

# GridAI: Cloud-Based Machine/Deep Learning For Power Grid Data Analytics

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# Project Purpose

## Problem Statement:

- Power grids are complex and critical infrastructure which leaves them vulnerable to instability and attack.

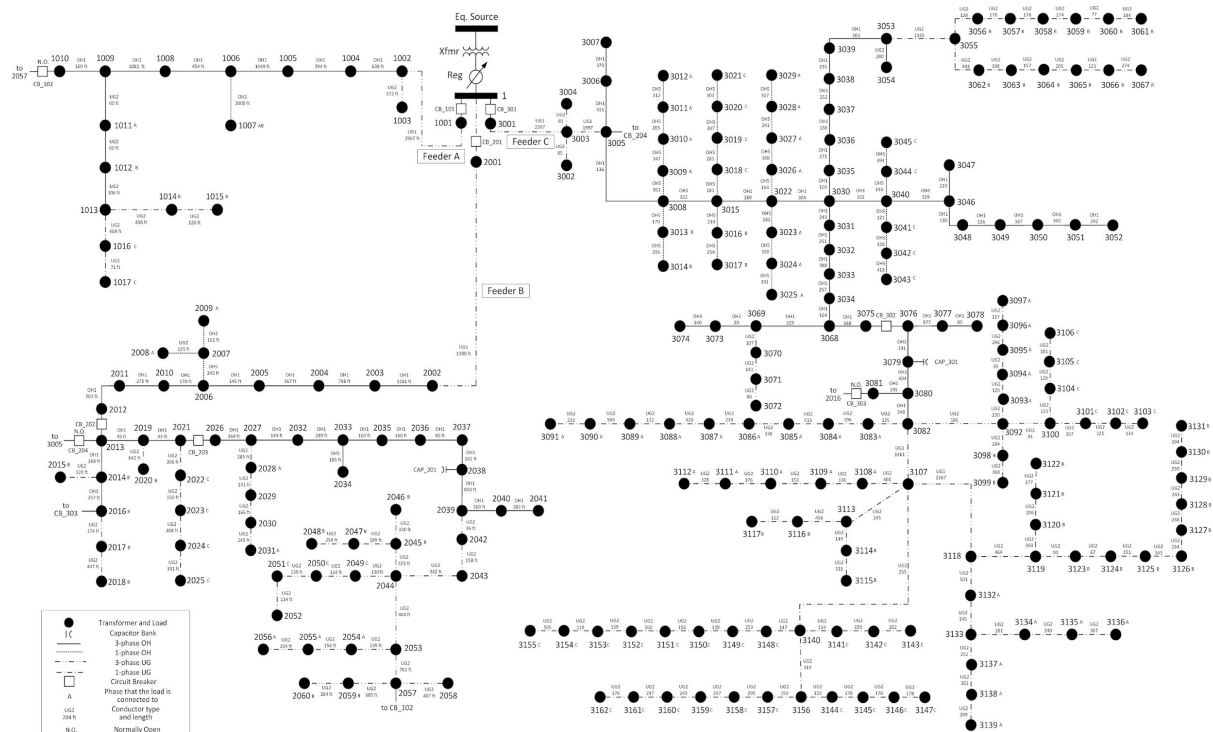
## Solution Approach:

- Develop a web application that implements a Machine Learning model to analyze power grid data and detect anomalies in power usage.



# Project Context

- Use Machine Learning on a simulated power grid to provide analytics and anomaly detection
  - Every node has some power output data associated
  - Static electrical properties
  - Location and connections in network



# Project Functional Requirements

- Machine Learning Requirements. The ML models should:
  - Use the most recent kWh value from the grid in the predictions.
  - Predict the next kWh output for each node in the grid.
  - Predict the probability of each anomaly class.
  - Use convolutional layers for deep learning.
- Front-end Requirements. The front-end should:
  - Receive data from the back-end
  - Visualize data on a dashboard:
    - Graph-based visualization
    - Geographical representation of the power grid
    - Charts for each node's history and predictions
    - Tabular data showing anomaly status for every node
  - Interface directly with the back-end
- Back-end Requirements The back-end should:
  - The server-side application will handle all data communication with the databases
  - All data processing, including ML analysis, will occur on the back-end
  - Provide real-time data to front-end

