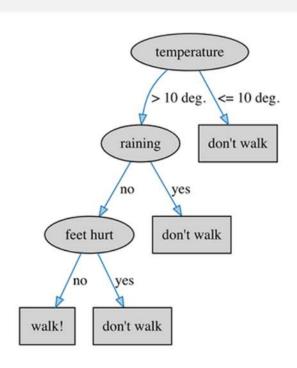
- This process changes based upon the "condition" of the data and the models you are using
- Some Data Formatting we did:
  - Establish AS data from 2022 and 2023 as training data and 2024 as testing data
    - ~750,000 data points
  - Remove data points that got removed from the physical process
  - Create labels for issue events
    - Only ~5% of the time are they in an issue event
  - Fill in a single missing datapoint with average of before and after data points
  - Fill in chunk of missing data points with mean of column
  - Normalize data points from 0-1



#### **AS Model Selection Decision Tree**

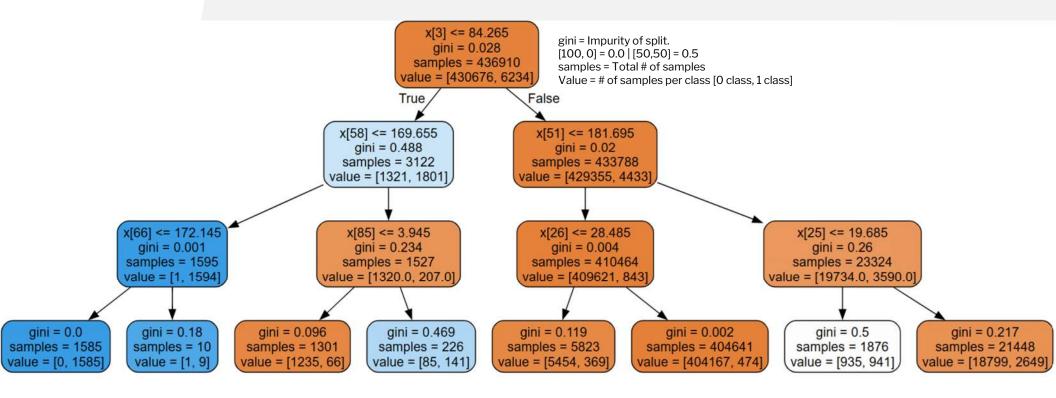
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- Usually there is some light research to be done here to select a model that fits your problem and data
  - Engineering decision to choose the right tool for the job
- The first model I chose was a decision tree model which functions in a flow chart like fashion
  - Just wanted to see if data showed a solution (without time involved)
- With this model to increase the accuracy I implemented:
  - Hyperparameter Tuning: changing how the model learns
    - IE: Counting with two hands compared to one
  - Adaboosting: Using multiple decision trees in conjunction in a voting fashion
    - IE: Three trees voting if there is an issue or not
- During PhD literature review I found this being used to determine bridge health