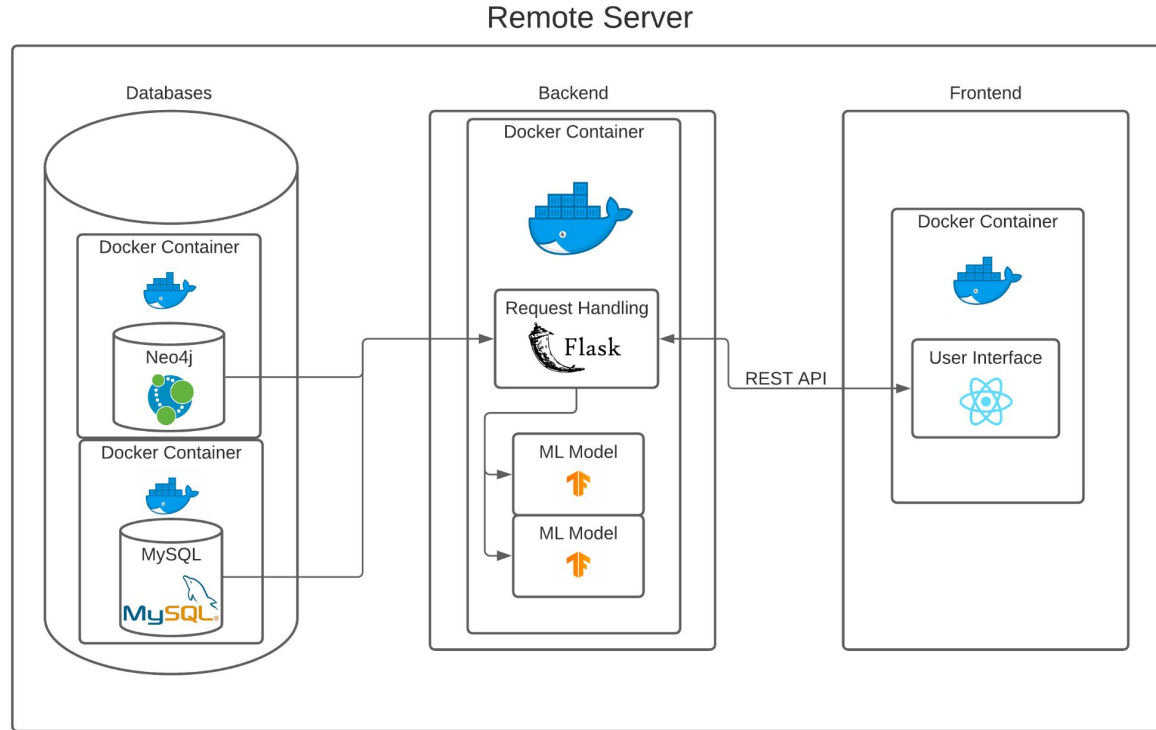


# Project Non-Functional Requirements

- Clear documentation
  - Allows future teams to improve on the baseline
- Maintainability
  - Modular coding and Docker containers
- Scalability
  - ML models are generalized predictors for nodes.
- Response time
  - Lightweight front-end to accommodate response rate of work heavy back-end

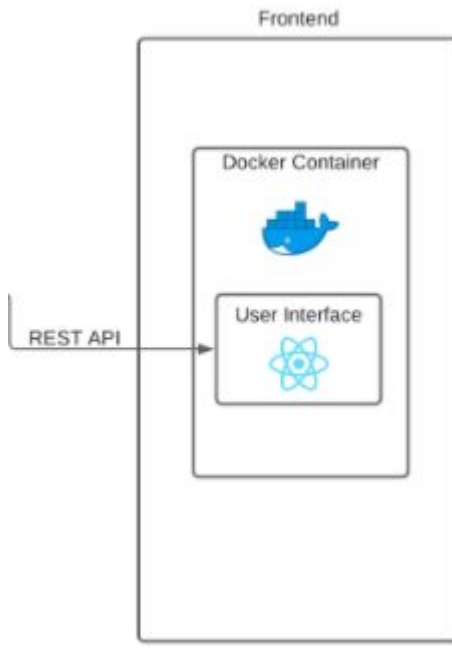


# High Level Design



# Front-end Design/Implementation

- Main Requirements:
  - Communicates with back-end
  - Accurate visualizations of data
  - Multiple kinds of visualizations
  - Clean-looking and easy to navigate
- One functional module
  - ReactJS frontend