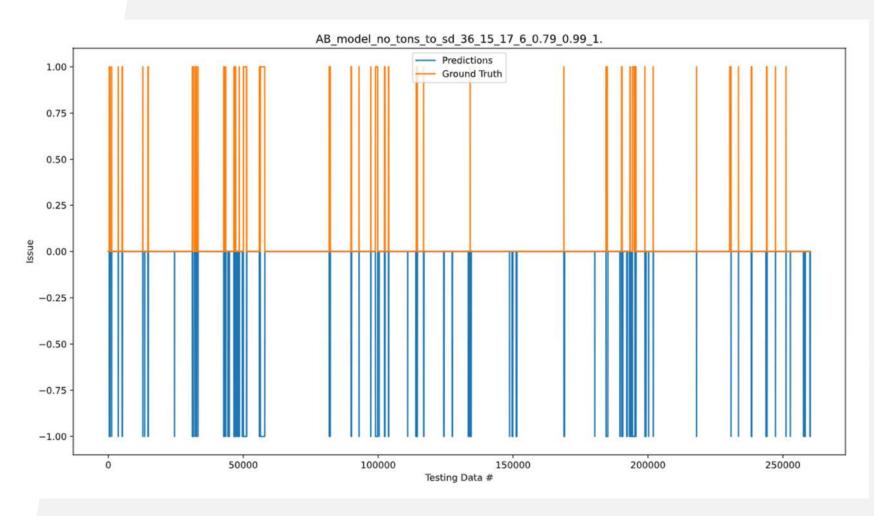
#### **OLD AS Decision Tree Model**





#### **OLD AS Decision Tree Model Results**

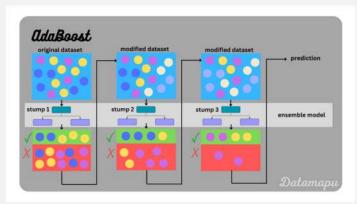




#### **AS Model Selection Time Offset Dec Tree**

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- Basically I needed a way to take my decision tree model and incorporate a time aspect so we could predict future issues
- To do this I took a group of data points at a particular time and gave them an outcome/label that was a variable number of minutes in the future
- This is one of the contributions/ unique things I am working on for my PhD
- This model also leveraged hyperparameter tuning and adaboosting



#### **5 Minute Offset Decision Tree Logic**

| Feature [0,0]    | Feature [0,1]   | Feature [0,2]   | **** | Feature_[0,n]  | Label [5]   |
|------------------|-----------------|-----------------|------|----------------|-------------|
| Feature [1,0]    | Feature [1,1]   | Feature [1,2]   | 2.65 | Feature_[1,n]  | Label [6]   |
| Feature [2,0]    | Feature [2,1]   | Feature [2,2]   | **** | Feature_[2,n]  | Label [7]   |
| ****             |                 |                 |      | 1              | ****        |
| Feature [m-5, 0] | Feature [m-5,1] | Feature [m-5,2] |      | Feature[m-5,n] | Label [m+5] |

N = Number of features (99 for Amalgamated Sugar Project)

M = Number of feature vectors

#### 10 Minute Offset Decision Tree Logic

| Feature [0,0]     | Feature [0,1]    | Feature [0,2]    | 55500 | Feature_[0,n]   | Label [10]   |
|-------------------|------------------|------------------|-------|-----------------|--------------|
| Feature [1,0]     | Feature [1,1]    | Feature [1,2]    |       | Feature_[1,n]   | Label [11]   |
| Feature [2,0]     | Feature [2,1]    | Feature [2,2]    | 2555  | Feature_[2,n]   | Label [12]   |
| ****              |                  | ****             | ****  |                 |              |
| Feature [m-10, 0] | Feature [m-10,1] | Feature [m-10,2] | ****  | Feature[m-10,n] | Label [m+10] |
|                   |                  |                  |       |                 |              |

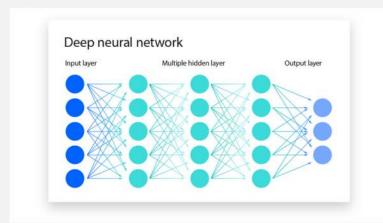
N = Number of features (99 for Amalgamated Sugar Project)

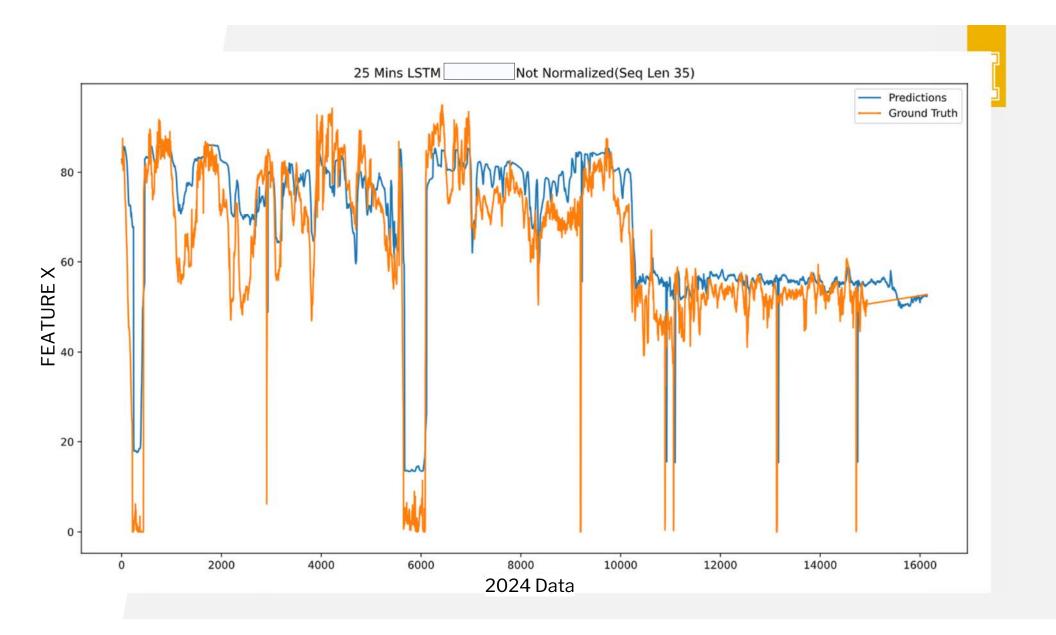
M = Number of feature vectors

## **AS Model Selection Long Short Term Memory Model**



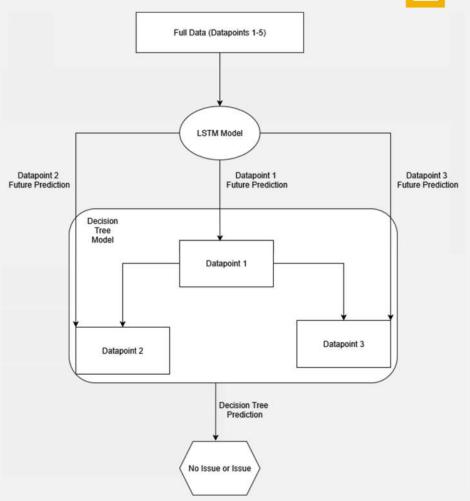
- Defacto model used for future time predictions
- Deep learning model
  - Multiple nodes (neurons) chained together
- Generally has a higher prediction accuracy compared to a decision tree model but lacks explainability
- Takes in a matrix of data where each row is a datapoint and each column is that data points value at that given time
  - This gives the model its "memory"
- For AS it is being used for regression compared to classification (Actually predicting a value)
- In PhD literature review found this model being used for future traffic forecasting





## **AS Model Selection Hybrid Model**

- Very technical model but basically I am using the data points that a decision tree is using to make a issue classification and trying to predict those in the future with the I STM model
- Unique thing I am implementing for my PhD
- Trying to combine the predictive power of the LSTM with the explainability of the LSTM
- Has been developed but is undergoing testing

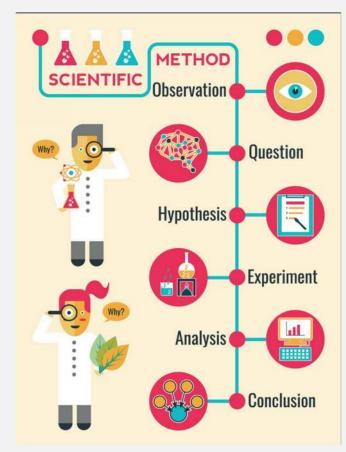




### **Training the Models**

- This is where the science kicks in
- Generally this process takes the longest amount of time as there is a large amount of trial and error
  - Many many iterations of highly inaccurate models that take forever to train
- For the Amalgamated Sugar Project the offset decision trees took about 96 days to train and resulted in about 600,000 models that scored above 65% accuracy
- The LSTM models we currently have take about a day per model to train and we are on our 54th iteration
  - Our data point we are predicting ranges from 0-120 units and we are on average off 6.6 units or 5.5%
- Hybrid models are more of an integration challenge given both models are already trained