# Dashboard - Home Screen

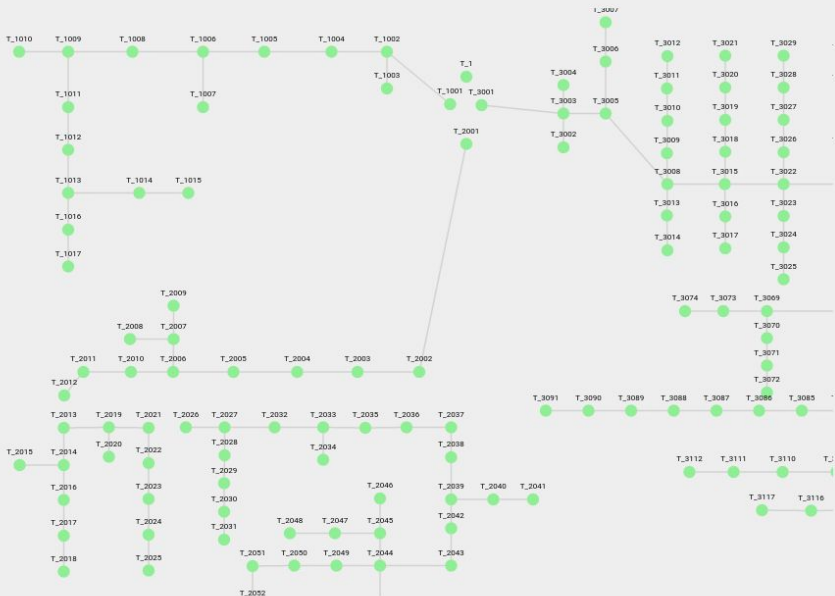
GRID AI

Dashboard

Anomaly Table

Node Info

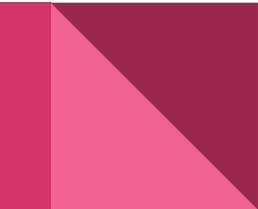
Dashboard



Graph Settings

Compare nodes?

Switch Simulation Speed(10sec/1hr):







# Time-series data display and Comparison

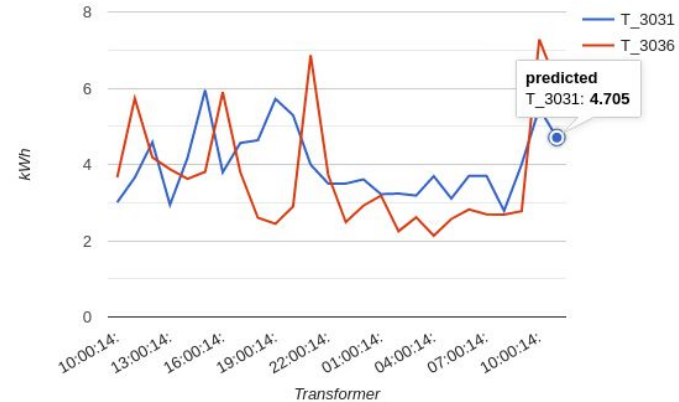
- 24-hr History Data
  - Click a node to display past 24-hrs kWh readings
  - Predicted kWh value shown based on ML prediction models
- Graph Settings
  - Compare Nodes option allows comparison of time-series history of 2 selected nodes
  - Option to switch simulation update speed - 1 hour(realtime) or 10 seconds



## Graph Settings

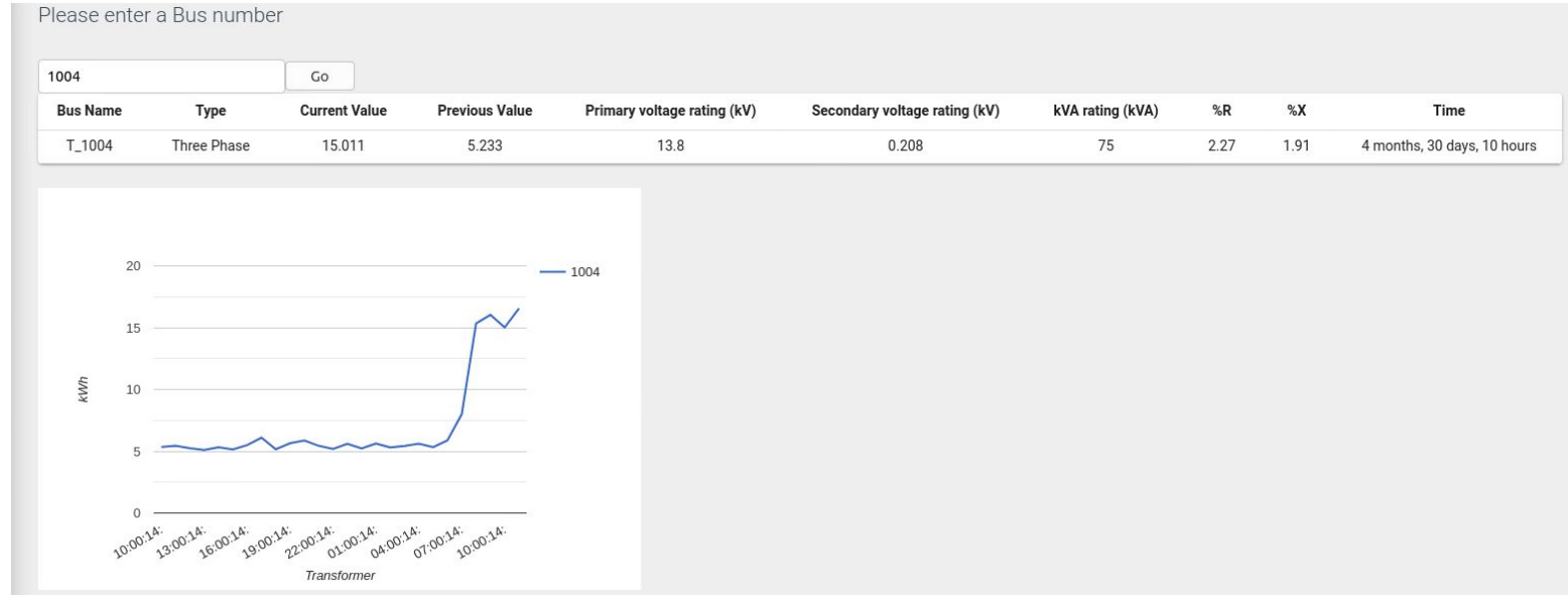
Compare nodes?

Switch Simulation Speed(10sec/1hr):



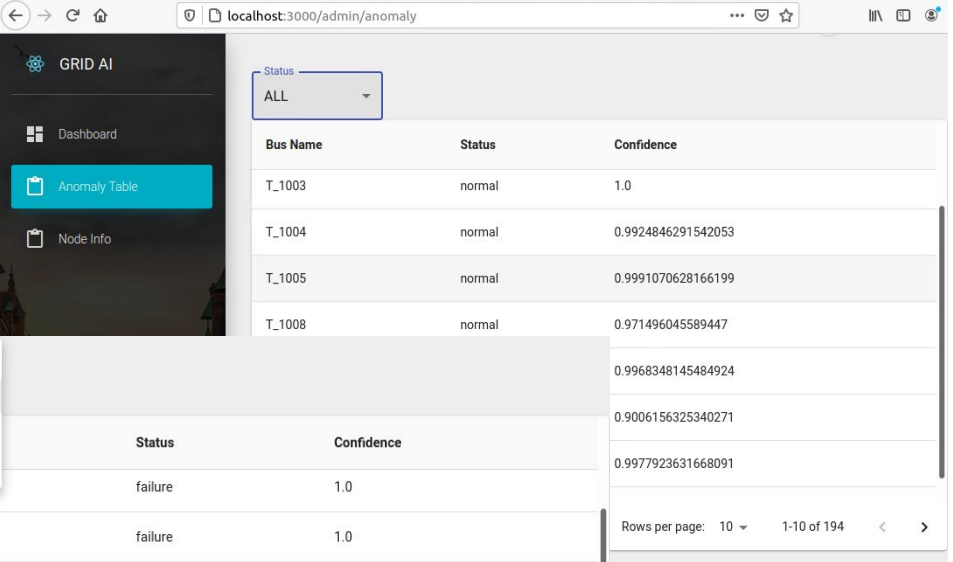
# Detailed Node Information

- Display Node Properties : Primary/Secondary voltage, Time running, Phase type, Resistance, Reactance, etc. (Properties vary based on phase type)



# Anomaly Data

- To view the predicted status of the node.
- Display the confidence level of the prediction in a table format.
- View the nodes by their Status “Normal”, “Spike”, or “Failure.”