#### Testing the models

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- Varies based upon the model type
- Decision Trees scored on F1 and Recall
  - F1 = Overall Accuracy
  - Recall = Accuracy of issue events
- Offset Decision Trees Scored on F1, Recall, Overall Time Scoring, Number of Preempted Events and Average Heads up
  - Overall time score = preemptive time reactive time
  - Number of Preempted Events = Total events out of 95 the model preempted
  - Average heads up = If the model was preemptive how many minutes on average did it give as a heads up

| A A  | В                          | C                          | D                          |
|--|----------------------------|----------------------------|----------------------------|
| Model Name                                 | Overall Time Score         | Number of Preempted Events | Average Heads up (Minutes) |
| AB_off_model_no_tons_to_sd_38_57_30_6_0    | .69_1.0_19.173469387755102 | 72                         | 12.583333333333334         |
| AB_off_model_no_tons_to_sd_19_8_28_6_0.6   | 67_0.83_18.540816326530612 | 71                         | 12.309859154929578         |
| AB_off_model_no_tons_to_sd_25_3_27_6_0.    | 74_0.99_18.918367346938776 | 71                         | 12.43661971830986          |
| AB_off_model_no_tons_to_sd_35_44_26_6_0    | .73_1.0_19.173469387755102 | 71                         | 12.76056338028169          |
| AB_off_model_no_tons_to_sd_44_39_29_6_0    | .7_0.99_19.551020408163266 | 71                         | 13.295774647887324         |
| AB_off_model_no_tons_to_sd_53_12_29_6_0    | .69_0.88_8.887755102040817 | 71                         | 12.408450704225352         |
| AB_off_model_no_tons_to_sd_41_23_29_6_0    |                            | 69                         | 13.318840579710145         |
| AB_off_model_no_tons_to_sd_11_46_29_6_0    | .71_0.99 6.622448979591836 | 68                         | 12.602941176470589         |
| O AB_off_model_no_tons_to_sd_10_30_28_6_0  | .7_0.99_17.010204081632653 | 68                         | 13.161764705882353         |
| AB_off_model_no_tons_to_sd_21_43_28_6_0    | .7_0.99_17.010204081632653 | 68                         | 13.161764705882353         |
| AB_off_model_no_tons_to_sd_20_22_29_6_0    | .71_0.99_6.622448979591836 | 68                         | 12.602941176470589         |
| 3 AB_off_model_no_tons_to_sd_11_56_28_6_0  |                            | 68                         | 13.161764705882353         |
| AB_off_model_no_tons_to_sd_14_3_28_6_0.    | 71_0.99_16.622448979591836 | 68                         | 12.602941176470589         |
| 5 AB_off_model_no_tons_to_sd_13_22_29_6_0  | .71_0.99_6.622448979591836 | 68                         | 12.602941176470589         |
| 6 AB_off_model_no_tons_to_sd_17_27_29_6_0  | .71_0.99_6.622448979591836 | 68                         | 12.602941176470589         |
| 7 AB_off_model_no_tons_to_sd_1_1_28_6_0.7  | 0.99_1_17.010204081632653  | 68                         | 13.161764705882353         |
| 8 AB_off_model_no_tons_to_sd_1_20_28_6_0.  | 7_0.99_1_7.010204081632653 | 68                         | 13.161764705882353         |
| 9 AB_off_model_no_tons_to_sd_22_0_29_6_0.1 | 71_0.99_16.622448979591836 | 68                         | 12.602941176470589         |

#### **Testing the models Cont**

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- LSTM in simple terms is scored on average how many units off is the prediction
  - Our data point we are predicting ranges from 0-120 units and we are on average off 6.6 units or 5.5%
- The hybrid model can be scored on all the prior metrics.
  - For PhD will we find all of these out
  - For the project itself we just care how many events it preempted and what was its average heads up
- Lastly subject matter expert verification
  - o Do data points make sense
  - ML researchers are really bad at overestimating their model accuracies