The screenshot shows a web application interface for GRID AI. The main content area displays a table with the following data:

Bus Name	Status	Confidence
T_1003	normal	1.0
T_1004	normal	0.9924846291542053
T_1005	normal	0.9991070628166199
T_1008	normal	0.971496045589447
		0.9968348145484924
		0.9006156325340271
		0.9977923631668091

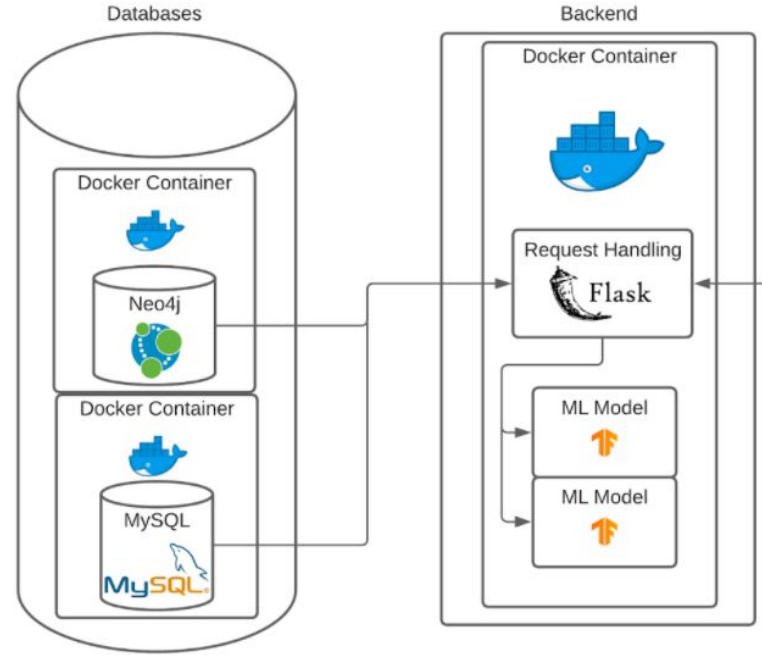
A dropdown menu is open, showing the following options:

- ALL
- Failure
- Spike
- Normal

The interface also includes a sidebar with navigation options: Dashboard, Anomaly Table, and Node Info. The bottom of the table shows pagination information: Rows per page: 10, 1-10 of 139.

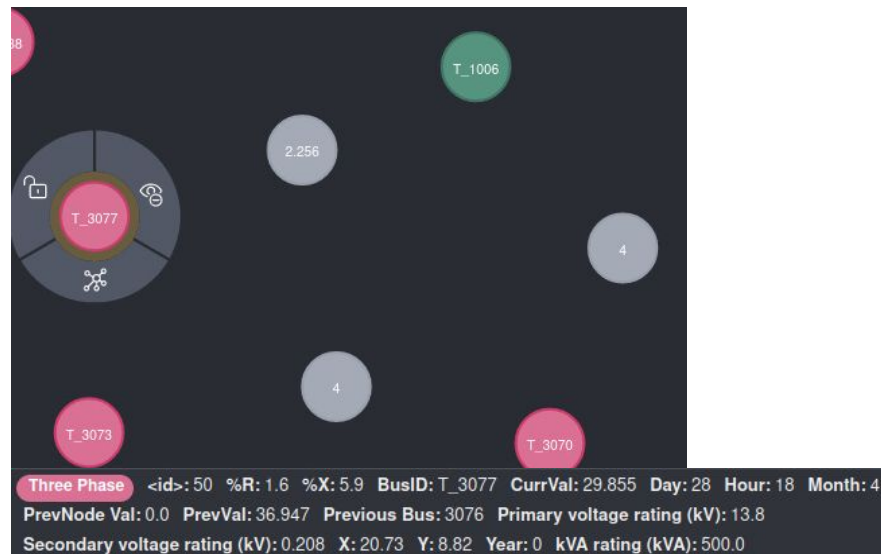
# Back-end Design/Implementation

- Main Requirements:
  - Data processing
  - Supply real-time data
- Three functional modules
  - Neo4j database
  - MySQL database
  - REST API



# Neo4j Database

- Graph-based database
  - Fast query response times
  - Practical power grid depiction
- Represent transformers in power grid
  - Store transformer features for ML
  - Up-to-date kWh output properties






# REST API

- Flask framework
  - Lightweight
  - Relatively easy learning curve
- Handle all data processing tasks
  - Provide access to necessary queries
  - Returns JSON formatted data
  - Implements ML models
  - Update Neo4j with time-series data



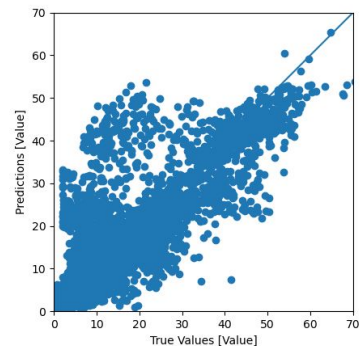


# ML Design/Implementation

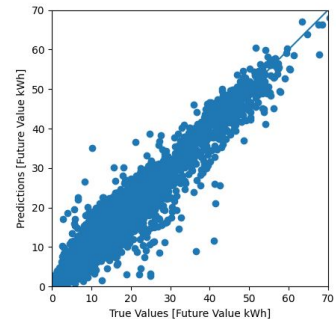
- Two key requirements
    - The ML models must predict the next kWh output for each node in the grid.
    - The ML models must predict the probability of each anomaly class.
  - Two types of models
    - One that predicts a continuous value
    - One that classifies a datapoint
  - Requires separate algorithms for each type.
  - The unique aspects of the three transformer types require their own version of the models
- 

# Linear Regression

- Linear Regression will output a continuous value
- Our implementation of Linear Regression
  - Multiple fully connected relu activated layers to add non-linearity
  - MAE loss function over MSE loss in order to limit the impact of outliers
    - Scalable and Generalized models (NFR)
- Feature Set
  - Static Transformer Data (Resistivities, Voltage Rating, etc)
  - Timestamp (insights on power usage by month and hour)
  - Previous Transformer in the line (Locality)
  - Previous and Current hour's data (Power Trend Context)



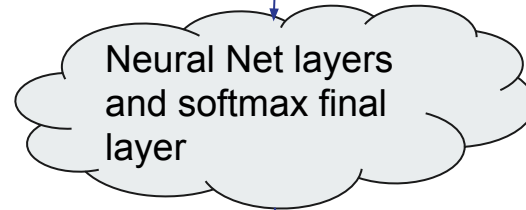
Non-linearity  
and context  
features



# Logistic Regression

- A continuous value does not tell us if there's an anomaly
- 3 classes of data
  - No Anomaly
  - Power Spike
  - Power Failure
- Softmax for  $K = 3$ 
  - $$\sigma(\mathbf{z})_i = \frac{e^{-\beta z_i}}{\sum_{j=1}^K e^{-\beta z_j}}$$
 for  $i = 1, \dots, K$ .
  - Returns 3 values summing to 1
  - Probabilities for each Anomaly Class
- Can use the same features

```
1 ,kVA rating,%R1,%R2,%R3,%X12,%X13,%X23,Year,Month,Day,Hour,Current Value,Prev Node,Prev Time,Anomaly
2 0,7.9677,0.665,1.33,1.33,2.256,2.256,1.504,2017,1,1,1,3.125,17.081,0.0,0
3 1,7.9677,0.665,1.33,1.33,2.256,2.256,1.504,2017,1,1,2,2.758,12.786,3.125,0
4 2,7.9677,0.665,1.33,1.33,2.256,2.256,1.504,2017,1,1,3,0.0,10.209,2.758,1
```

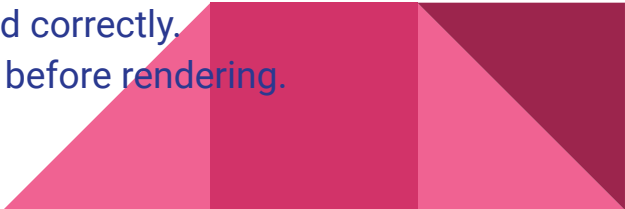


Anomaly 1 =  
Power Failure

```
[[7.2279609e-06 9.9999273e-01 2.7352313e-12]]
```