#### **Basic Decision Tree Results**



- Basic Decision Tree (No hyperparameter Tuning & No adaboosting)
  - Recall 42% and 50% on F1

- Enhanced Decision Tree (Hyperparameter Tuning)
  - Highest Recall Scoring Model: 99% recall and 78% on F1
  - Highest F1 Scoring Model: 93% recall and 85% on F1
- Advanced Decision Tree (Hyperparameter Tuning and Adaboosting)
  - Highest Recall Scoring Model: 99% recall and 79% on F1
  - Highest F1 Scoring Model: 96% recall and 86% on F1

#### Offset Decision Tree Results

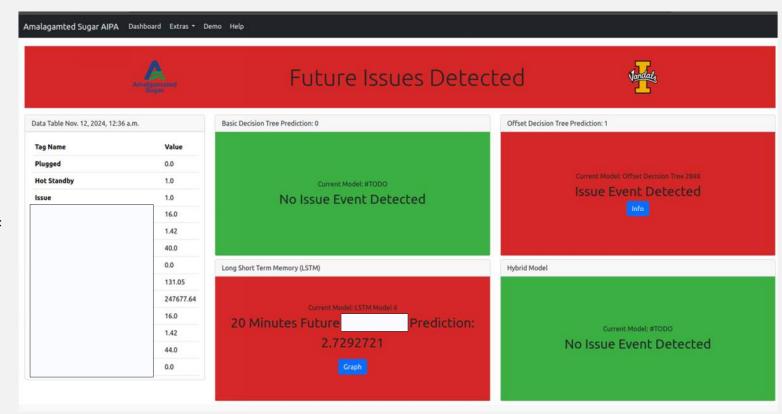


- Over 600,000 tree combinations scored above 65% on Recall and F1
- Not fully finished testing these models but the best predicted 75 of the 95 events in 2024 with an average heads up of 13 minutes
- Project ROI is hard to guess (due to safety being in involved) but from a product standpoint we estimate a break even of 7.11 hours of prevented down time

## **Model Integration: Al Predictive Appliance (AIPA)**



- Informative display of ML model predictions for an operator
- Will down the line be a basis for additional AI/ML projects
- The next steps:
  - Create digital twin of steam dryer
  - Have model make control decisions on simulator



#### **AS Problems Encountered**



- Non labeled data
  - Did not log when there was an issue so we needed to generate labels for the data
- Very few times where the steam dryer was labeled as an "Issue" (~5%)
  - Similar to infrastructure with minimal downtime
- Processes changes through campaigns
  - Decide what data points to keep and what to toss
- Cyber attack in 2024 which messed with testing data

#### **AS** Return on Investment



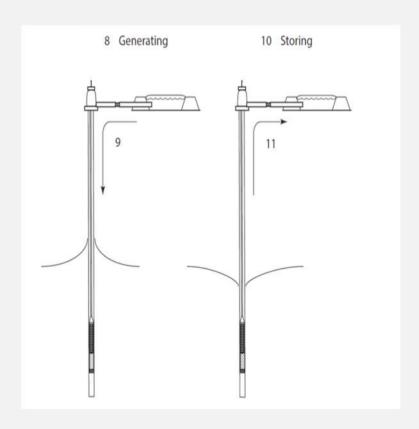
- Does not include safety and cascading problems into ROI
- Preventing 1 plugging event basically equals out the cost of the project
- Best model preempted 72/95 (75%) total events in 2024
- Beet processing is ~4 months or ~2880 hours
  - Roughly 5% of the 2,880 hours the SD is down
    - 144 hours of being down
  - If we can prevent 75% of the 144 hours
    - 108 more hours of the steam dryer being running
- 108 \* 25,500 = \$2.7 Million Cost savings
  - 25% preemption = \$918,000 Cost Savings