[Normal, Power Failure, Power Spike]

# Testing/Testing Results

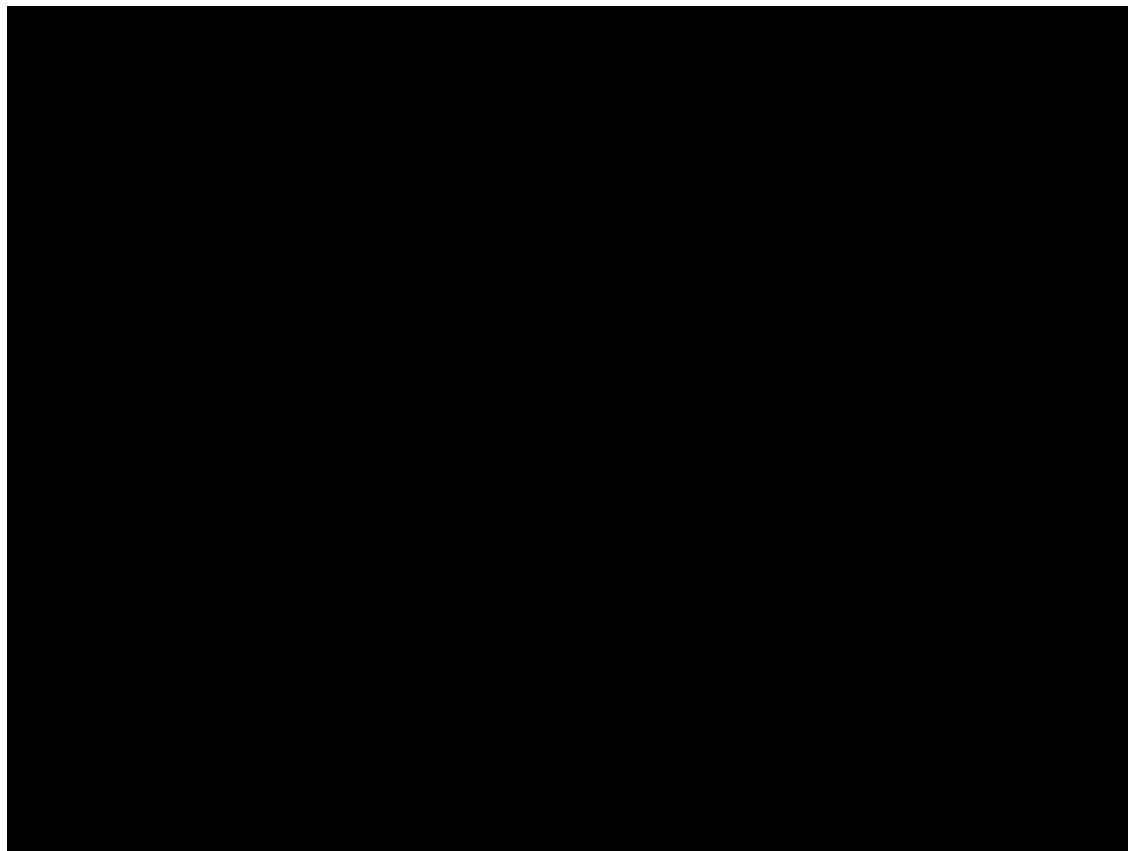
- **ML Models**
    - The average deviation of the original data is 6.97 kWh.
    - With the DNN Linear Regression model, this is 1.25 kWh
    - Correctly Classifying 96% of the dataset with the Logistic Models
  - **Backend**
    - Validated database queries manually
    - Verified functionality of endpoints with Postman
    - Identified bottleneck at startup due to database initialization
  - **Frontend**
    - Manually tested every component of the UI
    - Null/undefined errors were common when data was not loaded correctly.
    - Use of asynchronous functions to resolve data loading issues before rendering.
- 

# Engineering Standards

- IEEE/ISO/IEC 12207-2017: Software life cycle processes
  - Requirements Definition
  - Architecture Definition
  - Design Definition
  - Implementation
  - Integration



Demo



# The GridAI Team

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