| 40lbs of beet feed                   | \$17  | https://www.tractorsupply.com/tsc/product/s |  |
|--------------------------------------|---|---|--|
| 40lb beet feed * Store 50% Markup    | \$8.5 AS selling price                          |   |  |
| 60 tons an hour on average           | 120,000 lbs an hour on average                  | Convert Tons to lbs                         |  |
| 120,000 lbs / 40 lbs (sellable size) | 3,000 40lb bags made in an hour                 |   |  |
| 3,000 bags * \$8.50 per bag          | \$25,500 loss for being down for 1 hour         | Assuming Total Loss of beets during that ti |  |
| Project Cost \$200K / \$25,500       | 7.84 hours of prevented shutdowns to break even |   |  |

## **Aquifer Pumped Hydro Background**



- "The liquid battery that you already have"
  - Essentially taking a municipal well and allowing it to make power
- Hydropower generation by the potential energy difference between surface and groundwater via a well
- During the aquifer recharge or aquifer storage process a pumping motor is allowed to run in reverse and therefore is converted to a generator
  - Take power from the DC bus of Variable Frequency Drive and feed that into a inverter that synchronizes with the 3 phase AC power grid



# **Benefits of Aquifer Pumped Hydro**



- Works with both above ground vertical line shaft applications and submersible pumps
- Can also be easily retrofitted to existing well systems.
- NSF Certified
- Currently being funded by the California Energy Commission (CEC) and FERC
  - Current capacity cost estimate of \$380/kWh is less than a lithium battery at about \$470/kWh.
    Also has a service life of 25-50 years compared to 3.
  - o Right around 45% round trip efficient but there are lots of improvements that can be made
  - Biggest limiting factor is Hydraulic transmissivity of the aquifer (which should improve over time)
- "The flat Central Valley has over **100,000 wells**. They could be retrofitted to release energy. Each well could become a small energy storage facility."

# **Aquifer Pumped Hydro Need for Al**



- The U.S. grid consists of 6,400 power plants, 3,000 companies, and 55,000 substations, but they're usually not manned.
- In california's central valley alone there could be over 100,000
  APH units
  - How do you control these? Each well is unique
  - Solar Integration?
  - Controlling the grids power factor?
  - How to you ensure there is enough surface water for demand?
  - How do ensure there are no more rolling blackouts?
- There is the need for advanced prediction and controls capabilities

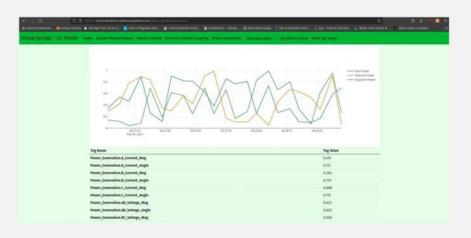


# Where the project stands

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- Currently still battling the permitting process of APH in the CEC and FEMA funded kern county project
  - 50KW project end of month
  - 200 KW by end of year
    - 4 wells creating microgrid
- Some other installations
  - Long Beach California startup next month (Behind the meter)
  - Mark Anthony Brewery waiting for plant expansion
  - City of beaverton oregon retrofit by end of year
  - Madison Farms
- The software has been written for the data gathering portion and once we have enough data we will use that to address problems and optimizations for system





#### **UI CDA Overview**



- Located directly on the North Idaho College campus in downtown CDA
- Home of the Center for Intelligent Robotics (CIIR)
  - Industry focused research center. Want to solve really hard problems
  - Currently have 4 main research areas with endless application areas
    - Robotics
    - Manufacturing
    - Artificial Intelligence/ Machine Learning
    - Precision Agriculture
  - Some notable industry projects
    - Inland Empire Paper Wastewater Treatment Project
    - Wildwood Grilling Rejection System
    - ATC Manufacturing (3D Scanner to use AI to compare scan to CAD file for inspection differences)
    - Laurel Grove Wine Farm (Predict frost events in future)
      - Sensor Collection and Remote Environment Care Reasoning Operation (Scarecro)
    - USDA & USFS Weed Eradication Robot
    - Schweitzer Engineering Lab Defect Detection

# **UI CDA Project Structure**



- Senior Capstone Project:
  - 4 undergraduates for 10 hours a week.
  - o Good to improve on something already existing, or small prototypes. Occasionally product oriented
  - Approx cost: \$2000 + expenses
  - o Example Projects: Simulate Paper cutting, wildwood grilling rejection system, etc.
- Masters Project:
  - Graduate student for 20 hours a week for 2 years
  - Can be work or research focused
  - Approx cost: \$120K
  - o Example Projects: LoRaWAN, AIPA dashboard and OPCUA connection, etc.
- PhD Project:
  - Graduate student for 30 hours a week for 2 years.
  - Must be research. Application of the research is generally required
  - Approx Cost: \$170K
  - Amalgamated Sugar AI Fault Prediction, SEL Manufacturing Data Analysis, IEP Wastewater Analysis etc.
- Contact jshovic@uidaho.edu

#### Sources



- Al Onion Image: https://www.youtube.com/watch?v=LoTuTu Z4Pk
- ML Flow Chart: https://devopedia.org/supervised-vs-unsupervised-learning
- Data Quality Image: <a href="https://www.cloudfactory.com/training-data-guide">https://www.cloudfactory.com/training-data-guide</a>
- Al workflow Image: <a href="https://www.acte.in/wp-content/uploads/2022/01/What-is-Supervised-Learning-ACTE.png">https://www.acte.in/wp-content/uploads/2022/01/What-is-Supervised-Learning-ACTE.png</a>
- Dec Tree Graph: https://help.pyramidanalytics.com/Content/Root/MainClient/apps/Model/Model%20Pro/Data%20Flow/ML/DecisionTree.htm
- APH1 <a href="https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/EPC-20-008%20Executive\_Summary%20Group\_1%20200%20kW.pdf?ver=1732641454730">https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/EPC-20-008%20Executive\_Summary%20Group\_1%20200%20kW.pdf?ver=1732641454730</a>
- APH 2 https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/EPC20-008%20Attachments.pdf?ver=1732641454730
- APH 3 <a href="https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/EPC-15-049%20Aquifer%20Pumped%20Hydro.pdf?ver=1732641455211">https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/EPC-15-049%20Aquifer%20Pumped%20Hydro.pdf?ver=1732641455211</a>
- APH 4 https://img1.wsimg.com/blobby/go/5d9ba30a-393d-4213-b97e-e1e678db29b6/downloads/NGWA%20MAR%20presentation%20April2023.pdf?ver=1732641455144
- APH 5 <a href="https://aquiferpumpedhydro.com/home">https://aquiferpumpedhydro.com/home</a>
- Power Grid Facts; https://www.heritage.org/homeland-security/commentary/substations-the-weakest-link-americas-power-grid
- Al Power Grid Image: <a href="https://www.researchgate.net/figure/Al-and-Distributed-Energy-Resources-utilization-of-existed-energy-resources-With-this\_fig1\_372174005">https://www.researchgate.net/figure/Al-and-Distributed-Energy-Resources-utilization-of-existed-energy-resources-With-this\_fig1\_372174005</a>
- LLM Issue Image: https://epoch.ai/blog/will-we-run-out-of-data-limits-of-llm-scaling-based-on-human-generated-data
- Epoch Al Image: https://epoch.ai/blog/will-we-run-out-of-data-limits-of-llm-scaling-based-on-human-generated-data
- Adaboosting Image: <a href="https://datamapu.com/posts/classical\_ml/adaboost/">https://datamapu.com/posts/classical\_ml/adaboost/</a>
- History of Al: https://en.wikipedia.org/wiki/History\_of\_artificial\_intelligence
- Feature Vector: https://www.hopsworks.ai/dictionary/feature-vector

# **Questions?**

